Journal of Environmental Psychology 79 (2022) 101742

Contents lists available at ScienceDirect

Journal of Environmental Psychology

journal homepage: www.elsevier.com/locate/jep

Predictors of hurricane evacuation decisions: A meta-analysis

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ARTICLE INFO

Handling Editor: Sander van der Linden

Keywords:
Natural hazard
Hurricane evacuation
Meta-analysis
Human-environment interaction
Evacuation model
Disaster informatics

ABSTRACT

We systematically review and meta-analyze quantitative prediction models for hurricane evacuation decisions. Drawing on data from 33 prediction models and 29,873 households, we estimate distributions of effects on evacuation decisions for 25 predictors. Mobile home occupancy, evacuation orders, and having an evacuation plan showed the largest positive effects on evacuation, whereas increased age and Black race showed the largest negative effects. These results highlight the importance of both social-economic-structural factors and government action, such as evacuation orders, for enabling evacuation behaviors. Moderator analyses showed that models built using real-hurricane decisions showed larger effects than models of hypothetical decisions, especially for the strongest predictors. Additionally, models in Florida had more consistent results than for other U.S. states, and models with a larger number of covariates showed smaller effect sizes than models with fewer covariates. Importantly, our study improves methodologically and inferentially over previous reviews of this literature (Preprint and supplemental materials are available at https://psyarxiv.com/d5ktm).

Hurricane evacuations pose immense challenges for governments, public officials, urban planners, and emergency managers. These challenges are both infrastructural (e.g., designing transportation systems for rapid evacuation) and behavioral (e.g., informing and motivating the population to evacuate). Behavioral factors can be particularly vexing for planners. Many people do not evacuate, even when instructed to do so or at high risk. Conversely, "shadow evacuees"—people who evacuate despite not being in an evacuation zone, can clog transportation routes and overwhelm shelters and support resources. This uncertainty makes it difficult for planners at all levels to evaluate community readiness for evacuation or manage evacuations as they occur. To facilitate effective management, a clear understanding of the factors that promote and inhibit people's evacuation decisions is needed. Such knowledge will enable accurate predictions of the number of people who will evacuate, as well as identification of specific communities that may need additional support to facilitate evacuation.

Much research has investigated factors that influence individual decisions to evacuate. Since Baker's (1991) pioneering study in this area, many researchers have examined diverse factors as predictors of evacuation behavior, including storm intensity, economic resources, and sociodemographic characteristics. However, despite the growing number of studies, there is little consensus regarding which factors are most important for determining evacuation behaviors or how variables should be combined into overall evacuation decision models (Tanim & Tobin, 2018). Most reviews of hurricane evacuation literature have been narrative and focused on statistical significance tests. Differences in significance test results across studies have often been attributed to specific hurricane, measurement, and location contexts. Though these causes of inconsistent results are legitimate, they have tended to obscure the possibility that an appreciable amount of this heterogeneity may also be attributable to sampling error (Schmidt & Hunter, 2015). In addition, rather than focusing on binary significance test results, evacuation research can be more informative for modeling and planning applications by concentrating as well on effect size magnitudes—which predictors have the largest effects and what are their precise consequences for predicted evacuation probabilities? A predictor may be statistically significant but practically negligible in effect size (Funder & Ozer, 2019). To this end, this study presents a systematic review and meta-analysis of studies modeling individual hurricane evacuation decisions. We quantitatively synthesize models to estimate the average predicted effect of diverse factors on evacuation decisions, as well as the degree of true heterogeneity in these effects across contexts. We seek to provide robust quantitative estimates that can inform future computational modeling for planning and emergency management applications.

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https://doi.org/10.1016/j.jenvp.2021.101742
Received 16 February 2021; Received in revised form 13 September 2021; Accepted 4 December 2021
Available online 10 December 2021
0272-4944/

1. Predictors of hurricane evacuation decisions

The most commonly included variables are indicators of the storm severity or risk level, such as hurricane category (e.g., Lazo et al., 2010; Smith & McCarty, 2009), people's perceived level of risk (e.g., Burnside, 2006; Horney et al., 2010), or whether an official evacuation order is issued (e.g., Hasan et al., 2011; Whitehead et al., 2001). These variables reflect factors that are largely outside of individual control[1] and apply broadly to entire communities. They have generally been found to be strongly related to evacuation decisions.

The second category of predictor variables includes factors related to a specific household's economic resources, preparedness for a hurricane, and enabling factors for, or barriers to, evacuation. This category includes having an evacuation plan (e.g., Burnside, 2006; Mozumder & Vásquez, 2018), homeownership (e.g., Hasan et al., 2012; Smith & McCarty, 2009), living in a mobile/manufactured home (e.g., Lazo et al., 2010; Whitehead et al., 2001), having window protection (e.g., Hasan et al., 2012; Mozumder & Vásquez, 2018), having mandatory work that cannot be skipped (e.g., Bateman & Edwards, 2002; Petrolia & Bhattacharjee, 2010), and having access to transportation to evacuate (e.g., Lazo et al., 2010; Rosenkoetter et al., 2007). We also include in this category length of residence in the community and previous hurricane experience, as such variables can be regarded as knowledge resources helping a person to evaluate evacuation needs better (Adeola, 2009; Gladwin & Peacock, 1997). Among these predictors, as would be expected, having an evacuation plan and having access to transportation tend to be positively related to evacuation, and having window protection and having mandatory work tend to be negatively associated with evacuation. However, these effects vary in magnitude, and some predictors, such as homeownership and hurricane experience, have even varied in the direction of their relationship across studies (e.g., Huang, 2014; Meyer et al., 2013).

The third category of predictors concerns characteristics of the household, particularly the presence of potentially vulnerable or less mobile members. These predictors include household size (e.g., Bateman & Edwards, 2002; Hasan et al., 2011), the presence and number of children (e.g., Adeola, 2009; Van Willigen et al., 2002), and the presence of other vulnerable household members, such as elderly persons, disabled persons, or pets (e.g., Gladwin & Peacock, 1997; Petrolia & Bhattacharjee, 2010). Among these predictors, presence of an elderly person and owning a pet have been consistently negatively related to evacuation. In contrast, the presence of children or a disabled person has generally been positively related to evacuation, though these relationships have been more variable (e.g., Stein et al., 2010; Van Willigen et al., 2005).

A final category of predictors is general sociodemographic characteristics, such as the gender, age, education, and race/ethnicity of the respondent, as well as household income. These variables certainly overlap with the predictors in the above categories, but they may also capture other social, structural, and psychological factors with unique impacts on evacuation decisions.

In this study, we meta-analyze relationships of variables in each of these categories with evacuation decisions and compare the relative sizes of their relationships with evacuation intentions and behavior.

2. Moderators of Predictor–Evacuation decision relationships

Hurricane evacuation studies have varied in several major ways that may influence the effect sizes observed for various predictors. We consider three major moderators—whether studies model real evacuation behavior or only behavioral intentions, the location of the hurricane being modeled, and the degree of statistical control for covariates.

2.1. Hypothetical versus real evacuation decisions

Most hurricane evacuation studies have assessed participants' evacuation behavior during a specific past hurricane (e.g., Hurricane Ivan). However, some studies have instead presented participants with hypothetical hurricane scenarios and then asked them whether they would evacuate during a hurricane with the described features. Such hypothetical hurricane studies can be useful to examine a wider range of predictor combinations than would be possible for retrospective real hurricane studies. However, they are limited in that they do not assess actual evacuation *behavior*, but rather only behavioral *intentions*. Much psychological research has found that behavioral intentions are only moderately related to actual behavior (e.g., $r \approx .40$–$.50$; Albarracín et al., 2001; Bamberg & Möser, 2007; Webb & Sheeran, 2006). Intentions can be strong predictors of subsequent behavior, but this relationship is far from perfect, and they should not be regarded as interchangeable measures. Predictor variables, such as risk-level or evacuation orders, may function differently when they reflect imagined versus real situations. Reading a vignette about a hurricane's risk level is a psychologically quite different experience than reacting to real-time news reports and warnings. This imperfect relationship between intentions and future behavior, as well as the variability in people's ability to predict their behavior, will function as a source of measurement error, increasing noise in the evacuation measure and attenuating potential relationships with predictors (Schmidt & Hunter, 2015; Wiernik & Dahlke, 2020). Accordingly, we expect real hurricane studies to show generally larger predictor effects than hypothetical hurricane studies.

Hypothesis 1. Real hurricane models will show larger effect sizes than hypothetical hurricane models.

2.2. Hurricane location

In previous reviews, location has often been posited as an explanation for variation in findings across evacuation studies due to locations' unique geographical, social, and cultural characteristics (Baker, 1991; Sarwar et al., 2018; Thiede & Brown, 2013). However, several researchers have explored whether models developed for one hurricane evacuation can readily be applied to other hurricanes in new locations, a process known as transferability (e.g., Fu et al., 2006; Hasan et al., 2012). These studies have found that evacuation models do tend to transfer well to new locations. In this study, we explore hurricane location as a moderator of predictor–evacuation relationships. As most hurricane evacuation studies have taken place in Florida we compare results for these studies to those for studies of other U.S. states. We expect the Florida-based studies to be more homogeneous in their effects than studies conducted in a diverse range of other states largely on account of the higher frequency with which Florida experiences, or is threatened by, hurricanes (NOAA, 2005).

Hypothesis 2. Predictor effects will be more consistent for Florida-based studies than for studies based on other U.S. states.

