Research Article

Psychological Science
2017, Vol. 28(1) 23–35

Reprints and permissions:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/0956797616671712
journals.sagepub.com/home/pss

The Role of Hedonic Behavior in Reducing Perceived Risk: Evidence From Postearthquake Mobile-App Data

Jayson S. Jia[1], Jianmin Jia[2], Christopher K. Hsee[3], and Baba Shiv[4]

[1]Faculty of Business and Economics, The University of Hong Kong; [2]CUHK Business School, The Chinese University of Hong Kong; [3]Booth School of Business, University of Chicago; and [4]Graduate School of Business, Stanford University

Abstract

Understanding how human populations naturally respond to and cope with risk is important for fields ranging from psychology to public health. We used geophysical and individual-level mobile-phone data (mobile-apps, telecommunications, and Web usage) of 157,358 victims of the 2013 Ya'an earthquake to diagnose the effects of the disaster and investigate how experiencing real risk (at different levels of intensity) changes behavior. Rather than limiting human activity, higher earthquake intensity resulted in graded increases in usage of communications apps (e.g., social networking, messaging), functional apps (e.g., informational tools), and hedonic apps (e.g., music, videos, games). Combining mobile data with a field survey (N = 2,000) completed 1 week after the earthquake, we use an instrumental-variable approach to show that only increases in hedonic behavior reduced perceived risk. Thus, hedonic behavior could potentially serve as a population-scale coping and recovery strategy that is often missing in risk management and policy considerations.

Keywords

mobile big data, earthquake disaster recovery, perceived risk, hedonic coping behavior, crisis management

Received 3/20/16; Revision accepted 9/8/16

Disasters, whether natural or human-made, are conceptual singularities in which the abstraction of risk is physically realized as a traumatic experience (Loewenstein, Weber, Hsee, & Welch, 2001; Slovic, 1987; Viscusi, 1993; Weber, 2006). Far from being rare events, disasters have regularly afflicted civilizations throughout human history (Butzer, 2012). Just in the decade from 2004 through 2013, 6,525 recorded disasters (3,867 of which were natural) resulted in more than 1 million deaths and U.S. $1 trillion of economic damage, and negatively affected the lives of more than 1 billion people globally (International Federation of Red Cross and Red Crescent Societies, 2014). In the coming years, the specter of disaster risk looms ever larger as a result of greater population pressures (Goldstone, 2002), rapidly growing technology-related risks (Slovic, 1987), and increased incidences of climate-change-related extreme weather (Weber, 2006). Given the regularity of disaster, one may wonder how peoples and societies are generally able to rebound from the recurring experience of devastation. Perhaps even more fundamental than the challenge of physical and economic recovery (Kunreuther & Slovic, 1996; Michel-Kerjan & Kunreuther, 2007) is the challenge of individual psychological recovery, without which human activity would be generally impeded (Bonanno, Galea, Bucciarelli, & Vlahov, 2006; Brickman & Campbell, 1971; Diener, Lucas, & Scollon, 2006; Perrin et al., 2007). In the study reported here, we explored the human element of

Corresponding Authors:
Jayson S. Jia, The University of Hong Kong, Faculty of Business and Economics, Pok Fu Lam Rd., Hong Kong
E-mail: jjia@hku.hk
Jianmin Jia, CUHK Business School, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong
E-mail: jjia@cuhk.edu.hk

disaster recovery by investigating how the experience of a disaster affects a population's daily behavioral patterns, and whether such changes affect psychological recovery from risk.

We used the 2013 Ya'an earthquake as a naturally occurring instrument to explore how experiencing risk affects human behavior. Ya'an residents at different locales were randomly subject to different levels of earthquake intensity[1] (a standard measure of earthquakes' impact), which we used to operationalize different levels of experienced risk (for a description of the earthquake and the damage that occurred, see Section 1 in the Supplemental Material available online). We measured the behavioral impact of experiencing the risk of disaster in several ways. First, we used longitudinal individual-level mobile-phone data of earthquake victims (N = 157,358; 10.1% of Ya'an's population), which captured daily-life patterns before and after the earthquake, to map how people responded to different levels of risk over time. Second, we explored the efficacy of these behaviors in alleviating perceived risk, a negative psychological state created by the earthquake experience. Perceived risk is a subjective estimate of danger commonly used in studies of natural, environmental, and health risks (Slovic, 1987), and it is related to feelings of uncertainty and fear (Loewenstein et al., 2001). Specifically, we linked respondents' mobile-phone data to a field survey (N = 2,000) that measured unobservable psychological constructs, including perceived risk, 1 week after the earthquake. We then used an instrumental-variable approach to test how communication, functional, and hedonic behaviors affected perceived risk. For further validation of our results, we conducted a retrospective survey of victims' recovery experiences (N = 3,100).

Whereas other research has examined how disasters affect information diffusion and physical mobility (Bagrow, Wang, & Barabasi, 2011; Gao et al., 2014; Lu, Bengtsson, & Holme, 2012), our research is, to the best of our knowledge, the first to document how experiencing a disaster affects day-to-day life patterns and to test the role of communication, functional, and hedonic behaviors in postdisaster recovery by using verifiable measures of individual behavior.

Conceptually, risk is a complex theoretical construct with multitudinous dimensions (Slovic, 1987) ranging from cognitively oriented informational components (e.g., probability estimates) to emotionally oriented experiential components (e.g., feelings of fear), both of which must be successfully assuaged to achieve psychological recovery (Loewenstein et al., 2001). In society-wide risk situations such as disasters, the experience of risk can also be interpersonal, as information and emotions flow between victims and the people with whom they have social ties, such as kin (Cohen & Wills, 1985). We thus expected that these different facets of risk would each trigger reflexive increases in corresponding adaptive behaviors:

- Hypothesis 1: By necessity, experiencing a disaster should increase the need for functional and informational behaviors (e.g., reading news updates to resolve uncertainty regarding risk).
- Hypothesis 2: Experiencing disaster should also increase communications behaviors (e.g., more calls, text messages, and communications-app usage) and the size of activated social networks (as measured by out-degree centrality—Eagle, Pentland, & Lazer, 2009), to satisfy interpersonal informational and emotional needs (e.g., to resolve uncertainty about the well-being of kin, share experiences, and seek social support; Bagrow et al., 2011; Cohen & Wills, 1985).

In addition, we tested two hypotheses concerning hedonic behavior:

- Hypothesis 3: Experiencing risk should lead to an increase in hedonic behaviors.
- Hypothesis 4: Engaging in more hedonic behavior after a disaster should reduce the overall feeling of being threatened by risk.

