



Human and Ecological Risk Assessment: An International Journal

ISSN: (Print) (Online) Journal homepage: <https://www.tandfonline.com/loi/bher20>

Temporal shifts in Americans' risk perceptions of the Zika outbreak

Branden B. Johnson & Marcus Mayorga

To cite this article: Branden B. Johnson & Marcus Mayorga (2020): Temporal shifts in Americans' risk perceptions of the Zika outbreak, Human and Ecological Risk Assessment: An International Journal

To link to this article: <https://doi.org/10.1080/10807039.2020.1820852>



Published online: 21 Sep 2020.



Submit your article to this journal [↗](#)



View related articles [↗](#)



View Crossmark data [↗](#)



Temporal shifts in Americans' risk perceptions of the Zika outbreak

Branden B. Johnson and Marcus Mayorga

Decision Research, Eugene, OR, USA

ABSTRACT

Cross-sectional surveys, despite their value, are unable to probe dynamics of risk perceptions over time. An earlier longitudinal panel study of Americans' views on Ebola risk inspired this partial replication on Americans' views of Zika risks, using multilevel modeling to assess temporal changes in these views and inter-individual factors affecting them, and to determine if similar factors were influential for both non-epidemics in the USA. Baseline Zika risk scores – as in the Ebola study – were influenced by dread of the Zika virus, perceptions of a near-miss outbreak, and perceived likelihood of an outbreak. Judgments of both personal risk and national risk from Zika declined significantly, and individual rates of news following predicted slower decline of perceived national risk in both cases. However, few other factors affected changes in Zika risk judgments, which did not replicate in a validation half-sample, whereas several factors slowed or increased the rate of decline in Ebola judgments of the U.S. risk. These differences might reflect differences in the diseases caused by these two viruses – e.g., Ebola's much greater lethality – but more longitudinal studies across multiple diseases will be needed to test that speculation. Benefits of such studies to health risk analysis outweigh the difficulties they pose.

ARTICLE HISTORY

Received 3 July 2020

Revised manuscript

Accepted 3 September 2020

KEYWORDS

risk perception dynamics;
temporal change;
Ebola; Zika

Introduction

As habitat destruction and fragmentation increase along with climate change, the combination of greater association of humans and wildlife with global transport greatly enhances the prospect for pandemics from zoonotic diseases, where viruses and bacteria skip from animals to humans and mutate to allow for human-to-human transmission. The novel coronavirus that causes COVID-19 is only the latest, and unlikely to be the last, of such threats. In this context, risk analysts need to understand many topics, including how risk perceptions do or do not change over time as epidemics and pandemics develop. Such changes can affect personal protective behavior, policy support, and preparedness for future outbreaks.

Cross-sectional surveys dominate risk perception research due to the cost and other logistical challenges of undertaking longitudinal quantitative research. While the cross-sectional approach has been enormously productive, it has limited value in probing the

dynamics of risk perceptions over time, which a few conceptual frameworks – such as that on the social amplification of risk (Kasperson et al. 1988) – have presented as significant for both risk management and risk communication. We take advantage of a longitudinal panel study of Americans' views on Zika risk to assess whether there were changes across time and individuals in these views. We also use a prior publication of a longitudinal panel study of Americans' views on Ebola risk (Mayorga and Johnson 2019) to determine if similar factors drove baseline and temporal changes in these two small outbreaks in the USA (much larger epidemics occurred elsewhere at the same time, in West Africa for Ebola, and Latin America and the Caribbean for Zika), and probe potential mediation effects. We find a significant mean decline in judgments of both personal risk and national risk over the entire survey period. Similar to the results of the Ebola virus study, reported dread around the Zika virus, perceptions of a near-miss outbreak, and perceived likelihood of an outbreak consistently predicted baseline risk scores. Additionally, individual rates of news following predicted a slower decline of perceived national risk over time in both cases. However, few other factors affected changes in Zika risk judgments over time, and these did not replicate in a validation half-sample, whereas several factors slowed or increased the rate of decline in Ebola judgments of the U.S. risk.

Ebola and Zika

Ebola virus transmission was identified decades ago, but came to the world's attention with the 2014–2015 outbreak in west Africa, particularly in Gambia, Liberia, and Sierra Leone. Ebola was highly lethal, transmitted by direct human contact with bodily fluids (e.g., blood, saliva, semen) when the infected person was symptomatic, and spread rapidly given local burial practices, slow publicity about its transmission routes, and limited local public health resources. Quarantines of 21 d for the infected were deemed effective at preventing transmission, although questions have been raised about this assumption (e.g., Haas 2014) and its effect on risk communication if found to be wrong (Johnson and Slovic 2015). Ultimately thousands died in West Africa.

Zika virus transmission also was relatively unknown to the public when a large breakout occurred in Brazil in 2015, and then elsewhere in South America and the Caribbean. In contrast to Ebola, Zika infection is rarely lethal and infected adults are often asymptomatic, but the virus can be transmitted multiple ways (primarily through transmission by mosquito vectors, but also sexually or through amniotic fluid from infected mothers to their fetuses or during childbirth). An outcome of maternal transmission, identified for the first time in the Brazilian outbreak, was varied birth defects in offspring, including microcephaly (unusually small and misshapen heads).

The USA was little affected by either outbreak in terms of actual disease cases. Two people infected with Ebola in West Africa died in the USA, two nurses in the USA were infected, and 11 patients (mostly infected in west Africa) were successfully treated in the USA. However, intense media coverage of these few cases toward the end of a heated national election led to high public concern and “elite panic” (Clarke and Chess 2008). Consequences included some stigmatizing behavior (e.g., against Africans or those who had been in Africa – Johnson 2019), enhanced Ebola infection screening at a