2.3. Statistical control for covariates (model size)

Previous reviews of hurricane evacuation decisions have often considered single predictors at a time and focused on bivariate predictor–evacuation relationships. A problem with this approach is that the predictive power of many variables may be shared or redundant with other predictors. A variable that shows a large bivariate relationship with evacuation may be a comparatively weaker predictor when considered as part of a more fully specified multivariate model. For example, income might show a strong bivariate relationship with evacuation, but this relationship may mostly reflect overlap with more proximal predictors, such as living in a mobile home or having access to

[1] Subjective risk perceptions vary across individuals, but they are of course related to objective storm features, as well as information conveyed by public officials and the media (Burnside, 2006; Lindell et al., 2005).

transportation. By analogy, personality trait relationships with important behaviors and life outcomes are substantially smaller when a person's full array of traits is considered than when traits are considered individually (Soto, 2020). It is also worth noting that the relative strength of highly correlated predictors may vary by study and Huang et al. (2016) make the important point, which we support, that hurricane evacuation modeling studies be encouraged to report the full matrix of correlations to allow for more accurate interpretations of findings.

Physical storm characteristics, economic and structural factors, and sociodemographic characteristics all operate in tandem to simultaneously influence people's decisions. To build an accurate computational model of hurricane evacuation decisions, rather than single-predictor bivariate relationships, it is more relevant to consider conditional relationships of predictors for evacuation from models that include other relevant predictors. Such multivariate models account for the shared variance and confounding across predictors and allow modelers to make more accurate quantitative predictions about people's evacuation propensities.

Accordingly, in this meta-analysis, we synthesize conditional effect sizes from the models studied, and we explored the number of predictor covariates included in the model as a moderator variable. Following findings from other domains (Soto, 2020), we expect to find that effect sizes from models with more covariates would be smaller than those from models with fewer covariates (especially single-predictor models).

Hypothesis 3. Models including many covariates will show smaller effect sizes than models with few covariates.

3. Methods

3.1. Literature search

We used several literature search strategies to identify studies reporting hurricane evacuation decision models. First, we searched in Google Scholar, Scopus, and ProQuest Dissertations & Theses using all combinations of the keywords: *evacuation, hurricane*, *evacuation decision*, and *evacuation model*. Second, we conducted a backward citation search by reviewing the reference lists of all studies found in the keyword searches for additional candidate studies. Third, we conducted a forward citation search. For each study found in the keyword searches that had been cited ≥200 times, we reviewed articles citing the study as reported by the "Cited by" function in Google Scholar and Scopus. Together, these searches yielded 287 unique sources for potential inclusion. We included both published and unpublished (theses, reports, etc.) studies to reduce possible effects of publication bias (Ones et al., 2017).

3.2. Inclusion criteria

To be included in our meta-analysis, studies needed to meet several inclusion criteria. The inclusion process is illustrated in Fig. 1. First, studies needed to report a statistical model predicting hurricane evacuation decisions using one or more predictors. Studies not reporting such a model were excluded ($n = 227$). Second, we excluded studies that were not based in the United States ($n = 8$). Third, studies needed to report effect sizes that could be converted to an odds ratio ($n = 20$ excluded). A total of 32 studies met these inclusion criteria. Although no

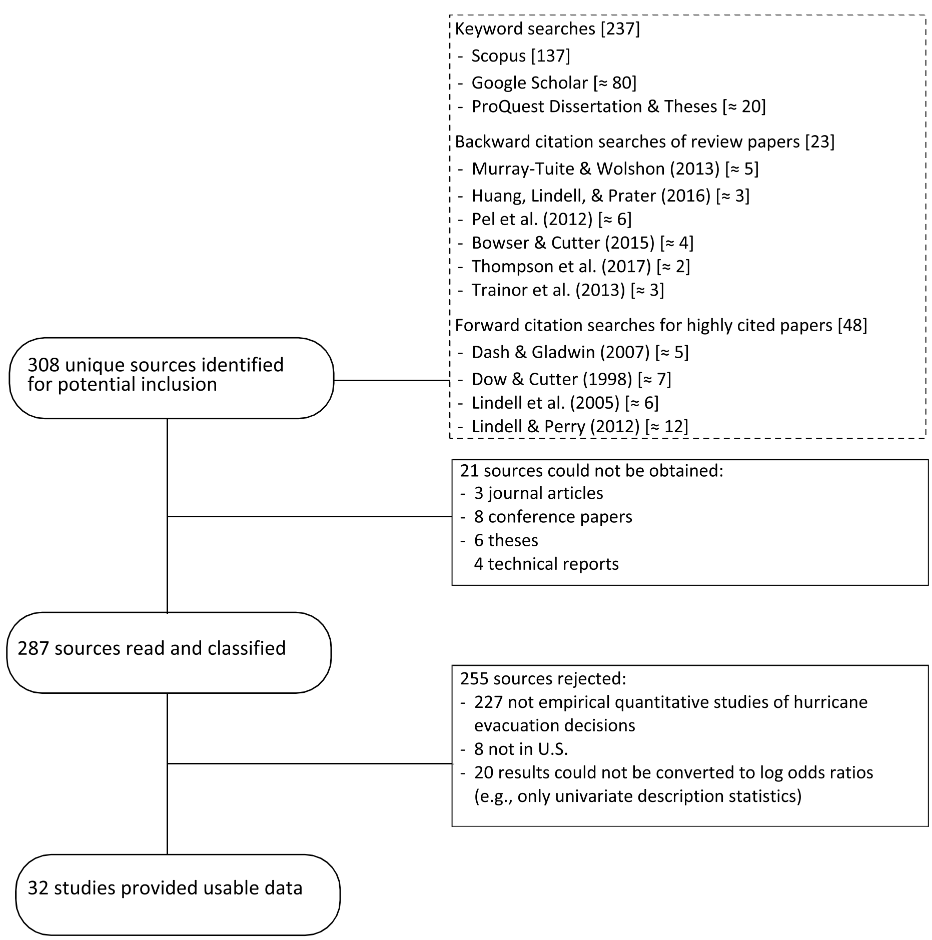

Fig. 1. Process of selecting studies for meta-analysis.

specific time period was targeted during the search, among the 32 studies, the earliest was from the year 1997 and the latest was a study from 2018.

Several included studies reported results for multiple hurricane evacuation models. If models were based on distinct samples of people, they were treated as independent and included separately in the meta-analysis. If models were reported for a total sample and several subsamples, only the models for the subsamples were included to maximize the number of effect sizes available and provide the most accurate estimates of random effects heterogeneity. If a study reported multiple models for the same sample, the model whose predictor set was most similar to those for other models included in this meta-analysis was included. Three research teams published multiple studies examining different combinations of predictor variables using the same sample of people. For these studies ($n = 7$), we averaged coefficients for each predictor across the models including them, producing three averaged models. Our final sample consisted of 33 models (Table S1).

3.3. Predictor variables

We conducted our meta-analysis for predictor variables that were represented in at least 3 of the 33 included models. A total of 25 predictors met this criterion. Among these 25 predictors, four predictors have 2 types of definition considering how the variable was scaled and another one (evacuation order) has 3 definitions depending on how it was described in the models. Table 1 describes these 25 predictors. Table S1 in the online supplement lists each included predictor variable by each model. Table S2 lists excluded predictor variables for each model. For these predictors, we estimated separate meta-analytic models for each operationalization to ensure commensurability in effect size metrics across the meta-analyzed studies.

We grouped the 25 analyzed predictors into 4 categories. *Risk and storm characteristics* includes predictors related to characteristics of the hurricane (hurricane category; whether an evacuation order was issued; perceived risk of flood, winds, or storm surge). *Resources and preparedness* includes predictors related to a household's tangible and intangible resources, preparations, or restrictions that could mitigate a hurricane's impact (e.g., homeownership; mobile home occupancy; length of residence; hurricane experience; having mandatory work; having an evacuation plan; having window protection such as shutters; car ownership). *Family characteristics* include features of respondents' household structure (household size; presence of children; presence of elderly persons; pet ownership; marital status; presence of disabled persons). *Sociodemographic characteristics* include other demographic characteristics (gender; age; income; education; race; ethnicity).

3.4. Effect size calculation

A hurricane evacuation decision is a binary outcome variable (evacuate or not). Most of the included studies reported results in the form of a logistic regression model. Accordingly, we conducted our meta-analysis using the log odds-ratio (unstandardized regression coefficient, β, from a logistic regression model) relating a predictor variable (e.g., gender, income, perceived risk) to a binary evacuation decision. Most included studies ($n = 24$) reported a logistic regression model, or models from which we coded β coefficients directly. A small number of studies ($n = 6$) reported results as univariate odds ratios (*OR*) computed from contingency tables; we computed β coefficients for these studies as $\beta = \log(OR)$. A small number of studies ($n = 2$) reported results as correlation coefficients. We converted these to log odds ratios using the formula given by Lipsey and Wilson (2001) if the study reported marginal variable proportions, and the formula given by (Chinn, 2000) if it did not.

Interpretation of odds ratios or log odds ratios depends on the baseline evacuation probability. To aid interpretation of the meta-analysis results, Table A1 shows predicted evacuation probabilities for various baseline evacuation probabilities and varying values of predictor odds ratios (*OR*) or log odds ratios (β). Generally, large changes in predicted evacuation probabilities become apparent when $\beta \geq 0.50$ (e.g., for a baseline probability of .50, $\beta = 0.50$ [$OR = 1.65$] corresponds to predicted evacuation probability of .62 [+12 percentage points]).