Although these hypotheses may seem contrary to lay intuition (e.g., that victims might be too busy or not in the mood for pleasurable activities), there are several reasons to believe that victims might seek pleasure and happiness in response to risk, and that this might benefit their sense of well-being. On a neurological level, aversive stimuli can stimulate the release of mesolimbic dopamine in the brain, which motivates pleasure seeking (Salamone & Correa, 2012). Indeed, excessive suppression in the dopamine circuit is associated with major depression and other psychiatric disorders, which implies that suppressing pleasure can have negative psychological consequences and that pleasure seeking may be an adaptive response to negative stimuli, such as risk (Hikosaka, 2010; Li et al., 2011). Furthermore, psychological research on emotional regulation suggests that seeking positive emotions is part of the mood-repair process (Salovey, Mayer, Goldman, Turvey, & Palfai, 1995); thus, victims may try to engage in hedonic activities to relieve a psychosomatic state of stress (Ferraro, Shiv, & Bettman, 2005). Despite evidence that positive affect can serve as a population-level fear-reduction strategy (Frederick & Loewenstein, 1999; Hsee, Hastie, & Chen, 2008; Loewenstein et al., 2001), hedonic behavior has traditionally been overlooked as a method for mitigating the psychological impact of disaster. Instead, efforts have focused on risk-related communications and clinical approaches (e.g., counseling or pharmaceuticals), with the underlying assumption that forgoing pleasure is simply part of the price of reducing risk (Fischhoff, 1995; Perrin et al., 2007; Ressler & Mayberg, 2007; Slovic, 1987; Zeckhauser & Viscusi, 1990).

Method

The Ya'an earthquake occurred at 8:02 a.m. (Beijing time) on Saturday, April 20, 2013. The epicenter was located in Lushan County, Ya'an, Sichuan, about 116 km from Chengdu, the capital of Sichuan province (in southwest China). In our primary analysis, we tested how the severity of experienced risk subsequently changed victims' behavior. The surface-wave magnitude of the earthquake was placed at 7.0 by the China Earthquake Data Center. To operationalize the degree of experienced risk, we used Typical Maximum Modified Mercalli Intensity, which varied from V to IX depending on geographic location (see Section 1 in the Supplemental Material). Local-government statistics indicated that intensity was highly correlated with real damage (r = .56 for injuries, r = .76 for population displacement, and r = .81 for estimated economic losses, ps < .01). Whereas previous research on risk has focused on estimations of risk, often in hypothetical contexts (Fischhoff, 1995; Slovic, 1987; Viscusi, 1993; Weber, 2006), we measured risk perceptions that were created by the experience of real and immediate danger.

Using the earthquake as an instrument provided several unique empirical advantages. First, the random shock of the earthquake created a quasiexperiment, insofar as residents did not know that it would occur. Second, the earthquake generated existential danger that would be difficult to replicate in a laboratory setting, and thus provided an opportunity to investigate how real risk affected people's lives. Third, the earthquake naturally created an interval scale of experienced risk because different locales in Ya'an prefecture experienced different levels of physical shaking and damage. Finally, the relatively moderate physical damage (196 deaths in a population of 1.5 million) mitigated ceiling effects and meant that telecommunications infrastructure was undamaged in most regions (only parts of two counties with relatively small populations had network outages).

We used various kinds of mobile-phone data, including data on usage of mobile applications (apps),[2] telecommunications (e.g., voice calls, texts), and usage of Web browsers, to capture the behavioral impact of the earthquake. Because of their ubiquity and frequent usage, mobile phones provide the most detailed individual-level records of human dynamics available (Eagle et al., 2009). Mobile-phone data are more than in vitro reflections of mobile-phone-based activity; they also reflect in vivo behavior in the physical world (e.g., increased frequency of calls to neighbors reflects increased physical interactions with them; Eagle et al., 2009; Saramäki et al., 2014). Whereas previous research has often used communication patterns and geolocation to infer human behavior, our analyses focused on mobile-app usage as a proxy for daily human interests and activities. We reasoned that changes in an individual's relative usage of different mobile apps reflect his or her general psychological interests (e.g., playing video games or listening to music-playing apps reflects a general interest in pleasurable activities). Mobile phones' portability, multifunctionality, and typical proximity to owners allowed for continuous, automatic, and unobtrusive measurements of behavior, before, during, and after the earthquake.

Individual-level telecommunications and earthquake data

We used 3 months of telecommunications records (March 1–May 31, 2013; centered on the April 20th earthquake) of 157,358 residents of Ya'an prefecture who were active subscribers of a major Chinese mobile-telecommunications carrier (10.1% of the total population, 59.0% urban). The data included 56 million time-stamped records of anonymized individuals' voice calls, text messages, and mobile Internet usage, as well as their basic demographics, home address, and cell-tower access. We were able to link location-based measurements of earthquake intensity from the China Earthquake Administration to individual Ya'an mobile-phone users by using their registered addresses, which we coded for neighborhood. These registered addresses were unlikely to be falsified because the carrier also provided fixed-line services (telephone, broadband) to many of the customers. We thus observed the precise seismic impact on each resident (the earthquake struck at 8:02 a.m. on a Saturday, when most people were at home), and also linked these residents to county-level economic and damage data provided by the People's Government of Ya'an (personal communication, June 2015).

Mobile-app data

The telecommunications data set was combined with a separate data set of mobile-phone-app usage patterns for 71,820 Ya'an residents (62.44% urban) who were active app users. We defined active users as those who had used a Web-based mobile app at least once the week before the earthquake and at least once the week after. The data showed how many times individual apps were accessed daily for each user. We examined 125 of the most popular mobile apps, which were precategorized by the carrier into 19 subcategories: WeChat (its own category because of its popularity and multifunctionality), instant messaging (not including WeChat), maps and GPS, tools, app market (for buying apps), multimedia messaging (Internet-based text messaging), blogs, mobile payment, news, browsers, games, living services (travel, weather, etc.), social networking, video, finance, shopping, e-mail, reading, and music (see Table S3 in the Supplemental Material for a summary of how individual apps were categorized). We divided mobile-app usage into three major categories—communications, functional usage, and hedonic usage (e.g., a weather-information app is functional, a music-player app is hedonic; see Section 3.1 in the Supplemental Material for further discussion on categorization)—and explored changes in usage after the earthquake (relative to before the earthquake).

Results

Overall, increasing levels of earthquake intensity corresponded with graded increases for all three forms of behavior (Fig. 1; also see Figs. S4 and S5 in the Supplemental Material); this increase began the day after the earthquake and persisted for about a month. During the first week, there was an exception in intensity IX regions, which suffered service outages the first few days after the earthquake because of infrastructure damage. However, app usage in those regions recovered rapidly the following week, after cell-tower infrastructure was repaired.