few airports to which people whose travel originated in affected African countries were directed, and some governors putting individuals into quarantine against public health professionals' advice. More cases occurred in the USA of Zika infection, but in contrast to Puerto Rico (with thousands of people infected by mosquitoes) only a few cases in the states themselves – in southern Florida and Brownsville, Texas – were local (mosquito-borne) vs. travel-related. Despite a heated election campaign as local transmission began in Miami, Zika did not become as politicized as did Ebola, and apparently garnered slightly less public concern; e.g., a 2017 Gallup Poll found – admittedly, 7 months after local transmission began on the mainland USA – that 7% of Americans polled thought someone in their family getting the Zika virus was “somewhat” or “very likely,” compared to 15% giving the same rating for Ebola at the height of concern in mid-October 2014, or 36% for swine flu in August 2009 (Gallup Poll 2017). According to the U.S. Centers for Disease Control and Prevention (CDC, 2020) data, the U.S. states featured 62 travel-related Zika cases in 2015; 4897 travel-related, 218 Florida and 6 Texas cases from local mosquito-borne transmission, and 47 other cases (sexual, laboratory, and unknown transmission routes) in 2016; and 437 travel-related, 2 Florida and 5 Texas local transmission, and 8 other cases in 2017. We also note that in the Americas generally, cases peaked in the first half of 2016 (for the year, 652,000 cases, 200,000 confirmed), before this longitudinal study began, and declined in almost all countries throughout 2017 (58,000 and 20,000), when the study ended (Pan American Health Organization 2020). All else equal, we should thus expect that accurate views of disease prevalence would result in mainland Americans' Zika risk perceptions to decline over the 2016–2017 period of this study, regardless of whether they were attending to the U.S. or Latin America/Caribbean news about Zika (we ask about both types of news following, but combine them for this analysis).

Temporal dynamics of risk perceptions

Concerns about the paucity of longitudinal studies allowing for assessment of risk perception's temporal changes and impacts have been voiced for at least 30 years (Loewenstein and Mather 1990), and are still applicable (Siegrist 2013). However, the nature of questions that researchers seek to answer with rare longitudinal studies has varied widely:

1. Do risk perceptions change, and how, when a singular event occurs, such as a disaster or policy change (e.g., Viscusi and O'Connor 1984; Smith and Michaels 1987)? This has been a major focus of longitudinal research.
2. Are risk perception changes accurate, in the sense that mean risk perceptions in the population rise when objective risks rise, and fall when objective risks fall? Economists have been particularly interested in this topic (e.g., Loewenstein and Mather 1990; Raude et al. 2019). Under the rubric of “elasticity-prevalence” of prevention decisions (e.g., Geoffard and Philipson 1996), their focus is the effect of the situation on mean risk perceptions in the population. For example, the incidence, prevalence, and mortality of an infectious disease are likely to vary over time, whereas much health behavior research has examined non-

communicable diseases, which are more stable on these epidemiological factors (Loewenstein and Mather 1990).

3. What is the relation between risk perceptions and risky or protective behavior? Brewer et al. (2004) argued that the accuracy of risk perceptions – defined here not as a match between mean perceptions and changes in disease incidence and prevalence, as just discussed, but as people engaged in risky behavior having higher risk perceptions – could be assessed in cross-sectional studies. However, the behavioral motivation hypothesis (high-risk perceptions motivate the adoption of protective behavior) and the risk reappraisal hypothesis (adoption of protective behavior reduces risk perceptions) require longitudinal panel or experimental studies to judge appropriately.

Only some of these and other literatures yield hypotheses about expected trends and reasons for them. Most would predict for Zika risk perceptions a downward trend over the 2016–2017 course of this study:

1. Accuracy: The elasticity-prevalence model would say that Zika risk perceptions will decline given that the actual number of cases was declining over this time for both the USA and the Americas generally.
2. Event valence: When studies of what happens when an event occurs are more than merely descriptive, they may assume a simple valence hypothesis: “bad” events raise risk perceptions, “good” events reduce them. Given the objective decline in Zika cases during the study period, this hypothesis would imply Zika risk perceptions should decline in light of this “good news.” Analyses of both specific events, and more abstract tests of hypotheses such as trust asymmetry (trust is easy to lose with bad events but hard to gain with good events; Slovic 1993) which find (dis)trust tends to persist regardless of event valence (Cvetkovich et al. 2002; White and Eiser 2005), may indicate a more complex situation than just a good-bad distinction.
3. Adaptation or habituation: This has been framed variously as hazard experience reducing risk perceptions as a function of current and expected future trends (Loewenstein and Mather 1990), or increasing familiarity tending people to progressively underestimate or neglect hazards over time (Raude et al. 2019, citing Thompson 2009, on repeated or prolonged exposure to a stimulus reducing cognitive, emotional or behavioral responses). Loewenstein and Mather (1990) did not find adaptation in their data,¹ but rather what they called partial adjustment, with a rise (drop) in concern lagging behind a rise (drop) in objective risk. They speculated partial adjustment might stem from delayed communication of objective risk data, an expectation of regression to earlier levels, or expectation of measurement error; they also suggested adaptation might be a long-run, and partial adjustment a short-run, phenomenon (Loewenstein and Mather 1990). Raude et al. (2019) found French Guineans experiencing a chikungunya epidemic in two within-person waves across 3 months (before case numbers decreased) increased protective behavior, consistent with the elasticity-prevalence hypothesis. However, perceptions of personal infection risk decreased, which further analyses

(e.g., no decrease in risk perceptions for those engaged in a specific protective behavior) suggested was more consistent with the risk habituation than the risk reappraisal hypothesis. In an eight-wave, 5-year longitudinal design before and after a waste incinerator began operation, Lima (2004) found a habituation (adaptation) effect among closer neighbors, whose risk perceptions decreased over time.

4. Risk reappraisal: If people adopt protective behaviors over time, their risk perceptions should drop as well to reflect this new condition: “I’ve acted to reduce my risk, so I believe I’m less at risk than before” (Brewer et al. 2004).

This collective expectation that the Zika case in 2016–2017 should reveal declining risk perceptions, if with divergent explanations, does not exhaust the literature: Loewenstein and Mather (1990) also noted the occurrence of panics (in which risk perception drastically departs from objective risks or overall perception trends), particularly for unfamiliar hazards, and the Raude et al. (2019) data showed the elasticity-preference pattern of *rising* risk perceptions when objective risks are rising. But this should be the dominant assumption:

H1. *Americans’ perceptions of personal and U.S. risk from the Zika virus in 2016–2017 should show declines.*

The above models all focus on average trends, without noting (much less addressing) that each respondent may have his or her own personal trend, and that these personal trends may reveal intriguing and varied explanations across individuals. As noted in the Introduction, longitudinal panel studies of risk perception² – i.e., where within-person changes in risk perceptions are assessed at two or more points in time – are rare because of their cost, and as a result when implemented they tend to post only two surveys (e.g., Flint 2007; Cutchin et al. 2008; Renner et al. 2008; Visschers and Siegrist 2013; Trumbo et al. 2014; Champ and Brenkert-Smith 2016; Raude et al. 2019). Such two-survey panels allow for identification of simple trends in the magnitude of judged risk – e.g., greater judgments of petrochemical health risks after a refinery explosion (Cutchin et al. 2008) or a decline in judged hurricane risks over a quiet period in the Gulf of Mexico (Trumbo et al. 2014) – and can identify factors important at each time point in these average judgments, but not assess whether factor impact varies across both time and individuals. Designs with three or more data collection points with the same subjects can be more informative, as they allow rates of change in risk perception – and in individual characteristics that might affect these judgments – to vary across individuals (e.g., in Americans’ reactions to the 2008 financial crisis across seven surveys; Burns et al. 2012).