To organize our results and discussion, we organized mean effect sizes into descriptive categories. Log odds ratios express effects in terms of changes in log odds per 1 unit change in the predictor. Expressed in terms of probability, log odds = 0 corresponds to .50 probability, log odds = 1 corresponds to ≈ 0.75 probability, log odds = 2 corresponds to ≈ 0.90 probability, and log odds = 3 corresponds to ≈ 0.95 probability.

Table 1
Variable coding for predictors included in meta-analysis.

Predictor	Predictor definition	*k*	*N*
Evacuation order (3 definitions)	1 = Evacuation order received, 0 = Otherwise	12	17105
	Mandatory: 1 = Mandatory evacuation order received, 0 = Otherwise	6	8463
	Voluntary: 1 = Voluntary evacuation order received, 0 = Otherwise	4	7466
Flood risk	Either binary (high vs. low risk) or 3-category (high, medium, low risk)	8	4557
Wind risk	Either binary (high vs. low risk) or 3-category (high, medium, low risk)	4	2006
Surge risk	Either binary (high vs. low risk) or 3-category (high, medium, low risk)	4	1702
Hurricane category	Hurricane category as impacted respondent's county, 0–5	5	9048
Homeownership	1 = Homeowners, 0 = Otherwise	19	20461
Mobile home	1 = Lives in a mobile home, 0 = Otherwise	14	17438
Length of residence	Number of years residing in current location	12	14354
Hurricane experience	1 = Previous hurricane experience, 0 = Otherwise	10	10923
Mandatory work	1 = Someone in the house had to work during the evacuation period, 0 = Otherwise	4	5572
Household evacuation plan	1 = Having an evacuation plan, 0 = Otherwise	4	4185
Window protection	1 = Having window protection, 0 = Otherwise	4	7151
Car ownership	1 = Owned a personal transport, 0 = Otherwise	2	539
Household size	Size of the household (number of members)	16	19598
Children in the household (2 definitions)	Continuous: Number of children in the household	6	6572
	Binary: 1 = Having a child in the household, 0 = Otherwise	8	4098
Presence of elderly person	1 = Having a household member aged 65 or older, 0 = Otherwise	7	10754
Pet ownership	1 = Household owns a pet, 0 = Otherwise	6	5214
Marital status	1 = Married family, 0 = Otherwise	6	4113
Disabled	1 = Person with special/medical needs in the household, 0 = Otherwise	3	2130
Female	1 = Female, 0 = Male	20	19096
Age (2 definitions)	Continuous: Age of respondent in years	12	8370
	Ordinal: 6–7 age categories for respondents	5	1611
Income (2 definitions)	Continuous: Household income in thousands of dollars	10	12432
	Ordinal: 6–11 household income categories	7	4731
Education (2 definitions)	Continuous: Years in school for respondents	9	12182
	Ordinal: 5–7 education level categories for respondents	6	2768
Black	Black: 1 = Non-Hispanic Black, 0 = Non-Hispanic White	9	12173
Hispanic	Hispanic: 1 = Hispanic, 0 = Non-Hispanic White	7	10754

Note. k = number of models included in meta-analysis; *N* = total sample size.

Exactly how a change in log odds corresponds to change in probability depends on the baseline evacuation probability (see Table A1). However, across baseline probabilities ranging .25–.75, a log odds change ≈ 0.20 generally corresponds to a probability change ≈ 0.05. Accordingly, for positive effect sizes, we interpreted odds ratios of 1.00–1.25 (β = 0.00 to 0.22) as small, 1.25 to 1.50 (β = 0.25 to 0.41) as moderate, and 1.50 or greater ($\beta \geq 0.41$) as large. For negative effect sizes, we considered odds ratios from 0.80 to 1.00 (β = 0.00 to −0.22) small, 0.67 to 0.80 (β = −0.22 to 0.41) moderate, and 0.67 or less ($\beta \leq -0.41$) large.

If a model reported multiple coefficients for the same predictor (e.g., "hurricane experience with major damage" and "hurricane experience without major damage"), we calculated a composite effect for these coefficients (Schmidt & Hunter, 2015). This composite effect size reflects the combined total effect of all uses of the predictor in the model.

4. Meta-analytic methods

For each predictor variable, we fitted a random-effects meta-analysis model (Hedges & Olkin, 1985; Hunter & Schmidt, 2000). We weighted effect sizes by sample size; these fixed weights yield more accurate results than sample-estimated inverse variance weights (Bakbergenuly et al., 2019). We estimated the random effects variance component (τ^2) using the restricted maximum likelihood (REML) estimator (Viechtbauer, 2005). The square root of the random effects variance component, τ (Schmidt & Hunter, 2015), is the estimated true (non-artefactual) random effects standard deviation of effect sizes across models and contexts. If τ is large, this suggests the presence of additional moderators (Wiernik et al., 2017). The mean effect size for a predictor was thus computed as $\overline{\beta} = \sum_{i=1}^{k} N_i \beta_i / \sum_{i=1}^{k} N_i$ with standard error $SE_{\overline{\beta}} = \sqrt{\sum_{i=1}^{k} N_i^2 (SE_{\beta_i}^2 + \tau^2) / (\sum_{i=1}^{k} N_i)^2}$, where $\overline{\beta}$ is the sample-size-weighted mean log odds ratio, k is the number of studies, N_i, β_i, and SE_{β_i} are the sample size, log odds ratio, and standard error of the log odds ratio for study i, and τ is the estimated random effects standard deviation.[2]

To quantify uncertainty and heterogeneity in effect sizes, we constructed prediction intervals (IntHout et al., 2016). The 95% prediction interval is calculated as $\overline{\beta} \pm 1.96 \times \sqrt{SE_{\overline{\beta}}^2 + \tau^2}$. The prediction interval combines the information typically presented separately in confidence and credibility intervals (Whitener, 1990). It reflects both uncertainty in the mean effect size estimate and estimated true variation of individual effects around the mean. The prediction interval can be interpreted as a range of plausible values that might be observed in future hurricane evacuation studies. We report results both in the log odds ratio (β) and odds ratio ($OR = e^{\beta}$) metrics.

Our meta-analysis was conducted using the *psychmeta* (version 2.3.2, Dahlke & Wiernik, 2017/2019, 2019) and *metafor* (version 2.1-0, Viechtbauer, 2010, 2019) packages in *R* (version 3.6.0, R Core Team, 2020).

4.1. Moderator analysis

We examined several moderator variables that may account for differences in observed effect sizes across our included models. We conducted our moderator analysis using the subgroup analysis method; we estimated separate meta-analysis models for all included models at each level of the moderators. Table S1 includes moderator coding for each model included this meta-analysis.

4.1.1. Hypothetical versus real hurricanes

First, we compared results for models of real hurricanes (modeling respondents' actual evacuation behaviors for a specific past hurricane) to those for models of hypothetical hurricanes (modeling respondents' intentions to evacuate for a hypothetical future hurricane).

4.1.2. Hurricane location

Second, among models of real hurricanes, we compared results for studies conducted using samples located in Florida to those located outside Florida. Most included studies modeled Florida hurricanes. The number of studies for specific non-Florida locations was small, so we combined all studies in a pooled "Non-Florida" group.

4.1.3. Statistical control for covariates

Third, among models of real hurricanes, we did a binary comparison for models including relatively more versus fewer covariates. This moderator serves to roughly evaluate the degree to which the estimated effect size is sensitive to the presence of other correlated predictors in models. We coded this moderator by counting how many of the 25 predictors considered in the current study the model included. Across the 33 included models, the highest number of the 25 predictors included was 15; the minimum number was 0 (a bivariate model). The median number of included predictors was 7 (mean = 6.8). Accordingly, we coded a model as having a high number of covariates if it included more than seven of the 25 predictor variables under consideration in this study. We coded models including seven or fewer of these predictors as having a low number of covariates.

4.1.4. Variable scaling method

For some predictors, studies varied in how a specific variable was scaled. For example, in some studies, age was measured as a continuous variable, but other studies used an ordinal age scale with 5–7 categories. Similarly, some studies included number of children as a predictor, whereas others used a binary indicator of no children versus any number. These alternative scales yield incommensurate effect sizes. Accordingly, for children, age, education, and income we also examined the scaling method as an additional moderator.

5. Results

Fig. 2 presents summary results for the meta-analysis. For each predictor, the figure shows the mean odds ratio and the 95% prediction interval for the real hurricane models and the hypothetical models.

5.1. Risk and storm characteristics

Table A2 presents full meta-analysis results for risk and storm characteristics predictors.

5.1.1. Evacuation order

Results showed that people were much more likely to evacuate when an evacuation order was issued than when no evacuation order was issued, though heterogeneity was large (overall $\overline{\beta} = 1.255$, $\tau = 0.56$, $\overline{OR} = 3.51$, 95% PI 1.08, 11.38). Effects were much larger for real hurricane models ($\overline{\beta} = 1.437$, $\tau = 0.39$, $\overline{OR} = 4.21$, 95% PI 1.82, 9.72) than for the 2 hypothetical hurricane models ($\overline{\beta} = 0.287$, $\tau = 0.22$, $\overline{OR} = 1.33$, 95% PI 0.77, 2.32).