Impact of earthquake intensity on behavior

To formally test if earthquake intensity changed behavior, we used a first-difference fixed-effects model[3] to test how mobile-app usage changed the first week after the earthquake compared with the week prior. This model was more appropriate than a random-effects ordinary least squares (OLS) regression, as confirmed by highly significant *F* tests and Hausman tests (*p*s < .001). We used the following linear model to capture individual behavioral change in mobile-app usage from before (t = 0) to after the earthquake:

$$y_{it} = \alpha + \boldsymbol{v}_i\rho + \boldsymbol{x}_{it}\beta + \boldsymbol{I}_{it}\theta + \varepsilon_{it},\ t = 0,\ 1,\ \ldots,\ \mathrm{T}, \qquad (1)$$

where the dependent variable, y_{it} is the mobile-app usage of individual i at time (week) t; α is a constant; $\boldsymbol{v}_i$ is a vector of time-invariant variables for individual i (e.g., age, gender, phone model, service plan, and geographic features, which are the same before and after the earthquake); $\boldsymbol{x}_{it}$ is a vector of telecommunications activities (outgoing calls and texts, activated social-network size as measured by the number of unique people contacted during the period, Web-usage frequency); $\boldsymbol{I}_{it}$ represents the treatment variables, including earthquake intensity and a dummy for telecom infrastructure damage ($\boldsymbol{I}_{it} = 0$ when $t = 0$, i.e., the week before the earthquake); and ε_{it} is a random error term. The first-difference model eliminated α and $\boldsymbol{v}_i$ by taking the difference between two time-consecutive equations, that is,

$$\Delta y_{it} = \Delta \boldsymbol{x}_{it}\beta + \boldsymbol{I}_{it}\theta + \Delta\varepsilon_{it},\ t = 1,\ \ldots,\ \mathrm{T}, \qquad (2)$$

where Δ indicates the difference of variables between the week before the earthquake and week t after the earthquake. This first-difference model took advantage of the fixed-effects estimator to isolate the effects of time-invariant observable and unobservable characteristics (Liker, Augustyniak, & Duncan, 1985). The first-difference (FD) estimators $\hat{\beta}_{\mathrm{FD}}$ and $\hat{\theta}_{\mathrm{FD}}$ were pooled OLS estimators (i.e., consistent and unbiased) from the regression model (Equation 1; Wooldridge, 2010).

Overall, higher earthquake intensity significantly predicted greater usage of communications, hedonic, and functional apps during the first week after the earthquake (see Table 1). Specifically, the first-difference model showed that intensity was a significant predictor of increases in usage of communications apps, t = 31.47, p < .001; hedonic apps, t = 25.95, p < .001; and functional apps, t = 14.08, p < .001, after the earthquake. Greater change in telecommunications frequency, Web-usage frequency, and size of social-network activation also predicted greater use of apps in all three categories. The infrastructure-damage dummy (intensity IX) predicted a reduction in usage of communications and hedonic apps, likely because of reduced Internet access during the first 4 days after the earthquake, but infrastructure damage was not a significant predictor of functional-app usage. As a robustness check, we used an alternative measure of earthquake intensity, distance from the epicenter, as the predictor and obtained the same results (see Section 4.1 in the Supplemental Material).

For cross-validation, we also ran the first-difference model using number of incoming and outgoing voice calls and text messages (with private residential and mobile numbers) as alternative dependent variables, and earthquake intensity and an infrastructure-damage dummy as independent variables. Greater earthquake intensity resulted in more outgoing voice calls, t = 65.53, p < .001, and text messages, t = 57.02, p < .001, and increased social-network activation (i.e., more people with social ties to the victim were contacted), t = 82.76, p < .001, controlling for infrastructure damage. Overall, the impact of the earthquake on telecommunications usage was similar to its effects on mobile-app usage.

Ex ante, one could have expected mobile-based activity to decrease after the earthquake because of increased

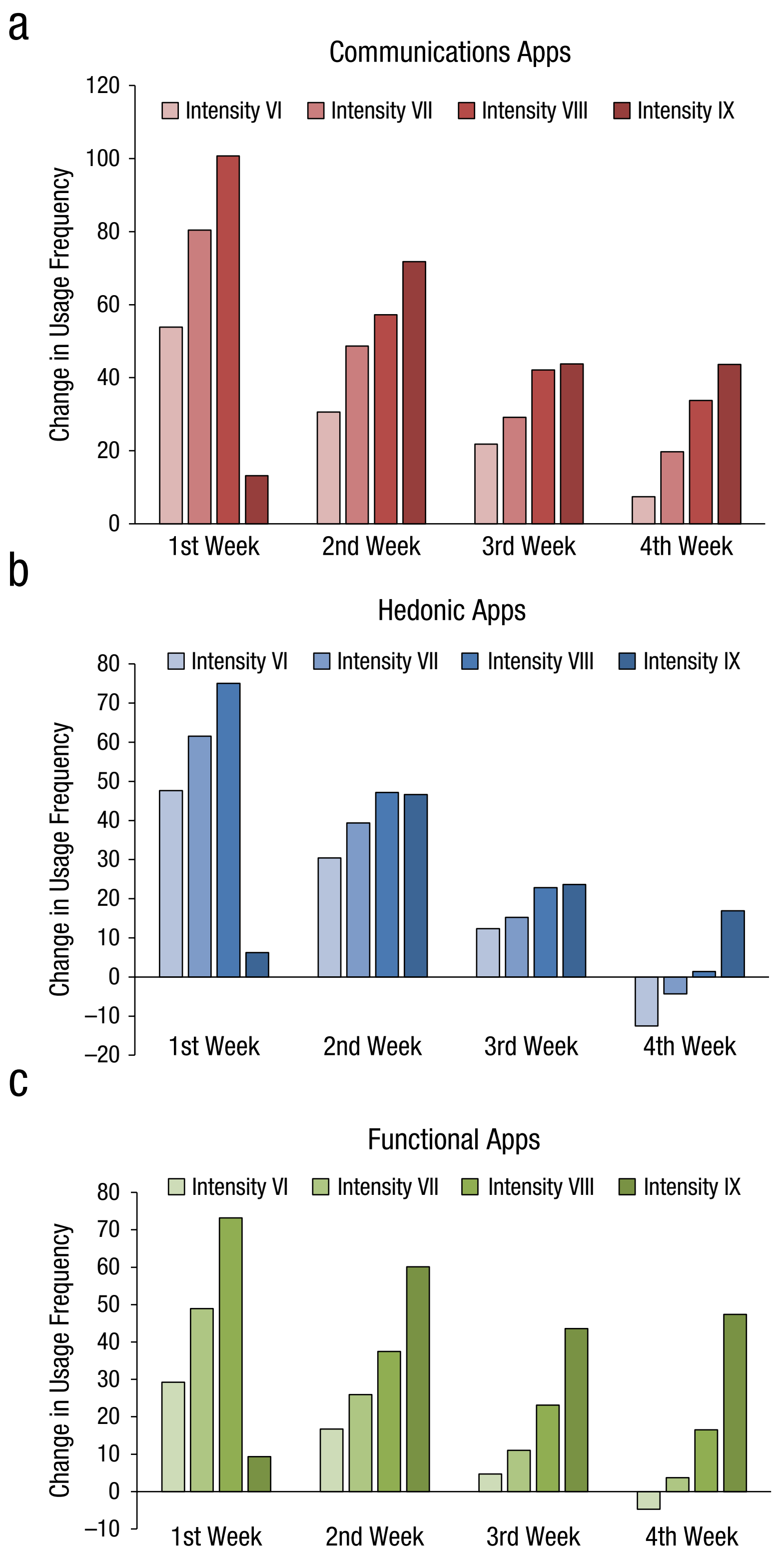

Fig. 1. Change in weekly usage frequency of (a) communications, (b) hedonic, and (c) functional apps for the 4 weeks after the earthquake. Usage during the week before the earthquake was the baseline. Results are shown separately for locales that experienced earthquake intensities of VI, VII, VIII, and XIII. Because very few samples came from intensity V locales, these samples were included in the results for intensity VI.