The inspiration for this paper was an article by Mayorga and Johnson (2019) on dynamics of perceived personal, USA, and global risk from Ebola, and concern that a large Ebola outbreak would occur in the USA within the next year. These authors had conducted a longitudinal study of Americans’ Ebola views in five surveys between December 2014 and May 2015,³ although only four of the surveys included data for their longitudinal analysis. They found no significant temporal trend in personal risk judgments, and little variation across individuals. However, the other three dependent variables exhibited significant declines over time. Initial U.S. risk ratings were higher

among those who closely followed Ebola news, dreaded Ebola more, thought the USA had had a “near miss” for a large outbreak, and thought such an outbreak highly likely. People who perceived a “near miss” or were more knowledgeable about Ebola transmission routes exhibited steeper drops in judged U.S. risk, while those seeing a higher likelihood of a future outbreak exhibited slower declines, over time. For global risk again news following, dread, and “near miss” perceptions led to higher initial ratings, as did exposure knowledge; again “near miss” views accelerated, and likelihood beliefs slowed, declines in global risk judgments over time. Concern at baseline was driven by news following, low trust in the CDC, dread, “near miss” views, judged likelihood, and belief in hierarchist views of society. Likelihood reduced the rate of decline in concern, while dread and “near miss” beliefs increased this rate of decline (the latter was the only finding that did not replicate in the validation half of the sample).

Our own longitudinal panel study of Americans’ Zika views offered the potential to assess both dynamic inter-individual responses to that particular U.S. non-pandemic, and whether there were similar dynamics and influential factors for Ebola and Zika responses in personal and U.S. risk judgments (the two dependent variables in common across these studies with three or more observations over time). Despite differences in transmission routes, lethality, and other characteristics of these two viral diseases, these factors may not make a substantive difference in risk responses, at least for “outbreaks” as small as these were in the mainland USA. If there had been more cases, or more prominent cases of Zika infections, the combination of greater motivation among individuals and greater dissemination of disease-specific information among threatened populations might promote greater divergence in such dynamics. But our default assumption was that we should see roughly similar patterns in Americans’ responses over time to Ebola and Zika incidence in the mainland USA. Thus we presumed:

H2. *Baseline factors in Americans’ risk perceptions will be similar for the Ebola and Zika cases.*

H3. *Factors influencing inter-individual differences in downward trends in Americans’ risk perceptions will be similar for the Ebola and Zika cases.*

Methods and materials

Sampling

Data came from a four-wave longitudinal panel study over 9 months – July 19–24, 2016 (Wave 1, $n = 1047$), August 1–13, 2016 (Wave 2, $n = 989$), January 25–February 6, 2017 (Wave 3, $n = 805$), and April 13–24, 2017 (Wave 4, $n = 743$) – using the Decision Research online panel, a diverse, quota-recruited (gender, age, education) sample of American adults. Its use sharply reduced the longitudinal study’s costs relative to use of a nationally representative sample. This study was reviewed by the Decision Research Institutional Review Board (IRB) for adherence to ethical research standards. The study was determined to be exempt by the Human Protections Officer, posing no more than minimal risk to participants (under federal regulation 45 CFR part 46). Participant consent was obtained through the Decision Research web panel privacy and participation agreement.

Table 1. Measures.

Measure	Scale	Source
Judged risk of Zika to self and the USA: "How much risk does Zika pose to you or your family [the USA]?"	1 <i>no risk</i> , 6 <i>very high risk</i>	Mertz et al. (1998)
News following (mean): "How closely are you following news about Zika in Latin America and the Caribbean [in the 50 states plus Washington, D.C.]?"	1 <i>not at all</i> , 4 <i>very closely</i>	Harvard School of Public Health/SSRS (2014)
Dread: "Where 'dread' means to be in terror of, or fear intensely, how much do you dread Zika?"	1 <i>no dread</i> , 6 <i>very high dread</i>	Adapted from Slovic (1987) and Fischhoff et al. (1978)
Zika as a "near miss" disaster (mean): "To what extent was Zika in the USA almost a disaster?", "How close was Zika in the USA to being a disaster?", and "To what extent was it just by chance that a bad Zika outbreak in the USA did not happen?"	1 <i>not at all</i> close/close/chance, 11 <i>extremely</i> close/close/reliant on chance	Adapted from Dillon et al. (2014)
Likelihood of a future outbreak, "How likely do you think it is that there will be a large outbreak of Zika infections in the USA in the next <i>five years</i> ?"	1 <i>not at all likely</i> , 4 <i>very likely</i>	Mayorga and Johnson (2019)
Cultural Cognition Worldviews Scales (Hierarchical-Egalitarian, 13 items; Individualist-Communitarian, 17 items; means: e.g., "We have gone too far in pushing equal rights in this country"; "The government interferes far too much in our everyday lives"	1 <i>strongly disagree</i> , 6 <i>strongly agree</i>	Kahan et al. (2007)
Zika knowledge (15 items, on causes, transmission, outcomes, and geographic incidence; count of correct answers): e.g., "A person can catch Zika from sitting next to someone who has been infected by the Zika virus"	1 <i>strongly disagree</i> , 6 <i>strongly agree</i>	Kahan et al. (2017)
Trust in CDC: "Please rate how much you trust the U.S. Centers for Disease Control and Prevention to protect Americans from the Zika virus"	1 <i>do not trust at all</i> , 5 <i>fully trust</i>	Adapted from Johnson and White (2010)

Measures

Age, gender (female as reference category), and education (treated as an ordinal variable) were collected for all panelists during recruitment; the dependent variables (personal and U.S. risk) and eight other independent variable measures and their sources are reported in Table 1. The personal and U.S. risk judgments in Survey 2 were collected only after information was provided to survey respondents about the official confirmation of local (mosquito) transmission of Zika in a Miami, Florida neighborhood a few days earlier. This was not an experimental manipulation, which has been done in some risk dynamics studies, but an attempt to assess reactions to a very recent event, compared to reactions in Survey 1. However, there might have been a jump in judged risk since the Survey 1 survey 3 weeks earlier due to this survey-provided information, separate from any change due to respondents' exposure to mass and social media, and to conversations with people in their social network. Omission of Study 2 did not change our findings. Subsequent risk ratings used in this analysis were collected *before* information manipulation experiments in Surveys 3–4.