Among real hurricane models, effects were somewhat larger for mandatory evacuation orders ($\overline{\beta} = 1.693$, $\tau = 0.48$, $\overline{OR} = 5.44$, 95% PI 1.76, 16.84) than for voluntary evacuation orders ($\overline{\beta} = 1.405$, $\tau = 0.56$, $\overline{OR} = 4.07$, 95% PI 1.09, 15.26). Effects were also somewhat smaller and

[2] A small number of studies (k = 5) did not report enough information to compute the standard error for every predictor. We contacted authors of these studies for missing information, but only one author was able to provide the requested information. The remaining models did provide statistical significance thresholds for significant predictors. For these models, we estimated standard errors using the boundary p value for the threshold (i.e., p = .10, p = .05, p = .01; for non-significant predictors, we used p = .10). This approach yields conservative (larger) τ values.

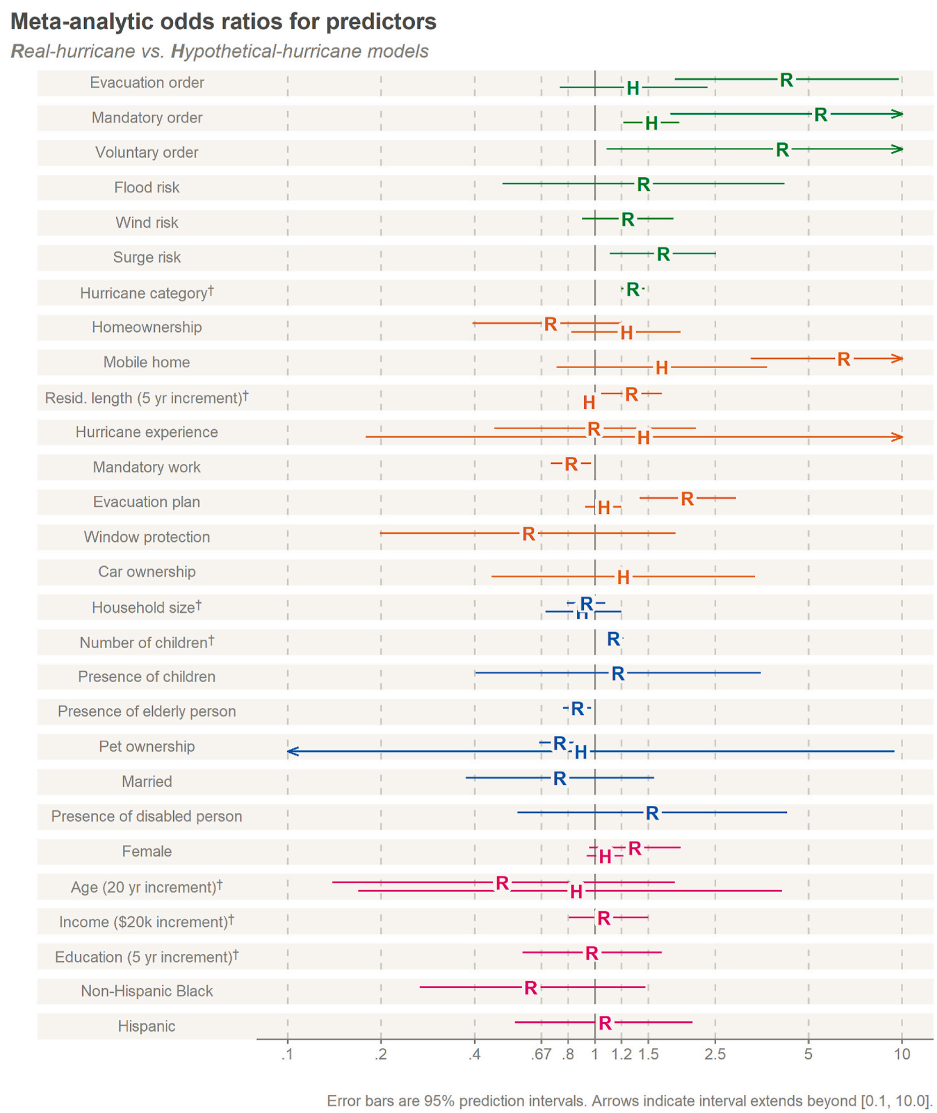

Fig. 2. Summary of meta-analysis results. Only analysis with $k \geq 2$ shown. Ordinal age, income, and education results omitted. Colors indicate conceptual categories of predictors. †indicates non-binary predictors.

less variable for models in Florida ($\overline{\beta} = 1.379$, $\tau = 0.16$, $\overline{OR} = 3.97$, 95% PI 2.71, 5.82) than in other locations ($\overline{\beta} = 1.573$, $\tau = 0.53$, $\overline{OR} = 4.82$, 95% PI 1.52, 15.31), as well as for models with more covariates ($\overline{\beta} = 1.360$, $\tau = 0.00$, $\overline{OR} = 3.90$, 95% PI 3.38, 4.49) compared to fewer ($\overline{\beta} = 1.612$, $\tau = 0.55$, $\overline{OR} = 5.01$, 95% PI 1.54, 16.31). Notably, the high-covariate models all modeled the same hurricane and showed homogeneous effects ($\tau = 0.00$). In general, these moderator effects were small; evacuation order was a consistently strong predictor of evacuation decisions.

5.1.2. *Perceived risk*

Except for one hypothetical hurricane model for perceived flood risk ($\beta = 0.199$), all perceived risk models were real hurricane models in non-Florida locations. Perceived flood risk was on average moderately associated with choosing to evacuate, but this relationship was highly heterogeneous with a prediction interval widely spanning 1.0 ($\overline{\beta} = 0.364$, $\tau = 0.49$, $\overline{OR} = 1.44$, 95% PI 0.50, 4.13). Results were similar for high-covariate ($\overline{\beta} = 0.344$, $\tau = 0.70$, $\overline{OR} = 1.41$) and low-covariate ($\overline{\beta} = 0.396$, $\tau = 0.31$, $\overline{OR} = 1.49$) models. Perceived storm surge risk, showed a larger, and consistently positive effect ($\overline{\beta} = 0.513$, $\tau = 0.12$, $\overline{OR} = 1.67$, 95% PI 1.12, 2.48). Perceived wind risk had a smaller effect but was quite consistent, although its prediction interval did extend just below 1.0 ($\overline{\beta} = 0.249$, $\tau = 0.1$, $\overline{OR} = 1.28$, 95% PI 0.91, 1.80).

5.1.3. *Hurricane category*

All models including hurricane category as a predictor were real hurricane, Florida, low-covariate models. These models showed that a 1-unit increase in hurricane category was associated with slightly higher evacuation odds ($\overline{\beta} = 0.284$, $\overline{OR} = 1.33$, 95% PI 1.22, 1.45). However, this effect translates to much larger evacuation odds for a category-5 hurricane compared to a category-1 hurricane ($\overline{\beta} = 1.136$, $\overline{OR} = 3.11$). Effect sizes were estimated to be homogeneous ($\tau = 0.00$).

6. Resources and preparedness

Table A3 presents full meta-analysis results for resources and preparedness predictors.

6.1. *Homeownership*

For real hurricane models, respondents who owned their home were moderately less likely to evacuate than respondents who did not ($\overline{\beta} = -0.331$, $\tau = 0.28$, $\overline{OR} = 0.72$, 95% PI 0.40, 1.29). The effect was reversed for hypothetical hurricane models ($\overline{\beta} = 0.236$, $\tau = 0.00$, $\overline{OR} = 1.27$, 95% PI 0.84, 1.90). Real hurricane effects were more consistent in Florida ($\overline{\beta} = -0.398$, $\tau = 0.00$, $\overline{OR} = 0.67$) than in other locations ($\overline{\beta} = -0.181$, $\tau = 0.41$, $\overline{OR} = 0.83$). Results were kind of similar for high-covariate ($\overline{\beta} = -0.350$, $\overline{OR} = 0.70$) and low-covariate ($\overline{\beta} = -0.275$, $\overline{OR} = 0.76$) models.

6.2. Manufactured or mobile home

For real hurricane models, respondents who lived in a manufactured or mobile home were much more likely to evacuate than respondents who did not ($\overline{\beta} = 1.867$, $\tau = 0.28$, $\overline{OR} = 6.47$, 95% PI 3.21, 13.04). The effect was much smaller, though still substantial, for the two hypothetical hurricane models ($\overline{\beta} = 0.498$, $\tau = 0.00$, $\overline{OR} = 1.65$, 95% PI 0.75, 3.62). Among real hurricane models, results were similar for Florida ($\overline{\beta} = 1.848$, $\overline{OR} = 6.35$) and other locations ($\overline{\beta} = 1.940$, $\overline{OR} = 6.96$), as well as for high-covariate ($\overline{\beta} = 1.838$, $\overline{OR} = 6.29$) and low-covariate ($\overline{\beta} = 1.984$, $\overline{OR} = 7.27$) models.

6.3. Length of residence

For real hurricane models, respondents who had resided for a longer time in their current location were moderately more likely to evacuate (5-year increment $\overline{\beta} = 0.276$, $\tau = 0.06$, $\overline{OR} = 1.32$, 95% PI 1.05, 1.65). The effect was absent in hypothetical hurricane models ($\overline{\beta} = -0.045$, $\tau = 0.02$, $\overline{OR} = 0.96$, 95% PI 0.90, 1.00), and it also disappeared when limiting to real hurricane models with many predictor covariates ($\overline{\beta} = 0.087$, $\tau = 0.06$, $\overline{OR} = 1.09$) or to Florida models ($\overline{\beta} = -0.055$, $\tau = 0.08$, $\overline{OR} = 0.95$). These results suggest that any length-of-residence effects may be redundant with other predictors (or potentially specific to certain locations).