Table 1. Results of the First-Difference Fixed-Effects Model Predicting Individual-Level Changes in Usage of Mobile Apps From the Week Before to the Week After the Earthquake (N = 45,574)

	Communications apps (adjusted R^2 = .139)				Hedonic apps (adjusted R^2 = .0366)				Functional apps (adjusted R^2 = .0253)			
Predictor	Coefficient	*SD*	*t*	*p*	Coefficient	*SD*	*t*	*p*	Coefficient	*SD*	*t*	*p*
Change in outgoing-call frequency	0.835	0.085	9.79	< .001	0.262	0.058	4.53	< .001	0.227	0.096	2.37	.018
Change in outgoing-text frequency	0.739	0.040	18.6	< .001	0.309	0.027	11.4	< .001	0.271	0.045	6.05	< .001
Change in activated social-network size	0.635	0.248	2.56	.011	0.395	0.170	2.34	.019	0.973	0.278	3.49	< .001
Change in Web-usage frequency	1.27	0.020	62.8	< .001	0.207	0.014	15.0	< .001	0.542	0.023	23.9	< .001
Infrastructure-damage dummy	–26.6	6.80	–3.91	< .001	–21.0	4.62	–4.53	< .001	–11.3	7.62	–1.49	.137
Earthquake intensity	5.21	0.166	31.5	< .001	2.92	0.113	26.0	< .001	2.61	0.186	14.1	< .001

Note: The dependent variables were changes in frequency of communications-, hedonic-, and functional-app usage between the week before and the week after the earthquake. F tests and Hausman tests for the three models were all highly significant (ps < .001), which suggested that fixed-effects models were appropriate.

busyness, situational constraints, or stress-induced social withdrawal. However, as predicted by Hypotheses 1 and 2, we observed an increase in usage of functional and communications apps immediately after the earthquake. Moreover, this pattern persisted for several weeks after the earthquake (Fig. 1). Usage of hedonic mobile apps also increased for several weeks (Fig. 1), as predicted by Hypothesis 3. Critically, increases for all app categories were greater in locations that experienced higher earthquake intensities (except for the first week in areas at intensity IX, because damage to mobile infrastructure impeded network access the first 4 days); in other words, greater physical shaking resulted in a graded increase in mobile-based activity, a finding that reduces the tenability of alternative, non-earthquake-related accounts of app usage.

There was a more nuanced effect of earthquake intensity on usage of Internet Web browsers, which can be thought of as multifunctional apps (see Fig. S6 in the Supplemental Material). Using the same fixed-effects model as before (Equation 1) to examine change in Web browsing behavior in the week after the earthquake, we found that although greater intensity predicted more visits to communications Web sites, $t = 14.0$, $p < .001$, and functional Web sites, $t = 12.23$, $p < .001$, it predicted fewer visits to hedonic Web sites, $t = -3.00$, $p < .01$ (see Section 4.2 in the Supplemental Material). The increase in visits to functional sites is in line with normative informational needs (Hypothesis 1), and the increase in visits to communications sites may have resulted because browser-based Web clients for popular social-media, chat, and messaging services were more common than dedicated apps in China at the time of the study. However, we note that the finding of fewer visits to hedonic Web sites after the earthquake is not inconsistent with the analysis in Table 1 or with Hypothesis 3. Given that mobile-phone Web browsers are more often used for information search than for hedonic activities (e.g., it is harder to play games or listen to music on a phone's browser than using a dedicated app), our findings might indicate only that earthquake victims did not search for new hedonic apps (on their Web browser) after the earthquake but did use their preexisting hedonic apps more. This would be in line with previous research showing that increased psychological pressure increases the desire for familiar options, irrespective of normative costs (Litt, Reich, Maymin, & Shiv, 2011). Indeed, this interpretation is also consistent with our analysis of the diversity of app usage (measured by Shannon entropy; see Section 5 in the Supplemental Material); after using a more diverse portfolio of apps on the day of the earthquake, victims immediately reverted to preearthquake levels of diversity starting the next day.

Efficacy of different behaviors in reducing perceived threat

We have shown that experiencing greater risk (i.e., higher earthquake intensity) resulted in greater usage of communications, hedonic, and functional apps, but one may wonder how these behaviors were related to postdisaster recovery. Although the purpose of communications and functional behavior is intuitive (e.g., social support, information seeking and sharing), the role of hedonic behavior is less clear. Our conceptualization suggests that hedonic behavior may be an adaptive coping strategy that abets psychological recovery from aversive experiences of risk (Hikosaka, 2010; Salamone & Correa, 2012). However, the increase in hedonic behavior we observed might have been driven by a factor unrelated to risk. For example, residents in regions that experienced higher earthquake intensity may have had more free time to spend on their mobile phones because earthquake damage reduced the availability of other activities. In order to test how different behaviors affected psychological recovery, we measured victims' immediate postdisaster psychological state in a large-scale field survey. This measure was used as a dependent variable in a statistical theory test.

Field survey. We telephoned 2,000 randomly drawn customers from our data set 5 to 7 days after the earthquake (final response rate = 43%; the high response rate was likely driven by residents' needs for posttrauma social support and their desire to share their plight with official institutions, as discussed in Section 6.1 of the Supplemental Material). The key dependent variable was perceived threat: "At this point, how threatened do you feel by the earthquake?" The rating scale ranged from 1, *no threat at all*, to 10, *a great deal of threat*. Perceived threat is a common measure of the overall feeling of being at risk (Slovic, 1987) and is related to feelings of anxiety, stress, and pessimistic future outlook (Loewenstein et al., 2001). Experienced physical damage and injury and initial feelings of fear were measured as covariates (for additional details on the survey, see Section 6.1 in the Supplemental Material). To conduct a strong test, we focused the survey on the counties with the most damage: Lu Shan (the epicenter county) and Bao Xing (a neighboring, hard-hit county).

Exploratory analyses showed that perceived risk 1 week after the earthquake was negatively correlated with overall usage of hedonic apps ($p < .001$) and with usage of specific subcategories of hedonic apps, including video ($p = .002$), music ($p = .019$), reading ($p = .025$), and shopping ($p = .040$) apps, during the first week. Although these results are in line with Hypothesis 3, correlations (and ordinary regression models) do not show causality because of possible endogeneity in the explanatory variables of interest (e.g., usage of communications and hedonic apps might be correlated with the error term as a result of omitted variables, measurement error, and simultaneity or causality).