Analysis

Baseline risk and individual trends in risk judgments were modeled using a multilevel approach for longitudinal data (Siller and Sigman 2008; Goldstein 2011). Data consisted

Table 2. Descriptive statistics.

Measure	Survey	M	SD	Median	α
Perceived dread (1–6)	4	2.81	1.42	3	
Zika as a “near miss” (1–11)	4	5.29	2.55	5.33	.90
Likelihood of outbreak (1–4)	4	2.45	0.88	2	
Cultural cognition worldviews (1–6)	1				
Hierarchical-Egalitarian (HE)		3.17	1.02	3.31	.87
Individualist-Communitarian (IC)		3.82	0.79	3.82	.83
Zika knowledge (0–15)	3	4.45	0.65	4.47	
Trust in the CDC (1–5)	4	3.17	0.89	1.49	
Repeated-measures means (SD)		Survey 1	Survey 2	Survey 3	Survey 4
Judged risk (1–6)					
Personal	1–5	2.99 (1.42)	2.97 (1.25)	2.57 (1.33)	2.74 (1.26)
USA	1–4	3.59 (1.29)	3.88 (1.12)	3.56 (1.14)	3.42 (1.16)
News following (1–4) ^a	2, 3, 4		2.55 (0.85)	2.34 (0.89)	2.23 (0.87)

^aAs news following was measured at three instead of four points, to retain focus on change over time as a predictor we fit a linear equation to the three waves, then extracted the slope coefficient for each participant and substituted this variable in the MLM analyses.

of up to four time points (level-1) nested within people (level-2). To reduce capitalizing on chance, a half-sample pseudo-replication approach randomly selected half of the sample for the initial modeling ($n = 310$), then fit a revised model based on those initial results to data from the other half-sample as a confirmatory test ($n = 370$).

A series of multilevel models for longitudinal data were built, using R 3.3.1 software and the *lme4* package using maximum-likelihood estimation. Multilevel modeling (MLM) provides several benefits for longitudinal data compared to general linear models (e.g., regression or repeated-measures ANOVA). MLM allows between-person linear slopes to vary randomly (i.e., so we can assess whether inter-individual differences affect the rate of the trend) while also testing for group trends (i.e., did people, on average, show an increase or decrease in judged risk over time?). All predictors (except demographic controls) were mean-centered. Two unconditional models were first run to test variability in dependent variables for the initial rating in July 2016 (intercepts) and growth trajectories (slopes) between subjects. Linear time was coded in the number of months from the first survey (0, 1, 7, 9). Then the 11 level-1 predictors specified in Table 1 were added to test their associations with baseline judged risk. Next, the interactions of the predictors with time were added (i.e., relationships between the individual difference variables and between-person temporal trends). Next, non-significant predictors were removed from the model. Lastly, the final model was fit to the second half of the sample (i.e., pseudo-replication).

Results

Sample

The 989 respondents to Survey 1 were, compared to American Community Survey 2016 1-year estimates by the U.S. Census, more female (61.9%, vs. 51.4% among the U.S. adults), younger ($M = 42.6$, $SD = 13.2$, median = 40, vs. $M = 47.3$, $SD = 18.5$, median = 49; latter estimates calculated from Census data by the first author), and better educated (48.6% bachelor’s degree or better, vs. 30.6% among adults 25+ years old).

Table 3. Multilevel modeling of judged risk.

Variable	Personal risk	PR	U.S. risk	PR
Fixed Effects: Initial Rating				
γ_{00} Intercept	1.43	1.79	1.37	1.57
γ_{10} Time (weeks)	−0.044*** (0.01)	−0.037*** (0.006)	−0.037*** (0.007)	−0.029*** (0.006)
γ_{01} News Following (slope) ^a	0.556 (0.430)		−0.364 (0.293)	
γ_{02} Trust in the CDC	0.261 (0.050)		0.022 (0.041)	
γ_{03} Dread	0.208*** (0.420)	0.249*** (0.036)	0.136*** (0.034)	0.167*** (0.030)
γ_{04} "Near Miss"	0.118*** (0.026)	0.090*** (0.022)	0.161*** (0.021)	0.118*** (0.018)
γ_{05} Worldviews HE	0.154** (0.058)	0.075* (0.038)	0.079 (0.047)	
γ_{06} Worldviews IC	−0.065 (0.074)		−0.101 (0.060)	
γ_{08} Likelihood	0.294*** (0.061)	0.229*** (0.052)	0.266*** (0.049)	0.369*** (0.042)
γ_{09} Zika Knowledge	−0.155* (0.074)	−0.221** (0.068)	0.078 (0.059)	
γ_{012} Age	−0.004 (0.003)		0.008 (0.003)	
γ_{013} Gender	0.113 (0.098)		−0.216 (0.078)	
γ_{014} Education	0.040 (0.033)		−0.004 (0.027)	
Fixed Effects: Rates of Change				
γ_{11} News Following ^a	0.116 (0.066)		0.148* (0.062)	0.301*** (0.063)
γ_{12} Trust in the CDC	0.027*** (0.008)	−0.005 (0.007)	0.029*** (0.007)	0.003 (0.063)
γ_{13} Dread	−0.008 (0.006)		−0.005 (0.006)	
γ_{14} "Near Miss"	0.001 (0.001)		0.007 (0.004)	
γ_{15} Worldviews HE	−0.012 (0.009)		−0.004 (0.008)	
γ_{16} Worldviews IC	0.016 (0.011)		0.011 (0.011)	
γ_{18} Likelihood	0.007 (0.009)		0.005 (0.009)	
γ_{19} Zika Knowledge	−0.014 (0.011)		0.022* (0.011)	0.016 (0.010)
Variance Components: Level 1				
σ_e^2 Within-person	0.690	0.680	0.682	0.613
Variance Components: Level 2				
σ_0^2 In initial risk	0.536	0.596	0.305	0.474
σ_1^2 In rate of change	0.002	0.003	0.0005	0.002
σ_{01} Covariance	−0.019	−0.036	−0.013	−0.030

^aAs news following was measured at three instead of four points, to retain focus on change over time as a predictor we fit a linear equation to the three waves, then extracted the slope coefficient for each participant and substituted this variable in the MLM analyses. PR = pseudo-replication results from the second half of the sample. * $p < .05$ ** $p < .01$ *** $p < .001$