6.4. Previous hurricane experience

For real hurricane models, previous hurricane experience was on average negligibly related to evacuation decisions ($\overline{\beta} = -0.004$, $\overline{OR} = 0.996$), but this effect was highly heterogeneous ($\tau = 0.34$, OR 95% PI 0.47, 2.13). In 2 Florida models, previous hurricane experience was small and negatively related to evacuation ($\overline{\beta} = -0.257$, $\tau = 0.00$, $\overline{OR} = 0.77$, 95% PI 0.63, 0.95). Effects outside of Florida remained highly heterogeneous ($\tau = 0.40$, OR 95% PI 0.53, 3.27). Significant differences were apparent between high-covariate ($\overline{\beta} = -0.027$, $\overline{OR} = 0.996$) and low-covariate models ($\overline{\beta} = 0.027$, $\overline{OR} = 1.03$). Hypothetical hurricane models showed effects that were stronger effects on average, but also much more variable ($\overline{\beta} = 0.366$, $\tau = 0.86$, $\overline{OR} = 1.44$, 95% PI 0.18, 11.74).

6.5. Other Resources and preparedness predictors

The other resources and preparedness predictors were each included in only a small number of models. Having mandatory work scheduled showed a consistently small negative relation with evacuation ($k = 3$ real hurricane, 1 hypothetical hurricane, $\overline{\beta} = -0.199$, $\tau = 0.00$, $\overline{OR} = 0.82$, 95% PI 0.71, 0.94). Having a household evacuation plan showed very small effect for 2 hypothetical hurricane models ($\overline{\beta} = 0.065$, $\tau = 0.00$, $\overline{OR} = 1.36$, 95% PI 0.63, 2.93), but a large positive effect for 2 real hurricane models ($\overline{\beta} = 0.696$, $\tau = 0.00$, $\overline{OR} = 2.00$, 95% PI 1.40, 2.87). In 3 real hurricane models, having window protection was on average largely negatively related to evacuation but this effect was highly heterogeneous ($\overline{\beta} = -0.497$, $\tau = 0.46$, $\overline{OR} = 0.61$, 95% PI 0.20, 1.83); 1 hypothetical hurricane model showed a smaller effect ($\beta = -0.106$). Three hypothetical hurricane models suggested that car owners were slightly more likely to evacuate ($\overline{\beta} = 0.216$, $\tau = 0.29$, $\overline{OR} = 1.25$, 95% PI 0.46, 3.31). Given the small number of studies, these results should be interpreted cautiously.

7. Family characteristics

Table A4 presents full meta-analysis results for family characteristics.

7.1. Household size

Household size was consistently small effect on evacuation decisions in both real hurricane (per additional person $\overline{\beta} = -0.065$, $\tau = 0.07$, $\overline{OR} = 0.94$, 95% PI 0.81, 1.08) and hypothetical hurricane models ($\overline{\beta} = -0.090$, $\tau = 0.10$, $\overline{OR} = 0.91$, 95% PI 0.69, 1.22). Effects were especially small in models including many predictor covariates ($\overline{\beta} = -0.027$, $\tau = 0.02$, $\overline{OR} = 0.97$, 95% PI 0.93, 1.02). These effects are larger if considering potential accumulating effects of additional members (e.g., comparing a 5-person household to a 1-person household, $\widehat{\beta} = -0.335$).

In a subset of 6 models that included both overall household size and number of children, household size could be interpreted as the number of adults, controlling for the number of children. In these models, household size had somewhat larger negative effect (per additional person $\overline{\beta} = -0.198$, $\tau = 0.13$, $\overline{OR} = 0.82$, 95% PI 0.61, 1.11; comparing a 3-adult household to a 1-adult household, $\widehat{\beta} = -0.396$).

7.2. Children

In contrast to overall household size, number of children showed small positive relationships with evacuation decisions in real hurricane models (per additional child $\overline{\beta} = 0.143$, $\tau = 0.00$, $\overline{OR} = 1.15$, 95% PI 1.08, 1.24; note that all models including children also controlled for overall household size). These effects are meaningfully large if considering potential accumulating effects of multiple children (e.g., comparing a household with three children to one with none, $\widehat{\beta} = 0.429$). Results were similar for Florida and non-Florida models, but slightly smaller in two models with many predictor covariates ($\overline{\beta} = 0.103$, $\tau = 0.00$, $\overline{OR} = 1.11$) versus models with few ($\overline{\beta} = 0.195$, $\tau = 0.00$, $\overline{OR} = 1.22$). Effects had a similar mean but were more heterogeneous when children predictor was operationalized as a binary variable ($\overline{\beta} = 0.171$, $\tau = 0.47$, $\overline{OR} = 1.19$, 95% PI 0.41, 3.46); this is potentially due to heterogeneity in the distribution of number of children across samples.

7.3. Presence of an elderly person

Presence of one or more elderly persons in the household showed a consistently small relationship with evacuation in real hurricane models ($\overline{\beta} = -0.133$, $\tau = 0.00$, $\overline{OR} = 0.88$, 95% PI 0.79, 0.97). When limiting the analysis to only models with many predictor covariates, the relationship was near-zero ($\overline{\beta} = -0.011$, $\tau = 0.00$, $\overline{OR} = 0.99$, 95% PI 0.96, 1.02).

7.4. Other family characteristics

Other family characteristics had a relatively small number of real hurricane models. Having a pet appeared to be moderately negatively related with evacuation. Relationships were larger and less heterogeneous in real hurricane models ($k = 3$, $\overline{\beta} = -0.258$, $\tau = 0.03$, $\overline{OR} = 0.77$, 95% PI 0.66, 0.90) than in hypothetical hurricane models ($k = 3$, $\overline{\beta} = -0.106$, $\tau = 1.00$, $\overline{OR} = 0.90$, 95% PI 0.09, 9.41). Whether the household was married or not was moderately negatively related to evacuation but showed substantial heterogeneity ($k = 5$, $\overline{\beta} = -0.266$, $\tau = 0.30$, $\overline{OR} = 0.77$, 95% PI 0.38, 1.56). We estimated having a disabled person in the household as having a largely positive relationship with evacuation, but effect sizes varied widely across the one hypothetical hurricane model ($N = 531$, $\beta = 1.079$) and two real hurricane models ($N_1 = 1029$,

$\beta_1 = 0.688$; $N_2 = 570$, $\beta_2 = -0.026$).

8. Sociodemographic characteristics

Table A5 presents full meta-analysis results for sociodemographic characteristics.

8.1. Female

In real hurricane models, when the survey respondent was female, they were on average moderately more likely to report evacuating, but this effect was fairly heterogeneous ($\overline{\beta} = 0.299$, $\tau = 0.16$, $\overline{OR} = 1.35$, 95% PI 0.96, 1.90). Results were also not similar in Florida and non-Florida models, as well as in models with many versus fewer predictor covariates. This effect was absent in hypothetical hurricane models ($\overline{\beta} = 0.079$, $\tau = 0.00$, $\overline{OR} = 1.08$, 95% PI 0.94, 1.24).

8.2. Age

For models measuring age as a continuous variable, we estimated meta-analysis for the estimated effect of a 20-year age difference (20 years age difference was considered to be more consistent with the ordinal scale of age predictor). For real hurricane models, respondent age was largely, but heterogeneously, negatively related to evacuation ($\overline{\beta} = -0.699$, $\tau = 0.49$, $\overline{OR} = 0.50$, 95% PI 0.14, 2.82). This effect disappeared in models with many predictor covariates ($\overline{\beta} = -0.115$, $\tau = 0.36$, $\overline{OR} = 0.89$, 95% PI 0.37, 2.23) compared to models with few ($\overline{\beta} = -1.101$, $\tau = 0.58$, $\overline{OR} = 0.33$, 95% PI 0.06, 1.82). The effect was also reduced in hypothetical hurricane models ($\overline{\beta} = -0.138$, $\tau = 0.64$, $\overline{OR} = 0.87$) and in all models using an ordinal age scale ($\overline{\beta} = -0.058$, $\tau = 0.10$, $\overline{OR} = 0.94$).

8.3. Income

For models measuring income as a continuous variable, we estimated meta-analysis for the estimated effect of a \$20,000 income difference. For real hurricane models including many predictor covariates, income was consistently having small effect with evacuation ($\overline{\beta} = 0.155$, $\tau = 0.00$, $\overline{OR} = 1.17$, 95% PI 0.83, 1.64). In real hurricane models with few predictor covariates, the income–evacuation relationship was much larger and negative, though the prediction interval was wide ($\overline{\beta} = -0.548$, $\tau = 0.00$, $\overline{OR} = 0.58$, 95% PI 0.14, 2.23). A single small hypothetical hurricane study suggested a moderate negative relationship between income and evacuation ($N = 400$, $\beta = -0.400$). Results were similarly negligible for real hurricane models measuring income using an ordinal scale, all of which included a high number of predictor covariates.

8.4. Education

For models measuring education as a continuous variable, we estimated meta-analysis for the estimated effect of a 5-year education difference. For real hurricane models, education was on average had very small (negligible) relation with evacuation, with a moderate degree of heterogeneity ($\overline{\beta} = -0.02$, $\tau = 0.24$, $\overline{OR} = 0.98$, 95% PI 0.58, 1.65). The prediction interval spanned large negative to large positive values. Results were similar across Florida and non-Florida models. All but one model included high numbers of predictor covariates. A single small hypothetical hurricane study suggested a large positive effect on evacuation ($N = 400$, $\beta = 0.850$). Results were similar, though somewhat less variable in studies measuring education with an ordinal scale.