Instrumental-variable analysis. To test for a causal relationship between app usage and perceived risk after the earthquake, we used an instrumental-variable approach, which addressed the endogeneity problem by taking advantage of the natural experimental setting of the earthquake to provide an unbiased estimator of app usage (Angrist & Krueger, 2001).

Specifically, we used an asymptotically efficient two-step minimum chi-square (MCS) estimator approach (Berkson, 1980; Newey, 1987) to estimate the following Tobit model:

$$y_{1i}^{*} = \boldsymbol{y}_{2i}\beta + \boldsymbol{x}_{1i}\gamma + \mu_i \tag{3}$$

$$\boldsymbol{y}_{2i} = \boldsymbol{x}_{1i}\Pi_1 + \boldsymbol{x}_{2i}\Pi_2 + \nu_i, \tag{4}$$

where y_{1i}^{*} is the dependent variable (i.e., perceived risk), $\boldsymbol{y}_{2i}$ is a vector of endogenous variables, $\boldsymbol{x}_{1i}$ is a vector of exogenous variables, $\boldsymbol{x}_{2i}$ is a vector of additional instruments, β and γ are vectors of parameters, Π_1 and Π_2 are matrices of parameters, and μ_i and ν_i are independent random error terms. In this analysis, usage of communications, hedonic, and functional apps and of Internet browsers during the week after the earthquake served as endogenous variables ($\boldsymbol{y}_{2i}$). The model tested whether these different forms of behavior helped reduce individuals' perceived risk. The corresponding usages during the week before the earthquake ($\boldsymbol{x}_{2i}$) together with other exogenous variables ($\boldsymbol{x}_{1i}$) served as instrumental variables.

The censored approach of the Tobit model also relieved the ceiling effect of extreme values for our survey measure of perceived risk, which was heavily right-censored at 10 (27.1% of the data points), in order to estimate the parameters correctly. Thus, we did not observe y_{1i}^{*} and instead observed y_{1i} as follows:

$$y_{1i} = \begin{cases} 0 & if\ y_{1i}^{*} < 1 \\ y_{1i}^{*} & if\ 0 \le y_{1i}^{*} \le 10 \\ 10 & if\ y_{1i}^{*} > 10 \end{cases}$$

The logic behind the instrumental-variable approach is as follows. First, if the explanatory equation (Equation 3) were run as a stand-alone ordinary regression, the model would suffer from endogeneity; for example, if greater hedonic-app usage predicted lower perceived risk, it might be that an omitted variable in the error term, such as free time, actually drove this relationship. In a two-stage MCS approach, however, an instrument (often from a natural experiment) is first used to create unbiased and consistent estimates. The formal requirements of this approach are that the instrument is (a) correlated with the endogenous explanatory variables (relevance condition), but (b) unrelated to the error term in the explanatory equation (orthogonality condition). Because the endogenous explanatory variables are unrelated to the instrument, they cannot explain why a model (and the relationships it tests) is significant.

In our analysis, app and Internet usage during the week before the earthquake served as instrumental variables because they were related to corresponding app and Internet usage during the week after the earthquake but unrelated to perceived risk. Indeed, the four instrumental variables were highly correlated with their corresponding endogenous variables (r = .697–.747, ps < .001), thus satisfying the relevance condition; smallest F statistic = 192.50. This correlation is intuitive because people have relatively stable behavioral habits across time, particularly on mobile phones (Diener et al., 2006; Lu et al., 2012; Saramäki et al., 2014; e.g., people who were music lovers before the earthquake still listened to music more than others after the earthquake). Furthermore, in accordance with the orthogonality condition, perceived risk after the earthquake was not significantly correlated with usage of communications, hedonic, and functional apps before the earthquake, and was only weakly negatively correlated with previous Internet (browser) usage (p = .04). However, this correlation was no longer significant when we controlled for age, gender, and rural-urban difference. This absence of a correlation is intuitive because app usage a week before the earthquake would be unrelated to the error terms (e.g., free time) generated by an earthquake that had not yet occurred.

In the first stage of the two-stage MCS approach (Equation 4), each of the four endogenous variables (app and Internet usage after the earthquake) was regressed against its corresponding set of instrumental variables, which included app and Internet usage before the earthquake, and against other exogenous variables, such as gender and age, to create unbiased estimates. Then, these estimates were used in the second-stage regression (Equation 3) to estimate all the parameters in the Tobit model.

Table 2 provides the final estimates of the Tobit model. Results were consistent with Hypothesis 4. Greater usage of hedonic mobile apps significantly predicted less perceived threat (p = .005). This result is in line with the notion that pleasure seeking may be a neurologically adaptive response to aversive experiences (Hikosaka, 2010; Salamone & Correa, 2012). Critically, the model showed that greater hedonic activity resulted in lower

Table 2. Results of the Instrumental-Variable Analysis of the Impact of App Usage on Perceived Threat (N = 811)

Predictor	Coefficient	*SD*	*z*	*p*
Constant	4.788	0.805	5.94	< .001
Age	0.013	0.011	1.16	.247
Gender (male = 1)	–0.732	0.245	–2.99	.003
Smartphone (yes = 1)	0.465	0.360	1.29	.197
County seat (yes = 1)	–0.574	0.257	–2.23	.026
Reported damage	0.321	0.054	5.97	< .001
Distance to epicenter	0.0000179	0.000016	1.12	.262
Activated social-network size	–0.005	0.005	–0.95	.341
Number of outgoing calls	0.090	0.155	0.58	.564
Number of outgoing texts	–0.263	0.109	–2.41	.016
Internet-browser usage	–0.298	0.175	–1.70	.089
Communications-app usage	0.454	0.180	2.53	.011
Hedonic-app usage	–0.396	0.142	–2.80	.005
Functional-app usage	0.041	0.146	0.28	.781

Note: In this analysis, perceived threat was the censored dependent variable (left censored at 0 = 77, uncensored = 474, right censored at 10 = 583). Frequencies of usage of communications, hedonic, and functional apps after the earthquake were identified as endogenous variables, and the corresponding frequencies of usage of these apps prior to the earthquake were used as instrumental values. *Activated social-network size* refers to the number of people with social ties to the victim that the victim called in the 28 days after the earthquake. *Number of outgoing calls* and *number of outgoing texts* refer to the quantity of communications initiated by the earthquake victim. All usage frequencies were log-transformed in the analysis. Age, gender, a smartphone dummy (whether the victim used a smartphone or not), physical distance to the epicenter, reported physical damage, and a dummy for county seat were included as exogenous variables. The basic test of the model's validity yielded a Wald χ^2 of 86.6, $p < .001$.

perceived threat regardless of differences in extraneous factors, such as free time or amount of damage suffered.[4]

Usage of communications (including social-networking) apps was a significant positive predictor of perceived threat (p = .011), which is contrary to the notion that increased communications are always beneficial during risky events, such as disasters. It is possible that conversation within social networks focused on sharing negative experiences and heightened the salience of risk, which made people feel more threatened (or slowed the alleviation of perceived risk). Usage of functional apps was not a significant predictor, which might reflect that their use was driven by practical necessity and was less related to regulation of perceived risk. A greater number of outgoing text messages predicted lower perceived threat. Also, men perceived less risk than did women, likely because of gender differences in risk perception (Byrnes, Miller, & Schafer, 1999; Finucane, Slovic, Mertz, Flynn, & Satterfield, 2000), and residents of the county seat perceived less risk than residents of other areas, likely because of the higher quality of building construction in that highly urbanized area. Other control variables had no significant effect.