Item responses

Descriptive statistics and the panel wave in which measures were collected are reported in Table 2. Judged personal risk declined over time, although the low was in Survey 3 (during winter, when mosquitoes are absent) with an intermediate value in Survey 4, when the mosquito season had begun except in the northernmost tier of the lower 48 states. There was no difference in mean personal risk judgments over the first two surveys, despite the announcement in Survey 2 of local Zika transmission commencing in Florida, officially announced 3 d before the survey's launch. The hundreds or thousands of miles between most respondents' residences and the Florida site may explain lack of response on this measure to this information in Survey 2. However, there was a substantial increase in mean judgments of the U.S. risk in Survey 2, which may reflect exposure to this survey information and/or exposure to this information via other sources (Johnson 2018 reported that residents of the U.S. states with more than 100 travel-related Zika cases exhibited higher personal risk and concern judgments, and reported more following of Zika news, in January 2017 than did Americans elsewhere, supporting at minimum the latter interpretation). After this point, mean U.S. risk judgments reverted to the Survey 1 level in Survey 3, and declined further in Survey 4. Thus both risk judgments declined overall over time, consistent with H1, and exhibited sufficient variation over time to justify MLM of temporal change.

Modeling

Modeling results appear in Table 3. The top section of the table (“Fixed Effects: Initial Rating”) shows the modeling coefficients of predictors on baseline (Survey 1) risk judgments. The middle section (“Fixed Effects: Rates of Change”) shows how these effects interact with time. In other words, did the variable predict the *slope* in the individual-level ratings of perceived risk? The bottom sections include variable components for each model. Level 1 variance components denote the residual variance of the dependent variable in the model; level 2 variance denotes the variance in the intercepts, slopes, and the covariance between the intercept and slope, respectively. For each dependent variable, results are presented in one column for the initial split-half results for all predictors (saturated model), and in the second column for the pseudo-replication split-half for those predictors that were statistically significant in the initial analyses.

The negative signs for time for both dependent variables confirm statistically significant decline over time, consistent with H1. Baseline judged personal risk was higher for people with higher dread, greater belief in the USA having had a “near miss” for disaster, hierarchist worldviews, greater belief in the likelihood of a large Zika outbreak in the next 5 years, and with less correct knowledge about Zika, in both the initial and pseudo-replication half-samples. There was a slower rate of decline in personal risk judgments among those with trust in the CDC in the initial half-sample, but this was not repeated in the pseudo-replication half-sample; no other factors significantly affected rates of change.

Comparing these results to the equivalent Ebola findings, personal risk judgments, in that case, did not change over time. Baseline personal risk ratings for Ebola were higher among those with high news following scores, high dread, high “near miss” beliefs, high likelihood beliefs, hierarchist worldviews (a finding not pseudo-replicated), lower ages, and low knowledge of how Ebola was transmitted (Mayorga and Johnson 2019). Thus for both Ebola and Zika baseline ratings of personal risk were associated with dread, “near miss,” likelihood, and knowledge factors, and (partly) also with hierarchist worldviews. They differed in whether there was a decline in judged personal risk over time, and baseline ratings of personal Ebola risk were associated with additional variables (news following, age) not associated with Zika judgments. These results were partly consistent with H2 and inconsistent with H3.

As for judgments of the U.S. Zika risks, at baseline these were high for people with higher dread, greater belief in “near miss,” and greater belief in outbreak likelihood, in both the initial and pseudo-replication half-samples. There was a slower rate of decline in the U.S. risk judgments for those who followed Zika news more in both half-samples, and in the initial half-sample only for both trust in the CDC and greater Zika knowledge.

Comparing these results to the equivalent Ebola findings, baseline U.S. risk ratings for Ebola were higher among those with high news following scores, high dread, high “near miss” beliefs, high likelihood beliefs, and (marginally) low trust in CDC. There was a sharper decline in the U.S. Ebola risk ratings among those with high “near miss” beliefs and high Ebola transmission knowledge, with slower declines among those with high likelihood beliefs (Mayorga and Johnson 2019). Thus for both Ebola and Zika baseline ratings of the U.S. risk were associated with dread, “near miss,” and likelihood

factors. Only the objective knowledge measures were influential (at least partly) for temporal changes in both virus responses, but they operated in different directions: high Ebola transmission knowledge steepened the decline in the U.S. Ebola risk ratings, while high Zika knowledge (in the initial half-sample only) flattened the decline for the U.S. Zika risk ratings. Other temporal-change factors differed across the viruses, with “near miss” beliefs increasing and likelihood beliefs decreasing the rate of change in Ebola ratings, and news following and trust in the CDC (initial half-sample only) decreasing the rate of change in Zika ratings. These results were partly consistent with H2 and inconsistent with H3.

Discussion

Major findings

Our first hypothesis, of overall downward trends in both personal and U.S. risk ratings for Zika over time, was confirmed, despite ups and downs in averages from one wave to another of this longitudinal panel study. Our second hypothesis, of similarity in factors influencing baseline risk across the Ebola study (Mayorga and Johnson 2019) and the current Zika study, was largely confirmed: for personal risk, dread, “near miss” beliefs, expected likelihood of a near-future Zika outbreak, low knowledge of virus transmission; hierarchist cultural biases were a factor for Zika and were initially for Ebola but not pseudo-replicated; for the U.S. risk, dread, “near miss” beliefs, likelihood). Our third hypothesis, about similar inter-individual factors influencing different downward trends across Ebola and Zika, was largely unsupported. Besides the absence of any change in personal risk perceptions for Ebola, no inter-individual differences affected trends in Zika personal risk perceptions in both half-samples; Zika U.S. risk perceptions declined more slowly for people who followed the Zika news, while for Ebola such perceptions dropped more quickly with high “near miss” beliefs and transmission knowledge, and more slowly with high likelihood beliefs.

Research implications

Multiple possibilities could explain the downward trend in personal and U.S. risk perceptions for Zika over this 9-month period: accurate assessments of objective Zika prevalence (elasticity-prevalence), which is confounded with the “good news” hypothesis (e.g., is it the awareness of objective risk, or of the trend implied by news coverage?); risk reappraisal as a result of adopting protective behaviors that lower one’s sense of personal risk (it is not clear what equivalent would apply to the U.S. risk, unless people generalize from personal risk perceptions); or adaptation or habituation, in which familiarity dulls the sense of harm.⁴ The data reviewed here do not allow us to definitively identify the best explanation. We note that risk reappraisal seems conceptually implausible as a reason for the decline in the U.S. risk perceptions, and that controlling for the downward trend shaped by time alone, self-reported attention to news coverage of Zika increased rather than decreased both risk perceptions, as well as judged need for the USA to act against Zika (Wirz et al. 2020).