8.5. Race and ethnicity

In real hurricane models, non-Hispanic Black respondents were largely less likely to evacuate than non-Hispanic White respondents, but with moderate heterogeneity ($\overline{\beta} = -0.474$, $\tau = 0.39$, $\overline{OR} = 0.62$, 95% PI 0.27, 1.46). Black–White differences appeared to be somewhat larger in non-Florida models and in models with few predictor covariates. Conversely, a single small hypothetical hurricane model found the opposite effect ($N = 400$, $\beta = 0.323$).

Hispanic respondents reported very small evacuation rates as non-Hispanic White respondents, with substantial heterogeneity across models ($\overline{\beta} = 0.072$, $\tau = 0.29$, $\overline{OR} = 1.08$, 95% PI 0.55, 2.08). All of these models were real hurricane, and all but one included a high number of predictor covariates.

9. Discussion

We conducted a systematic review and quantitative meta-analysis of hurricane evacuation models. Our goal was to estimate distributions of model parameters for various predictors of evacuation decisions, including both mean effect sizes and heterogeneity across models. We explored effects of 3 moderators: hurricane type (real vs. hypothetical), location (Florida vs. other U.S. states), and model size (number of predictors).

9.1. Effect sizes and heterogeneity

For clarity of discussion, we focus on results for real-hurricane models. For each predictor, Fig. 3 illustrates the mean effect size across all models used for that predictor, along with the individual effect sizes from included models.

9.1.1. Large effects

We observed the largest positive effects on evacuation decisions for *mobile home residency* and *issuance of evacuation orders*, by a large margin. Vulnerability of mobile homes to hurricane damage is well documented (Bowser & Cutter, 2015; Chakraborty et al., 2005; Cutter et al., 2000), as is confidence in hurricane evacuation orders (Bowser & Cutter, 2015; Sorensen, 2000). For evacuation orders, mandatory evacuation orders, as expected, tend to have a stronger impact than voluntary evacuation orders. None of the studies in this meta-analysis considered possible interaction of mobile home residency with evacuation orders despite mobile home residents typically being in the primary category for such orders, and often given additional advisories.

Other predictors with large positive effects on evacuation, albeit less than the two above, were *hurricane category*, *storm surge risk*, *having an evacuation plan*, and *presence of a disabled person in the household*. For hurricane category, it should be emphasized that the effect size in Fig. 2 and Table A2 is for a 1-unit increase on the Saffir-Simpson hurricane scale. This effect is thus quite large when comparing a category 1 hurricane to a category 5 hurricane (see Fig. 3). The effect of storm surge risk is also large and demonstrates considerable consistency. The effect of a having an evacuation plan was also consistently positive across all studies. Presence of a disabled person effect sizes were reported by only two studies, which gave highly inconsistent estimates.

We observed the largest negative mean effect on evacuation decisions for a *20 years age increment*. However, this predictor showed considerable heterogeneity across models; this inconsistency has been noted by previous studies (Bowser & Cutter, 2015; Gladwin & Peacock, 1997; Perry & Lindell, 1997). Other predictors that showed large negative effects on evacuation were *window protection* and *non-Hispanic Black households*. For the latter, there are well-documented socioeconomic and structural disparities across racial groups that impact resources available for evacuation (Fussell et al., 2010; Huddy & Feldman, 2006; Sigelman & Welch, 1994).

Fig. 3. Study effects arranged by mean effect magnitude. Colors indicate effect size magnitude category (large, medium, and small). † indicates non-binary predictors. Only real hurricane models with $k \geq 3$ shown.

9.1.2. Moderate effects

Predictors which show a moderately positive effect size on the evacuation decision include *flood risk, wind risk, being female*, and *increased length of residence*. For flood risk, five models showed a positive effect, and two models had negative effects. This heterogeneity may reflect variability in contexts across samples. For example, in some areas, flood risk may be highest for wealthier neighborhoods occupied by higher income homeowners. In these areas, people at flood risk may prefer to remain and manage the effects of the flood, rather than evacuate. However, it is worth noting that, on average, flood risk showed stronger effects than wind risk. Together with the earlier observation of large effects of perceived storm surge risk, this suggests that people are more likely to evacuate due to hydro-meteorological hurricane hazards (i.e., surge and flood).

Gender effects were highly consistent across models. Women tend to more occupy caregiving family roles and to have higher levels of communication with neighbors; both of these factors have been cited as possible explanations for gender effects in previous evacuation studies (Bateman & Edwards, 2002; Drabek, 1969; Gladwin & Peacock, 1997). Most length of residence effects were very small, though three relatively smaller studies showed moderate positive effects. Previous studies have linked longer residence with stronger social networks and better evacuation preparation (Adeola, 2009; Smith & McCarty, 2009); future studies might explore these factors as moderators of residence length–evacuation decision relationships.

Homeownership, being *married*, and *pet ownership* each moderately negatively predicted evacuation and did so fairly consistently. Homeownership effects might be attributable to a desire to protect property and resources (Horney et al., 2012; Smith & McCarty, 2009). Pet ownership effects might be due to inability to safely transport and shelter pets when evacuating (Brackenridge et al., 2012; Lowe et al., 2009; Whitehead et al., 2000). Previous research has not identified potential explanations for marital status effects; notably, the models with marital status that were included the meta-analysis controlled for obvious covariates of marital status, such as age and homeownership.

9.1.3. Small effect sizes

When predictors show only small effects on evacuation, consistency of these small relationships is particularly important—are these variables consistently weak predictors or are there contexts in which they are more important? Several predictors showed *consistently* negligible relationships with evacuation, including *mandatory work* and *presence of an elderly person* (though 1 smaller study had a large negative effect). Inflexible work schedules and lack of social support among retired persons have been cited as potential barriers to evacuation (Baker, 1991; Kaniasty & Norris, 1995). The overall negligible effect of mandatory work is perhaps surprising on the surface and one hypothesis is that the minimal effect may be a reflection of shared variance in larger models. However, among the three models that included this predictor, two that showed small negative effects were based on large models and the one showing a very negligible effect was based on a small model. That said, the overall number of models is low for this predictor and it warrants further research.

In interpreting results for *number of children* and *household size*, it important to remember that results are for each increment of one person. Compared to a 0- or 1-children family, having 2 or more children was consistently estimated to have a moderate positive effect on evacuation. Conversely, when controlling for children, 2- or 3- adult families were consistently moderately less likely to evacuate than 1-adult families.

The remaining predictors with small mean effects were more heterogeneous across studies. *Income* had generally near-zero effects across studies, but also 2 studies with (opposing) extreme values. *Hispanic ethnicity*, *hurricane experience*, and *education* each were more broadly heterogeneous, with a range of negligible to moderate positive and negative effects across studies. These variables' inconsistent effects have been noted in previous research (e.g., Hasan et al., 2011; Riad et al., 1999; Tinsley et al., 2012; Yin et al., 2014). Future research should investigate moderators of these relationships.

10. Effects of moderators

10.1. Type of model: real versus hypothetical hurricanes

Our first moderator hypothesis was that models based on real hurricane studies would show larger effect sizes than those based on hypothetical hurricane studies. There were sufficient models of each type in our study to investigate this hypothesis for 12 predictors.

Across these 12 predictors, a consistent pattern emerged—effect sizes from hypothetical-hurricane studies tended to be smaller than effect sizes from real-hurricane studies. These differences were minor for predictors with small mean effects, but became quite pronounced for predictors with large mean effects (e.g., *evacuation orders*, *mobile home residency*, *having an evacuation plan*, *age*). For the effects with the largest discrepancies, there was negligible to no overlap in prediction intervals between the two types of studies. Hypothetical-hurricane studies thus appeared to systematically underestimate the strength of the most important predictors of real hurricane behaviors. This was also noted in Huang et al. (2016) for mobile homes and evacuation orders. The notion that stated intent and actual behavior may be quite different is well known (cf. Bamberg & Möser, 2007); our analyses suggest that this general finding applies in the context of hurricane evacuation decisions, particularly for those predictors which may be most impactful.

10.2. Study location: Florida versus elsewhere

Our second moderator hypothesis was that predictor effects would be more consistent for Florida-based real hurricane models than for real hurricane models in other states. There were sufficient models in our study to investigate this hypothesis for 11 predictors. Among these predictors, *evacuation order, length of residence, homeownership, income,* and *previous hurricane experience* provided strong evidence to support our hypothesis in the sense that their prediction intervals for Florida-based models were much narrower than those for non-Florida-based models. Other predictors—*mobile home residency, non-Hispanic Black,* and *education*—showed more consistency for non-Florida-based models. The remaining predictors—*number of children, household size,* and *being female*—showed very similar levels of consistency across both Florida and non-Florida based models. It is perhaps noteworthy that the predictors which were more consistent for Florida-based models were those that were more directly linked to familiarity with hurricanes (evacuation orders, length of residence, and hurricane experience); this would seem to support our original rationale for this hypothesis.

10.3. Model size

Our third moderator hypothesis was that real hurricane models including many predictors (>7) would show smaller effect sizes than real hurricane models with fewer predictors (≤7). There were sufficient models of each type in our study to investigate this hypothesis for 13 predictors.

Of the 13 predictors, 11 predictors, a large proportion, showed smaller effect sizes in larger models. These differences were most pronounced for *age*, *length of residence*, *income*, and *mandatory evacuation order*. These results underscore the importance of considering evacuation predictors in a multivariate context, lest the importance of individual factors be overstated.