Individual differences account. We also considered an alternative explanation based on individual differences in risk tolerance.[5] According to this account, people with different levels of risk tolerance reacted differently to the earthquake; those with higher risk tolerance (who would naturally perceive less risk) reacted to risk by seeking more hedonic activities, relative to communication activities, than those with lower risk tolerance. We conducted a theory test by using initial fear as a proxy for risk tolerance. Initial fear was measured in the field survey by the following item: "How much fear did you experience at the time of the April 20th earthquake?" The rating scale ranged from 1, *none*, to 10, *a great deal of fear*. We categorized respondents into two groups, those who increased their app usage and those who decreased their app usage in the first week after the earthquake, and then compared the groups' initial fear. We ran this analysis separately for usage of communications and use of hedonic apps. The results revealed that initial fear was almost the same for respondents who increased their usage of communications apps (M = 7.56) and those who decreased their usage of communications apps (M = 7.52; p = .891). We observed a similar pattern for hedonic apps; initial fear was similar for respondents who increased their usage of hedonic apps (M = 7.48) and those who decreased their usage of hedonic apps (M = 7.35; p = .650). In other words, the level of fear elicited by the earthquake did not vary with usage of hedonic and communications apps, which is not in line with an account based on differences in risk tolerance.

As a robustness check, we also reran the instrumental-variable model with initial fear as a covariate (see Table S8 in the Supplemental Material). Hedonic-app usage remained a significant negative predictor of perceived risk (p < .05), but communications-app usage was no longer a significant predictor (p = .14), perhaps because our measure of initial fear also measured the dependent variable, perceived threat. The more important finding, however, is that the effect of hedonic-app usage remained robust.

Alternative explanations need to account for the change in patterns of behavior after the earthquake, relative to before the earthquake, and this is precisely the logic of an instrumental-variable approach. On an individual basis, communications- and hedonic-app usage were highly correlated both before, r = .587, p < .001, and after, r = .607, p < .001, the earthquake. Furthermore, change in usage of communications apps was highly correlated with change in usage of hedonic apps (r = .500, p < .001). In other words, people who used communications apps more after the earthquake also used hedonic apps more. Again, this is not consistent with the notion that people changed their behaviors because of individual differences in risk tolerance.

Retrospective Survey

For cross-validation, we conducted a retrospective telephone survey of victims' earthquake experiences in June 2015 (during the 2-year anniversary of the earthquake, when memories were salient because of official commemorations). We called 3,100 active app users randomly drawn from our mobile telecom data set, and 1,134 (36.6%) completed the survey. The survey measured postdisaster living situation (home vs. tent), postdisaster network accessibility, how long physical recovery took, how long psychological recovery took, and experienced damage and harm (see Section 7 of the Supplemental Material for the full survey and results). These questions provided additional subjective and objective measures of risk experience. Taken in a stable environment with the benefit of hindsight, they served as a counterpoint to the field survey's measurement of perceived risk, which took place during the immediate aftermath of the earthquake. Overall, we found the two sets of measures to be consistent.

In a validity check, we found that the earthquake intensity respondents experienced (based on their geolocation) corresponded with self-reported perceived damage (see Tables S10 and S11 in the Supplemental Material). The survey also offered previously unobservable insights on victims' recovery experiences. Respondents estimated that their physical living conditions returned to normal after an average of 68 days. This estimate varied by intensity level, from approximately 1 month at intensities V and VI, to approximately 2 months at intensities VII and VIII, to approximately 6 months at intensity IX (Table S10). However, victims' moods ("How much did your psychological mood recover about 1 week after the earthquake?" rating scale from 1, *not at all*, to 10, *fully recovered*) recovered much faster than their physical or economic environments (see Section 7.2 and Table S10 in the Supplemental Material); 79.3% of respondents reported experiencing some mood recovery by the end of the first week. This result is consistent with our observation that victims began increasing their hedonic behavior almost immediately after the earthquake (Fig. 1). Notably, reported mood recovery was lower in areas where the earthquake's intensity was higher, which runs against the notion that people engaged in more hedonic behavior because they had already recovered psychologically. Rather, it seems that those who recovered the least (people in high-intensity areas) ended up engaging in the most hedonic behavior.

The survey also allowed us to test whether differences in postearthquake living conditions affected hedonic-app usage (e.g., whether hedonic-app usage increased more in regions where the earthquake's intensity was higher because fewer alternative activities were available). We compared usage of hedonic apps during the first week after the earthquake for respondents who stayed at home and those who lived in outdoor tents, where there was no access to fixed-line entertainment such as television or fixed-line Internet (62% of Ya'an residents stayed at home, 30% stayed in outdoor tents, and 8% left their hometown; the percentage who lived in tents increased with intensity level). However, there were no differences in mobile-phone activities between these two groups (see Table S12 in the Supplemental Material), which is inconsistent with the notion that the changes in behavior were caused by postearthquake differences in physical conditions, infrastructure accessibility, or busyness.

Discussion

Overall, we used a multimethod population-scale field approach to document how individual behavior changed over time in response to the experience of real risk. We found that higher earthquake intensity resulted in graded increases in usage of communications, hedonic, and functional apps after the earthquake (first-difference model). However, only hedonic behavior reduced perceived risk (instrumental-variable analysis); communications behaviors (i.e., use of communications apps, calls, and text messages) had mixed effects (only the number of outgoing text messages, which might reflect the size of people's weak-tie networks and availability of social support, helped), and functional behaviors (which largely comprised information search) had no significant effect on perceived risk.

Taken together, our results suggest that the increase in hedonic behavior was an active element of psychological recovery and not merely an artifact of increased postdisaster activity. Despite an established literature documenting the psychological benefits of positive affect, neurological reward, and happiness, there is relatively little scientific and public-policy emphasis on promoting hedonic behavior as a means of aiding psychological recovery. Traditionally, hedonic behavior (and neurological reward in general) is perceived to be at odds with the socially appropriate response to risk. Indeed, some governments even enforce antihedonic policies, such as somber dress codes or bans on fun television programming, in the extended aftermath of disaster. Although we are not arguing that hedonic behavior should be the sole response to tragedy, our results suggest that pleasure has a naturally occurring role in psychological healing and that hedonic activities can potentially promote population-scale psychological recovery from traumatic events.