We found that a core set of beliefs – particularly dread, beliefs that the USA had had a “near miss” for a large outbreak, and judged likelihood of a large outbreak in the near future – was associated with risk perceptions at baseline (i.e., the first wave of the longitudinal panel) for both Ebola and Zika. This is consistent with the notions that hazards that evoke dread or can yield catastrophic results are particularly likely to prompt high-risk perceptions (Slovic 1987), and that emotion is a substantial factor as well (Slovic 1993). It is unclear whether we should attribute this apparent common core to the nature of the threat (both infectious diseases), personal traits (e.g., a neurotic personality) that predispose certain people to respond strongly to these three questions, and/or a social environment (e.g., the inadequate U.S. healthcare system) that fosters a sense of vulnerability. This study cannot answer these questions, but they are worth further consideration. We note that dread, “near miss” beliefs, and likelihood were only moderately associated with a measure of risk sensitivity ($rs = 0.38\text{--}0.46$), the mean of personal and U.S. risk judgments in Survey 1 for eight diverse, potentially hazardous events or entities ($\alpha = 0.92$; airplane crashes, gun control, nuclear power, genetically modified organisms, abortion, climate change, pesticides, food additives). Thus it does not appear that these factors in baseline disease risk perceptions can be explained solely by appeal to the notion of risk sensitivity.

Our initial supposition that the dynamic longitudinal patterns of risk perceptions of low-scale (in the USA) and close-in-time outbreaks of two viral diseases would be similar was not supported by the evidence, e.g., Ebola personal risk exhibited no change⁵ (Mayorga and Johnson 2019) while Zika personal risk judgments declined; Ebola showed more inter-individual variation in the U.S. risk perception trends than did Zika. The literature we reviewed focused on why there might be a particular trend in risk perceptions overall, but other than (potentially) differences in protective action leading to risk reappraisal (Brewer et al. 2004), none of these hypotheses can explain the relative lack of inter-individual differences altering Zika risk perception trends.

The fact that the health conditions produced by the two viruses differ on multiple dimensions, it is tempting to posit *post hoc* that Ebola’s greater lethality explains why personal risk perceptions did not change over 5 months of surveys by Mayorga and Johnson (2019), despite the two pseudo-outbreaks being very similar in low overall incidence on the mainland USA (if much higher for Zika) and low aggregate transmission potential (Ebola is infectious when someone is symptomatic; Zika is infectious via sex or maternal transmission to a fetus, but otherwise requires a mosquito vector that during 2016–2017 was possible on the mainland USA in few, very small geographic areas). However, this lethality explanation – even if correct – seems less plausible to apply to the greater number of inter-individual factors in temporal trends for Ebola views.

These speculations suggest that the dynamics of risk perception over the current coronavirus pandemic would be much more volatile and closer to the Ebola than the Zika case, as this pandemic is by definition much more widespread and intensive in the USA (e.g., over 175,000 deaths as of the end of August 2020) than either of the other two outbreaks. Yet systematic analysis will be needed to root this speculation firmly in models of risk perception. Future research that uses medical taxonomies of disease to develop dimension-specific questions (i.e., on causes, transmission routes, and consequences of infection) for surveys, with replications across multiple diseases, would be

needed to rule in or out this disease-dimension hypothesis for risk perception dynamics. The same would be true, if with different dimensions, for probing similarities or differences in temporal dynamics regarding non-disease threats. Another major group of *post hoc* explanations would entail time-specific variation (e.g., in mass or social media coverage and exposure; signal events, occurring by chance, that drastically alter public conceptions of the hazard or its past or future course), which require detailed qualitative assessment outside the present scope.

Limitations

This study's findings about several factors in judged risk over time are limited by dependence on self-report and non-experimental design. Concurrent use of psychophysical (e.g., to measure concern), observational, or other independent measures of changes in self-reported reactions could address the first issue in future longitudinal research. Although the method used here allowed us to take advantage of measures assessed late in the study (e.g., outbreak expectation in April 2017) to understand reactions as early as the baseline survey in July 2016, we have assessed associations only. Probing causal relationships would require either changes in the temporal sequence of measures or experimental manipulations. Some factors in the dynamics observed here were omitted, such as potential mediators for cultural effects. Because the discussion of similarity in risk perception dynamics for non-pandemics currently includes only two examples – Ebola and Zika in the USA during 2014–2017 – future research also needs to confirm whether there is a similar decay rate for concern and judged risk for other hazards under similar conditions, and whether similar results obtain in non-U.S. populations. The authors are collecting data on the U.S. coronavirus views to address some of these issues.

Conclusion

This analysis, in conjunction with the earlier Mayorga and Johnson (2019) study, illustrates the benefit of MLM in longitudinal studies with at least three data collection points to risk perception studies in general, and to health-focused analyses in particular. We can supplement the “baseline” explanations offered by more typical cross-sectional surveys with a more dynamic understanding of how, and why, responses vary over time, including individual variations. Extension of this approach to other cases, with suitable emendations of variables collected from both survey respondents and other sources, can expand our understanding of risk perception dynamics in general and help test specific models of such dynamics (e.g., SARF).

We also need to incorporate these approaches into human and ecological risk assessment more broadly. As noted in the Introduction, zoonoses are likely to increase due to several factors, making the dynamics of public response increasingly important. Our focus here was on risk perceptions rather than on personal protective behavior or policy support, but there are important implications for the latter variables for both human health and ecological health. For example, will people subject to repeated pandemics, or with slower rates of decline in risk perception for a given epidemic, be more willing to

support habitat and species conservation, or more willing to see bats and other zoonotic vectors eliminated? Will people be willing to undo globalization, which among its benefits has helped improve public health, as an ineffective means to protect themselves against pandemics as well as against economic competition? The more we understand the temporal dynamics of risk responses, the better prepared we will be for assessing related human and ecological risks and their personal and policy implications.