Differences across model sizes for remaining predictors were modest. It should be noted that for two predictors—*length of residence* and *being female*—all many-predictor models were also Florida-based models, so separate effects of these moderators could not be examined.

In sum, there was some evidence supporting the hypothesis that factors overlap in their predictive power for hurricane evacuation decisions, but the size of this impact varies across predictors. This finding is consistent with results from other literatures (e.g., Soto, 2020, found that personality trait–outcome relationships reduced substantially when controlling for correlated traits). Given the somewhat crude distinction between large and small models necessitated by the number of included models, it is noteworthy that we nevertheless observed this evidence for our hypothesis.

11. Comparison with previous meta-analysis of this literature

Huang et al. (2016) reported a previous meta-analysis of the hurricane evacuation literature. It is informative to compare our findings with those from their study. It should be noted, however, that the two studies have several important differences. First, the two reviews considered somewhat different sets of studies, with 25 studies (i.e., models) overlapping. Some of the reasons for the differences is that we chose to restrict our study to the USA whereas Huang et al. included studies from India and Mexico. In terms of predictors, Huang et al. examined 36 predictors and we examined 25, with an overlap of 17. Given our inclusion criteria, we were not able to investigate some predictors that Huang et al. found to have a consistently positive effect on evacuation, such as peer evacuation, business closures, nearby landfall, and casualties, although we note these predictors were only examined in a small number of quantitative studies. There were 7 predictors that we examined that were not examined by Huang et al., including some with consistently positive effects on evacuation—evacuation plan and length of residence, and some with consistently negative effects—pet ownership and mandatory work. One other difference in the studies is that where predictors were measured on very different scales (e.g., ordinal versus continuous); we analyzed those predictors, such as age, education, and income separately for each type of measurement scale. It is not clear from Huang et al. how they handled different measurement scales for such predictors; as we found, measurement scale can have important impacts on observed results.

Despite these differences, the two studies show some similarity in results. In terms of large positive effects on evacuation, both studies found the use of official warnings/evacuation orders and mobile home residence to be highly predictive. The studies also gave similar results for storm surge, flood, and wind risk, including the same sequence in the sizing of their relative effects. Both studies also noted the highly consistent nature of hurricane category (intensity); though the difference in evacuation odds may be small between adjacent categories, the cumulative effect across several categories can be large. Both studies also identified female gender as a positive effect on evacuation. Finally, the two studies were similar in the sense that their prediction intervals (confidence intervals in Huang et al.) for common predictors with negative effects on evacuation were not exclusively on the negative side. Within that, both studies did note that homeownership likely has a quite large negative impact on evacuation. Among other negative effects, our study did estimate somewhat different relative effect sizes to that of Huang et al., particularly for Non-Hispanic Black (coded Black in Huang et al.) where we estimated a larger mean effect than for homeownership.

However, despite many similarities in patterns of results, several of the overall conclusions differ between the two reviews. Most notably, in the current review, we conclude that studies of hypothetical and real hurricanes tended to yield notably different results, with hypothetical studies tending to show smaller effect sizes, particularly for those predictors with the largest effect sizes. In contrast, Huang et al. concluded "… the effect sizes from actual hurricane evacuation studies are similar to those from studies of hypothetical hurricane scenarios …" (abstract) and based on this similarity suggested "laboratory and Internet experiments could be used to examine people's cognitive processing of different types of hurricane warning messages" (abstract).

As noted above, the overall pattern of quantitative results across the two reviews was similar, so we argue that the difference in conclusions stems primarily from a difference in inferential approaches, rather than differences in results per se. Huang et al.'s conclusion that hypothetical and real hurricane studies yielded similar results appears to stem primarily from their Fig. 2, which shows a correlation between mean effect sizes for the of the two types of studies of r = .58 for 17 variables. However, the correlation coefficient is not an appropriate for indexing *agreement* (Putka et al., 2008); the correlation coefficient indexes consistency in the relative ordering of two variables. By definition, the correlation coefficient is the covariance between two *standardized* variables—any differences in *means* or *variances* between the two variables are removed. If there are substantial mean differences between two variables, the correlation is by definition insensitive to these differences. Similarly, if there are variance differences (e.g., if large effects are pulled toward the mean for one variable), the correlation is also insensitive to these differences. Both of these types of differences are relevant for the current review. Hypothetical hurricane studies showed smaller mean effects than real hurricane studies. Thus, if we are interested in the predictive power of a particular predictor (e.g., is an evacuation order beneficial), rather than merely its relative effect compared to another predictor (is an evacuation order more important than a person's risk perceptions), the hypothetical hurricane studies would underestimate the predictive utility of this predictor. This pattern is shown both in the current study's Fig. 2 and in Huang et al.'s Fig. 2, where real hurricane studies also consistently showed larger mean effect sizes. Similarly, hypothetical hurricane studies also showed less variance in effects across predictors—the largest effects were pulled toward the mean much more than smaller effects. There are much larger real vs. hypothetical differences for the largest effects. Thus, the bias in the estimates of the individual predictor utilities suggested by hypothetical hurricane studies is largest for the predictors that are likely to be most relevant for decision making. This pattern was also apparent in Huang et al.'s Fig. 2.

These differences are important for practical interpretation of the meta-analysis results. That the relative ordering of the two sets of results is similar does not mean that the differences between these two sets of studies is not important. Policymaking and planning around hurricane evacuations depends on how impactful each predictor is on people's decisions, not only the relative effectiveness of one factor over another. Both of these reviews suggest that laboratory studies will underestimate of the impact of major policy decisions such as evacuation disorders. Insights from laboratory studies should be treated with caution until they can be confirmed with operational behavioral data.

12. Limitations and future directions

A meta-analysis of statistical models is necessarily constrained by the types of statistical models, predictors, and approaches used in the synthesized literature. None of the models included in our meta-analyses included interaction effects, and, with the exception of one model including some polynomial terms, they modeled only linear effects. Additionally, meta-analyses such as this one, which largely rely on reported results, are not privy to the variable-selection procedures used by investigators, so nothing is known as to the extent that issues such as multi-collinearity may have played a role in reported effect sizes and standard errors. These issues are mentioned here since there is good *a priori* rationale to expect that some of the predictors typically investigated in hurricane evacuation research do indeed interact with each other, some may exhibit high levels of multicollinearity with each other, and the effects of some of the predictors may indeed be non-linear. Interpretation of our results regarding predictor–evacuation decision relationships should bear these possibilities in mind.

A second limitation of any statistical meta-analysis is the number of input models available for any predictor. This issue is exacerbated when a particular variable concept, such as income or education, is defined or operationalized in different ways, such as ordinal versus continuous scales. In such circumstances, each operationalization must generally be modeled as a separate predictor. In our meta-analyses, the median number of models per predictor across the 30 predictors for real hurricane studies was 6.5, with five predictors having at least ten models as input, but nine predictors having fewer than four models. Due to the limited number of studies available for some models, prediction intervals for these effects were quite wide and limited the scope of moderator analyses that could be conducted.

Finally, a third potential limitation is that the included models varied in the specific predictors they included. On the one hand, this means that the coefficients included in our meta-analyses did not all have the same covariates adjusted. This would be unlikely to affect mean estimates, but would tend to increase estimates of τ and the widths of prediction intervals. On the other hand, as we argued in the introduction, partial effect sizes that account for correlated predictors more accurately convey predictor impacts and are more informative for policy, modeling, and research. Moreover, in logistic regression, unlike linear regression, coefficients do not exhibit collapsibility; that is, omitting an important predictor can bias coefficients, even if the predictors are uncorrelated (Kuha & Mills, 2017). Thus, zero-order logistic regression coefficients are not necessarily more accurate or appropriate for meta-analysis.

13. Conclusion

The meta-analyses presented in this paper identify several clear, strong predictors of evacuation decisions, as well as other factors that appear to have consistently small impacts. These results can inform future modeling of evacuation behavior, as well as help to guide policy regarding preparation and communication of hurricane risks to various populations. Importantly, the current study improves in several ways over existing reviews in this literature, increasing confidence in the results and providing results in more practically actionable metrics.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvp.2021.101742.

Appendix

Table A1
Predicted evacuation probabilities for varying baseline evacuation probabilities and various values of β_1 (OR)

β_1	−3.00	−2.00	−1.50	−1.00	−0.75	−0.50	−0.25	−0.10	0.00	0.10	0.25	0.50	0.75	1.00	1.50	2.00	3.00
OR	0.05	0.14	0.22	0.37	0.47	0.61	0.78	0.90	1.00	1.11	1.28	1.65	2.12	2.72	4.48	7.39	20.09
Baseline evacuation probability = 0.20 ($\beta_0 = -1.39$)																	
Predicted evacuation probability	.01	.03	.05	.08	.11	.13	.16	.18	.20	.22	.24	.29	.35	.40	.53	.65	.83
Difference from baseline	−.19	−.17	−.15	−.12	−.09	−.07	−.04	−.02	.00	+.02	+.04	+.09	+.15	+.20	+.33	+.45	+.63
Baseline evacuation probability = 0.50 ($\beta_0 = +0.00$)																	
Predicted evacuation probability	0.05	0.12	0.18	0.27	0.32	0.38	0.44	0.48	0.50	0.52	0.56	0.62	0.68	0.73	0.82	0.88	0.95
Difference from baseline	−.45	−.38	−.32	−.23	−.18	−.12	−.06	−.02	.00	+.02	+.06	+.12	+.18	+.23	+.32	+.38	+.45
Baseline evacuation probability = 0.80 ($\beta_0 = +1.39$)																	
Predicted evacuation probability	0.17	0.35	0.47	0.60	0.65	0.71	0.76	0.78	0.80	0.82	0.84	0.87	0.89	0.92	0.95	0.97	0.99
Difference from baseline	−.63	−.45	−.33	−.20	−.15	−.09	−.06	−.02	.00	+.02	+.04	+.07	+.09	+.12	+.15	+.17	+.19

Note: β_1 = predictor regression coefficient (log odds), *OR* = predictor odds ratio, β_0 = regression intercept (baseline log odds).