It is important to take particular care in interpreting our statistical models. Although an instrumental-variable approach is causal (at least in a statistical sense), it does not by itself demonstrate a precise mechanism or psychological process. Identifying underlying mechanisms is a separate concern beyond the scope of this field study. Nonetheless, our results are not devoid of evidence regarding process and suggest that hedonic behavior has a role in reducing perceived risk, whereas communications behavior may increase perceived risk. Furthermore, our analyses rule out many simple nonpsychological accounts for the documented phenomena: Our fixed-effects model showed that the behavioral changes could not have been driven by heterogeneity (e.g., economic differences between regions cannot explain the increase in app usage because we tested changes in usage after the earthquake for each locale), and our instrumental-variable model addressed endogeneity concerns (e.g., omitted variables such as free time, measurement error, and simultaneity). We also tested alternative accounts focusing on individual differences in risk tolerance and living conditions. However, the precise process by which hedonic behavior drives recovery from experienced risk remains an open question that we hope future research can explore at a more fundamental level.

Although understanding the precise cognitive and neurological process by which pleasure stimulates recovery from aversive experiences might require a functional MRI approach (Hikosaka, 2010; Salamone & Correa, 2012), future social- and cognitive-psychology research can extend our findings by testing the relative efficacy of different types of emotions and behaviors in abetting recovery from risk. Such work could also offer additional insight into underlying processes; for example, it could be that hedonic activities eliciting low-arousal positive emotions, such as serenity, are more effective in reducing perceived risk than are hedonic activities eliciting high-arousal positive emotions, such as excitement. Research along these lines not only would deepen the theoretical understanding of how risk perception interacts with experienced emotions (Loewenstein et al., 2001), but also could generate numerous policy interventions based on affective psychology. Such secondary psychological treatment strategies, particularly those that can leverage the ubiquity of mobile phones, could be the psychological equivalent of public-health interventions in medicine and could be particularly important when primary treatments are difficult to scale up in scope in the immediate aftermath of population-level events, such as disasters (e.g., because of costs, limited number of on-site counselors, physical access).

Considering the normative benefits of information and the extensive literature documenting the benefits of risk communications (e.g., crisis communications, media communications, and information diffusion via word of mouth; Fischhoff, 1995), one may wonder why increased private communications behavior increased perceived risk. One possibility is that if conversations about the earthquake dominated these private communications, they might have reinforced feelings of fear and uncertainty. This effect might have persisted for a long time given that many significant aftershocks (magnitude > 5.0) occurred during the first 2 weeks after the earthquake. Although such an effect should not be surprising, its implications run against established wisdom in risk and crisis management (Slovic, 1987): Blanket media coverage and intensive communications about the risk are standard practice after disasters in modern societies.

We do not dispute the value of information; clearly, communications might serve other beneficial functions (Fischhoff, 1995), such as increasing vigilance for aftershocks. Rather, our findings suggest that future research can better define the trade-off between informational benefits and psychological well-being, and investigate when communications focusing on risk can backfire during crisis management. For example, after the first few days following the earthquake, communications about the risk probably yielded marginal informational benefits but incurred increasing morale costs for Ya'an's residents, who were already painfully aware of the risk. Indeed, unlike communications and informational activities, the activities most effective in reducing perceived risk (listening to music, watching videos, playing games, and shopping) are diverting in nature. Thus, a risk-management strategy might optimize victims' psychological well-being by shifting attention away from stressful stimuli, such as media coverage of an already salient risk.

This study makes a methodological contribution to psychology and the behavioral sciences by illustrating how population-scale mobile-phone data (and by extension, data from other digital or mobile platforms) can be used to infer psychological behavior and be linked to psychological theory. Our findings, which were derived from large quantities of longitudinal individual-level field data, would have been difficult to obtain in a laboratory setting. Social-science fields that have traditionally been criticized for small sample sizes, biased selection, reliance on self-report, and other methodological flaws (Eagle et al., 2009) stand to benefit from new methodological opportunities of the big-data revolution. At the same time, our results highlight the value of combining behavioral theory with statistical hypothesis testing, rather than relying on a purely data-driven approach, to generate insights. This is particularly true in the age of mobile-data platforms, which offer unprecedented opportunities to link theory-based experimental manipulations (natural or otherwise) with individual-level, population-scale, and in vivo behavioral data. Such mobile platforms can potentially extend psychological theory from static to longitudinal frameworks that capture the temporal dynamics of behavior and reduce operational distinctions between the laboratory and the field. In bridging these traditional temporal and spatial gaps between theory and practice, mobile platforms also allow for psychological phenomena that have previously been studied only in laboratories to be studied in real-world contexts, at a massive scale, to improve society's well-being.

Action Editor

Bill von Hippel served as action editor for this article.

Author Contributions

J. S. Jia designed the study and wrote the manuscript. J. S. Jia and J. Jia conducted the field survey, the retrospective survey, and the data analysis. J. Jia secured funding. All the authors helped develop the theoretical conceptualization, discussed the results, and contributed critical revisions of the manuscript.

Acknowledgments

We thank our research assistants, Yiwei Li and Yijian Ning, for aiding us with data preparation and analysis. We also thank Robert Wyer, Yuxin Chen, Nicholas Christakis, Anuj Shah, Jeff Inman, Dominic Coey, Harikesh Nair, Mark Granovetter, Benjamin Wah, and seminar participants at the Human Nature Lab at Yale University and New York University for their feedback and suggestions. We are especially grateful to three anonymous reviewers for their help during the review process.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Funding

This research was supported as a Major Program of the National Natural Science Foundation of China (71090402, 71490722) through Southwest Jiaotong University, Chengdu, China, where J. Jia is affiliated, and by the Research Grants Council of Hong Kong (27500114, 17506316), which supports J. S. Jia.

Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Notes

1. Intensity, a subjective measure of impact, should not be confused with magnitude measures such as the Richter scale or moment magnitude, which indicates energy released by an earthquake (see Section 1.3 in the Supplemental Material).
2. Apps are software programs installed in a mobile phone (e.g., a music player, a program that plays YouTube videos, a program that provides weather information).
3. Note that this model accounted for unobserved heterogeneity (e.g., regions experiencing different levels of earthquake intensity might have had unobserved demographic differences), because it compared change in usage (i.e., difference between usage before and after the earthquake).
4. It is unlikely that people in the counties experiencing higher earthquake intensity had more free time. An official state of emergency was declared for the entire prefecture, so work was canceled in all counties. Furthermore, a retrospective field survey we report later in the article did not provide evidence for a relationship between mobile-phone use and living conditions (an indirect reflection of free time).
5. This account was suggested by an anonymous reviewer. It should be noted that the Tobit model is silent regarding effects of individual differences because it eliminated endogeneity.

References

Angrist, J. D., & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic Perspectives*, *15*(4), 69–85.