Notes

1. It is unclear whether this failure reflects the data used, dominated by official statistics and frequency of mass media coverage. Although the authors noted that the three measures were highly correlated, only three of 18 measures across nine hazards were public opinion data and thus “risk perceptions” (~1955–1985 unemployment; ~1956–1986 inflation; ~1965–1987 fear of crime).
2. Note that comparison of early respondents to late respondents in a single cross-sectional survey, or cross-sectional surveys of different samples from the same population at different times, do not study risk perception dynamics in the sense used here, as results may confound changes over time in population responses with other differences between these different-timing respondent groups (e.g., Ibuka et al. 2010). This does not make these other designs illegitimate, but we must grasp these various designs’ differing implications for exploring dynamics of risk perceptions.
3. Specifically, the first survey in the Ebola panel study (Mayorga and Johnson 2019) was launched 3 weeks after the second death in the U.S. from Ebola (November 18, 2014). The five surveys included 815 (December 8–21, 2014), 748 (January 2–12, 2015), 704 (February 2–9, 2015), 666 (March 16–24, 2015), and 625 (May 8–20, 2015) respondents; all May respondents completed all five surveys, or 76.7% of those recruited in December 2014. Median gaps between these surveys for individual respondents were 25, 31, 27, and 54 days, respectively.
4. Two other approaches raised by Loewenstein and Mather (1990) are moot here. Partial adjustment, in which changes in public opinion lag objective changes in risk, cannot be assessed without a clear way to define “lag” when surveys are infrequent and exhibit varying intervals, and objective measures are currently available only in annual figures. Panic does not apply in the sense of a large departure from objective trends, nor is it clear that there is a departure from overall perception trends.
5. Mayorga and Johnson (2019) suggested this lack of a trend in personal Ebola risk perception might be due to a floor effect as well as greater variance in later waves than seen in the U.S. and global risk ratings: on a 1–6 scale, means over four waves were 2.45–2.60.

Acknowledgments

We appreciate comments by two anonymous reviewers. This material is based upon work supported by the U.S. National Science Foundation under Grant No. 1644853.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This material is based upon work supported by the U.S. National Science Foundation under Grant No. 1644853.

References

- Brewer NT, Weinstein ND, Cuite CL, Herrington J. 2004. Risk perceptions and their relation to risk behavior. *Ann Behav Med.* 27(2):125–130. doi:[10.1207/s15324796abm2702_7](https://doi.org/10.1207/s15324796abm2702_7)
- Burns WJ, Peters E, Slovic P. 2012. Risk perception and the economic crisis: a longitudinal study of the trajectory of perceived risk. *Risk Anal.* 32(4):659–677. doi:[10.1111/j.1539-6924.2011.01733.x](https://doi.org/10.1111/j.1539-6924.2011.01733.x)
- Champ PA, Brenkert-Smith H. 2016. Is seeing believing? Perceptions of wildfire risk over time. *Risk Anal.* 36(4):816–830. doi:[10.1111/risa.12465](https://doi.org/10.1111/risa.12465)
- Clarke L, Chess C. 2008. Elites and panic: more to fear than fear itself. *Soc Forces.* 87(2):993–1014. doi:[10.1353/sof.0.0155](https://doi.org/10.1353/sof.0.0155)
- Cutchin MP, Martin KR, Owen SV, Goodwin JS. 2008. Concern about petrochemical health risk before and after a refinery explosion. *Risk Anal.* 28(3):589–601. doi:[10.1111/j.1539-6924.2008.01050.x](https://doi.org/10.1111/j.1539-6924.2008.01050.x)
- Cvetkovich G, Siegrist M, Murray R, Tragesser S. 2002. New information and social trust: asymmetry and perseverance of attributions about hazard managers. *Risk Anal.* 22(2):359–367. doi:[10.1111/0272-4332.00030](https://doi.org/10.1111/0272-4332.00030)
- Dillon RL, Tinsley CH, Burns WJ. 2014. Evolving risk perceptions about near-miss terrorist events. *Decis Anal.* 11(1):27–42. doi:[10.1287/deca.2013.0286](https://doi.org/10.1287/deca.2013.0286)
- Fischhoff B, Slovic P, Lichtenstein S, Read S, Combs B. 1978. How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy Sci.* 9(2):127–152. doi:[10.1007/BF00143739](https://doi.org/10.1007/BF00143739)
- Flint CG. 2007. Changing forest disturbance regimes and risk perceptions in Homer, Alaska. *Risk Anal.* 27(6):1597–1608. doi:[10.1111/j.1539-6924.2007.00991.x](https://doi.org/10.1111/j.1539-6924.2007.00991.x)
- Gallup Poll. 2017. Zika virus not a worry to Americans. [accessed 2018 Mar 26]. <http://news.gallup.com/poll/207422/zika-virus-not-worry-americans.aspx>.
- Geoffard P-Y, Philipson T. 1996. Rational epidemics and their public control. *Int Econ Rev.* 37(3):603–624. doi:[10.2307/2527443](https://doi.org/10.2307/2527443)
- Goldstein H. 2011. Multilevel statistical models. Chichester (UK): John Wiley & Sons.
- Haas CN. 2014. On the quarantine period for Ebola virus. *PLoS Curr.* 6. doi:[10.1371/currents.outbreaks.2ab4b76ba7263ff0f084766e43abbd89](https://doi.org/10.1371/currents.outbreaks.2ab4b76ba7263ff0f084766e43abbd89)
- Harvard School of Public Health/SSRS. 2014. Ebola poll topline. [accessed 2016 Oct 4]. http://cdn1.sph.harvard.edu/wp-content/uploads/sites/21/2014/08/ebola_Topline_final_08-20-14.pdf.
- Ibuka Y, Chapman GB, Meyers LA, Li M, Galvani AP. 2010. The dynamics of risk perceptions and precautionary behavior in response to 2009 (H1N1) pandemic influenza. *BMC Infect Dis.* 10:296. doi:[10.1186/1471-2334-10-296](https://doi.org/10.1186/1471-2334-10-296)
- Johnson BB. 2018. Residential location and psychological distance in Americans' risk views and behavioral intentions regarding Zika virus. *Risk Anal.* 38(12):2561–2579. doi:[10.1111/risa.13184](https://doi.org/10.1111/risa.13184)
- Johnson BB. 2019. Hazard avoidance, symbolic and practical: the case of Americans' reported responses to Ebola. *J Risk Res.* 22(3):346–363. doi:[10.1080/13669877.2017.1378252](https://doi.org/10.1080/13669877.2017.1378252)
- Johnson BB, Slovic P. 2015. Fearing or fearsome Ebola communication? Keeping the public in the dark about possible post-21-day symptoms and infectiousness could backfire. *Health Risk Soc.* 17(5–6):458–471. doi:[10.1080/13698575.2015.1113237](https://doi.org/10.1080/13698575.2015.1113237)
- Johnson BB, White MP. 2010. The importance of multiple performance criteria for understanding trust in risk managers. *Risk Anal.* 30(7):1099–1115. doi:[10.1111/j.1539-6924.2010.01405.x](https://doi.org/10.1111/j.1539-6924.2010.01405.x)
- Kahan DM, Braman D, Gastil J, Slovic P, Mertz CK. 2007. Culture and identity-protective cognition: explaining the white-male effect in risk perception. *J Empir Legal Stud.* 4(3):465–505. doi:[10.1111/j.1740-1461.2007.00097.x](https://doi.org/10.1111/j.1740-1461.2007.00097.x)
- Kahan DM, Jamieson KH, Landrum A, Winneg K. 2017. Culturally antagonistic memes and the Zika virus: an experimental test. *J Risk Res.* 20(1):1–40. doi:[10.1080/13669877.2016.1260631](https://doi.org/10.1080/13669877.2016.1260631)
- Kasperson RE, Renn O, Slovic P, Brown HS, Emel J, Goble R, Kasperson JX, Ratick S. 1988. The social amplification of risk: a conceptual framework. *Risk Anal.* 8(2):177–187. doi:[10.1111/j.1539-6924.1988.tb01168.x](https://doi.org/10.1111/j.1539-6924.1988.tb01168.x)