Bagrow, J. P., Wang, D., & Barabasi, A. L. (2011). Collective response of human populations to large-scale emergencies. *PLoS ONE*, *6*(3), Article e17680. doi:10.1371/journal.pone.0017680

Berkson, J. (1980). Minimum chi-square, not maximum likelihood! *The Annals of Statistics*, *8*, 457–487.

Bonanno, G. A., Galea, S., Bucciarelli, A., & Vlahov, D. (2006). Psychological resilience after disaster: New York City in the aftermath of the September 11th terrorist attack. *Psychological Science*, *17*, 181–186. doi:10.1111/j.1467-9280.2006.01682.x

Brickman, P., & Campbell, D. T. (1971). Hedonic relativism and planning the good society. In M. H. Apley (Ed.), *Adaptation-level theory* (pp. 287–302). New York, NY: Academic Press.

Butzer, K. W. (2012). Collapse, environment, and society. *Proceedings of the National Academy of Sciences, USA*, *109*, 3632–3639. doi:10.1073/pnas.1114845109

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. *Psychological Bulletin*, *125*, 367–383. doi:10.1037/0033-2909.125.3.367

Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, *98*, 310–357.

Diener, E., Lucas, R. E., & Scollon, C. N. (2006). Beyond the hedonic treadmill: Revising the adaptation theory of well-being. *American Psychologist*, *61*, 305–314. doi:10.1037/0003-066X.61.4.305

Eagle, N., Pentland, A. S., & Lazer, D. (2009). Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences, USA*, *106*, 15274–15278. doi:10.1073/pnas.0900282106

Ferraro, R., Shiv, B., & Bettman, J. R. (2005). Let us eat and drink, for tomorrow we shall die: Effects of mortality salience and self-esteem on self-regulation in consumer choice. *Journal of Consumer Research*, *32*, 65–75. doi:10.1086/429601

Finucane, M. L., Slovic, P., Mertz, C. K., Flynn, J., & Satterfield, T. A. (2000). Gender, race, and perceived risk: The 'white male' effect. *Health, Risk & Society*, *2*, 159–172. doi:10.1080/713670162

Fischhoff, B. (1995). Risk perception and communication unplugged: Twenty years of process. *Risk Analysis*, *15*, 137–145. doi:10.1111/j.1539-6924.1995.tb00308.x

Frederick, S., & Loewenstein, G. (1999). Hedonic adaptation. In D. Kahneman & E. Diener (Eds.), *Well-being: The foundations of hedonic psychology* (pp. 302–329). New York, NY: Russell Sage.

Gao, L., Song, C., Gao, Z., Barabási, A.-L., Bagrow, J. P., & Wang, D. (2014). Quantifying information flow during emergencies. *Scientific Reports, 4*, Article 3997. doi:10.1038/srep03997

Goldstone, J. A. (2002). Population and security: How demographic change can lead to violent conflict. *Journal of International Affairs*, *56*, 3–21.

Hikosaka, O. (2010). The habenula: From stress evasion to value-based decision-making. *Nature Reviews Neuroscience*, *11*, 503–513. doi:10.1038/nrn2866

Hsee, C. K., Hastie, R., & Chen, J. (2008). Hedonomics: Bridging decision research with happiness research. *Perspectives on Psychological Science*, *3*, 224–243. doi:10.1111/j.1745-6924.2008.00076.x

International Federation of Red Cross and Red Crescent Societies. (2014). *World Disasters Report 2014 – data*. Retrieved from http://www.ifrc.org/world-disasters-report-2014/data

Kunreuther, H., & Slovic, P. (1996). Science, values, and risk. *Annals of the American Academy of Political and Social Science*, *545*, 116–125.

Li, B., Piriz, J., Mirrione, M., Chung, C., Proulx, C. D., Schulz, D., . . . Malinow, R. (2011). Synaptic potentiation onto habenula neurons in the learned helplessness model of depression. *Nature*, *470*, 535–539. doi:10.1038/nature09742

Liker, J. K., Augustyniak, S., & Duncan, G. J. (1985). Panel data and models of change: A comparison of first difference and conventional two-wave models. *Social Science Research*, *14*, 80–101.

Litt, A., Reich, T., Maymin, S., & Shiv, B. (2011). Pressure and perverse flights to familiarity. *Psychological Science*, *22*, 523–531. doi:10.1016/0049-089X(85)90013-4

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*, 267–286. doi:10.1037/0033-2909.127.2.267

Lu, X., Bengtsson, L., & Holme, P. (2012). Predictability of population displacement after the 2010 Haiti earthquake. *Proceedings of the National Academy of Sciences, USA*, *109*, 11576–11581. doi:10.1073/pnas.1203882109

Michel-Kerjan, E., & Kunreuther, H. (2007). Redesigning flood insurance. *Science*, *333*, 408–409. doi:10.1126/science.1202616

Newey, W. K. (1987). Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, *36*, 231–250.

Perrin, M. A., DiGrande, L., Wheeler, K., Thorpe, L., Farfel, M., & Brackbill, R. (2007). Differences in PTSD prevalence and associated risk factors among World Trade Center disaster rescue and recovery workers. *American Journal of Psychiatry*, *164*, 1385–1394. doi:10.1176/appi.ajp.2007.06101645

Ressler, K. J., & Mayberg, H. S. (2007). Targeting abnormal neural circuits in mood and anxiety disorders: From the laboratory to the clinic. *Nature Neuroscience*, *10*, 1116–1124. doi:10.1038/nn1944

Salamone, J. D., & Correa, M. (2012). The mysterious motivational functions of mesolimbic dopamine. *Neuron*, *76*, 470–485. doi:10.1016/j.neuron.2012.10.021

Salovey, P., Mayer, J. D., Goldman, S. L., Turvey, C., & Palfai, T. P. (1995). Emotional attention, clarity, and repair: Exploring emotional intelligence using the Trait Meta-Mood Scale. In J. W. Pennebaker (Ed.), *Emotion, disclosure, and health* (pp. 125–154). Washington, DC: American Psychological Association.

Saramäki, J., Leicht, E. A., López, E., Roberts, S. G., Reed-Tsochas, F., & Dunbar, R. I. (2014). Persistence of social signatures in human communication. *Proceedings of the National Academy of Sciences, USA*, *111*, 942–947. doi:10.1073/pnas.1308540110

Slovic, P. (1987). Perception of risk. *Science*, *236*, 280–285. doi:10.1126/science.3563507

Viscusi, W. K. (1993). The value of risks to life and health. *Journal of Economic Literature*, *31*, 1912–1946.

Weber, E. U. (2006). Experience-based and description-based perceptions of long-term risk: Why global warming does not scare us (yet). *Climatic Change*, *77*, 103–120. doi:10.1007/s10584-006-9060-3

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). Cambridge, MA: MIT Press.

Zeckhauser, R., & Viscusi, W. K. (1990). Risk within reason. *Science*, *248*, 559–564. doi:10.1126/science.2333509