- Lima ML. 2004. On the influence of risk perception on mental health: living near an incinerator. *J Environ Psychol.* 24(1):71–84. doi:[10.1016/S0272-4944\(03\)00026-4](https://doi.org/10.1016/S0272-4944(03)00026-4)
- Loewenstein G, Mather J. 1990. Dynamic processes in risk perception. *J Risk Uncertainty.* 3(2): 155–175. doi:[10.1007/BF00056370](https://doi.org/10.1007/BF00056370)
- Mayorga M, Johnson BB. 2019. A longitudinal study of concern and judged risk: the case of Ebola in the United States, 2014–2015. *J Risk Res.* 22(10):1280–1293. doi:[10.1080/13669877.2018.1466827](https://doi.org/10.1080/13669877.2018.1466827)
- Mertz CK, Slovic P, Purchase IFH. 1998. Judgments of chemical risks: comparisons among senior managers, toxicologists, and the public. *Risk Anal.* 18(4):391–404. doi:[10.1111/j.1539-6924.1998.tb00353.x](https://doi.org/10.1111/j.1539-6924.1998.tb00353.x)
- Pan American Health Organization. 2020. PLISA Health Information Platform for the Americas: Zika. [accessed 2020 Aug 27]. <https://www.paho.org/data/index.php/en/mnu-topics/zika.html>.
- Raude J, McColl K, Flamand C, Apostolidis T. 2019. Understanding health behaviour changes in response to outbreaks: findings from a longitudinal study of a large epidemic of mosquito-borne disease. *Soc Sci Med.* 230:184–193. doi:[10.1016/j.socscimed.2019.04.009](https://doi.org/10.1016/j.socscimed.2019.04.009)
- Renner B, Schüz B, Sniehotta FF. 2008. Preventive health behavior and adaptive accuracy of risk perceptions. *Risk Anal.* 28(3):741–748. doi:[10.1111/j.1539-6924.2008.01047.x](https://doi.org/10.1111/j.1539-6924.2008.01047.x)
- Siegrist M. 2013. The necessity for longitudinal studies in risk perception research. *Risk Anal.* 33(1):50–51. doi:[10.1111/j.1539-6924.2012.01941.x](https://doi.org/10.1111/j.1539-6924.2012.01941.x)
- Siller M, Sigman M. 2008. Modeling longitudinal change in the language abilities of children with autism: parent behaviors and child characteristics as predictors of change. *Dev Psychol.* 44(6):1691–1704. doi:[10.1037/a0013771](https://doi.org/10.1037/a0013771)
- Slovic P. 1987. Perception of risk. *Science.* 236(4799):280–285. doi:[10.1126/science.3563507](https://doi.org/10.1126/science.3563507)
- Slovic P. 1993. Perceived risk, trust, and democracy. *Risk Anal.* 13(6):675–682. doi:[10.1111/j.1539-6924.1993.tb01329.x](https://doi.org/10.1111/j.1539-6924.1993.tb01329.x)
- Smith VK, Michaels RG. 1987. How did households interpret Chernobyl? A Bayesian analysis of risk perceptions. *Econ Lett.* 23(4):359–364. doi:[10.1016/0165-1765\(87\)90145-5](https://doi.org/10.1016/0165-1765(87)90145-5)
- Thompson RF. 2009. Habituation: a history. *Neurobiol Learn Mem.* 92(2):127–134. doi:[10.1016/j.nlm.2008.07.011](https://doi.org/10.1016/j.nlm.2008.07.011)
- Trumbo C, Meyer MA, Marlatt H, Peek L, Morrissey B. 2014. An assessment of change in risk perception and optimistic bias for hurricanes among Gulf Coast residents. *Risk Anal.* 34(6): 1013–1024. doi:[10.1111/risa.12149](https://doi.org/10.1111/risa.12149)
- U.S. Centers for Disease Control and Prevention (CDC). 2020. Statistics & Maps, 2015–2017 Case Counts. [accessed 2020 Aug 27]. <https://www.cdc.gov/zika/reporting/index.html>.
- Viscusi WK, O'Connor CJ. 1984. Adaptive responses to chemical labeling: are workers Bayesian decision makers? *Am Econ Rev.* 74:942–956.
- Visschers VHM, Siegrist M. 2013. How a nuclear power plant accident influences acceptance of nuclear power: results of a longitudinal study before and after the Fukushima disaster. *Risk Anal.* 33(2):333–347. doi:[10.1111/j.1539-6924.2012.01861.x](https://doi.org/10.1111/j.1539-6924.2012.01861.x)
- White MP, Eiser JR. 2005. Information specificity and hazard risk potential as moderators of trust asymmetry. *Risk Anal.* 25(5):1187–1198. doi:[10.1111/j.1539-6924.2005.00659.x](https://doi.org/10.1111/j.1539-6924.2005.00659.x)
- Wirz CD, Mayorga M, Johnson BB. 2020. A longitudinal analysis of Americans' media sources, risk perceptions, and judged need for action during the Zika outbreak. *Health Commun.* doi:[10.1080/10410236.2020.1773707](https://doi.org/10.1080/10410236.2020.1773707)