Table A2
Full meta-analysis results for risk and storm characteristics

Predictor	*k*	*N*	$\overline{\beta}$	$SE_{\overline{\beta}}$	τ	95% pred. int.	$\overline{OR}$	95% pred. int.
Evacuation orders (3 definitions)								
Any evacuation orders	12	17105	1.255	0.207	0.56	(0.08, 2.43)	3.51	(1.08, 11.38)
Hypothetical	2	2717	0.287	0.181	0.22	(−0.27, 0.84)	1.33	(0.77, 2.32)
Real	10	14388	1.437	0.165	0.39	(0.60, 2.27)	4.21	(1.82, 9.72)
Florida	4	10033	1.379	0.111	0.16	(1.00, 1.76)	3.97	(2.71, 5.82)
Non-Florida	6	4355	1.573	0.251	0.53	(0.42, 2.73)	4.82	(1.52, 15.31)
High covariates	4	9974	1.360	0.072	0.00	(1.22, 1.50)	3.90	(3.38, 4.49)
Low covariates	6	4414	1.612	0.254	0.55	(0.43, 2.79)	5.01	(1.54, 16.31)
Mandatory order	6	8463	1.286	0.404	0.80	(−0.48, 3.05)	3.62	(0.62, 21.09)
Hypothetical	2	2717	0.424	0.071	0.08	(0.22, 0.63)	1.53	(1.24, 1.88)
Real	4	5746	1.693	0.313	0.48	(0.56, 2.82)	5.44	(1.76, 16.84)
Florida	1	3200	1.348	0.127	–	–	3.85	–
Non-Florida	3	2546	2.127	0.266	0.39	(1.21, 3.05)	8.39	(3.34, 21.06)
High covariates	2	4095	1.530	0.466	0.56	(0.10, 2.96)	4.62	(1.11, 19.22)
Low covariates	2	1651	2.097	0.483	0.60	(0.59, 3.61)	8.15	(1.80, 36.89)
Voluntary order	4	7466	1.009	0.474	0.85	(−0.89, 2.91)	2.74	(0.41, 18.34)
Hypothetical	1	2186	0.054	0.028	–	–	1.06	–
Real	3	5280	1.405	0.380	0.56	(0.08, 2.73)	4.07	(1.09, 15.26)
Florida	1	3200	1.258	0.107	–	–	3.52	–
Non-Florida	2	2080	1.631	0.562	0.77	(−0.23, 3.49)	5.11	(0.79, 32.91)
High covariates	2	4095	1.200	0.112	0.07	(0.94, 1.46)	3.32	(2.56, 4.30)
Low covariates	1	1185	2.111	0.149	–	–	8.26	–
Perceived risk								
Flood risk	8	4557	0.344	0.192	0.44	(−0.60, 1.29)	1.41	(0.55, 3.65)
Hypothetical	1	532	0.199	0.121	–	–	1.22	–
Real[NF]	7	4025	0.364	0.225	0.49	(−0.69, 1.42)	1.44	(0.50, 4.13)
High covariates	3	2486	0.344	0.434	0.70	(−1.27, 1.96)	1.41	(0.28, 7.08)
Low covariates	4	1539	0.396	0.213	0.31	(−0.34, 1.13)	1.49	(0.71, 3.10)
Wind risk[R,NF]	4	2006	0.249	0.143	0.10	(−0.09, 0.59)	1.28	(0.91, 1.80)
High covariates	1	895	0.246	0.248	–	–	1.28	–
Low covariates	3	1111	0.251	0.168	0.17	(−0.21, 0.72)	1.29	(0.80, 2.05)
Storm surge risk[R,NF]	4	1702	0.513	0.165	0.12	(0.12, 0.91)	1.67	(1.12, 2.48)
High covariates	1	309	0.698	0.21	–	–	2.01	–
Low covariates	3	1393	0.472	0.217	0.19	(−0.09, 1.03)	1.6	(0.92, 2.80)
Hurricane category (1–5)[R,F,L]	5	9048	0.284	0.044	0	(0.20, 0.37)	1.33	(1.22, 1.45)

Note. k = number of models included in meta-analysis, N = total sample size, $\overline{\beta}$ = sample-size weighted mean log odds ratio (unstandardized logistic regression coefficient), SE = standard error of $\overline{\beta}$, τ = residual random effects standard deviation of β after accounting for sampling error (τ), pred. int. = prediction interval, $\overline{OR}$ = mean odds ratio ($\exp[\overline{\beta}]$).
[R] All included models were real hurricane.
[F] All included models were Florida.
[NF] All included models were non-Florida.
[L] All included models included a low number of the predictor covariates.

Table A3
Full meta-analysis results for resources and preparedness

Predictor	k	N	$\overline{\beta}$	$SE_{\overline{\beta}}$	τ	95% pred. int.	$\overline{OR}$	95% pred. int.
Homeownership	19	20461	−0.295	0.107	0.30	(−0.92, 0.33)	0.74	(0.40, 1.39)
Hypothetical	3	1288	0.236	0.207	0.00	(−0.17, 0.64)	1.27	(0.84, 1.90)
Real	16	19173	−0.331	0.108	0.28	(−0.92, 0.26)	0.72	(0.40, 1.29)
Florida	7	13202	−0.398	0.076	0.00	(−0.55, −0.25)	0.67	(0.58, 0.78)
Non-Florida	9	5971	−0.181	0.195	0.41	(−1.08, 0.72)	0.83	(0.34, 2.05)
High covariates	10	14208	−0.350	0.135	0.29	(−0.98, 0.28)	0.70	(0.38, 1.32)
Low covariates	6	4965	−0.275	0.135	0.00	(−0.54, −0.01)	0.76	(0.58, 0.99)
Mobile home	14	17438	1.794	0.238	0.42	(0.85, 2.74)	6.01	(2.34, 15.44)
Hypothetical	2	932	0.498	0.402	0.00	(−0.29, 1.29)	1.65	(0.75, 3.62)
Real	12	16506	1.867	0.225	0.28	(1.17, 2.57)	6.47	(3.21, 13.04)
Florida	7	13202	1.848	0.306	0.47	(0.75, 2.95)	6.35	(2.11, 19.12)
Non−Florida	5	3304	1.940	0.392	0.00	(1.17, 2.71)	6.96	(3.23, 15.00)
High covariates	7	13277	1.838	0.296	0.45	(0.78, 2.90)	6.29	(2.18, 18.13)
Low covariates	5	3229	1.984	0.443	0.00	(1.12, 2.85)	7.27	(3.05, 17.32)
Length of residence (5 years)	12	14354	0.207	0.076	0.042	(0.05, 0.4)	1.23	(1.05, 1.49)
Hypothetical	3	3118	−0.045	0.025	0.022	(−0.10, 0.00)	0.96	(0.90, 1.00)
Real	9	11236	0.276	0.098	0.061	(0.05, 0.50)	1.32	(1.05, 1.65)
Florida	5	9048	−0.055	0.041	0.078	(−0.23, 0.12)	0.95	(0.80, 1.12)
Non−Florida	4	2188	1.647	0.734	1.059	(−0.88, 4.17)	5.19	(0.42, 64.9)
High covariates	7	10137	0.087	0.076	0.062	(−0.10, 0.28)	1.09	(0.90, 1.32)
Low covariates	2	1099	2.021	0.717	0.000	(0.62, 3.43)	7.54	(1.85, 30.74)
Previous hurricane experience	10	10923	0.100	0.238	0.57	(−1.11, 1.31)	1.11	(0.33, 3.7)
Hypothetical	3	3073	0.366	0.64	0.86	(−1.73, 2.46)	1.44	(0.18, 11.74)
Real	7	7850	−0.004	0.184	0.34	(−0.76, 0.76)	0.99	(0.47, 2.13)
Florida	2	4129	−0.257	0.106	0.00	(−0.47, −0.05)	0.77	(0.63, 0.95)
Non-Florida	5	3721	0.277	0.232	0.40	(−0.63, 1.19)	1.32	(0.53, 3.27)
High covariates	3	4539	−0.027	0.329	0.43	(−1.08, 1.03)	0.97	(0.34, 2.8)
Low covariates	4	3311	0.027	0.210	0.29	(−0.67, 0.73)	1.03	(0.51, 2.07)
Mandatory work	4	5572	−0.199	0.071	0.00	(−0.34, −0.06)	0.82	(0.71, 0.94)
Hypothetical	1	532	−0.390	0.199	–	–	0.68	–
Real	3	5040	−0.179	0.075	0.00	(−0.33, −0.03)	0.84	(0.72, 0.97)
Florida	1	3200	−0.235	0.097	–	–	0.79	–
Non-Florida	2	1840	−0.080	0.120	0.00	(−0.32, 0.15)	0.92	(0.73, 1.17)
High covariates	2	4229	−0.209	0.076	0.00	(−0.36, −0.06)	0.81	(0.70, 0.94)
Low covariates	1	811	−0.020	0.254	–	–	0.98	–
Household evacuation plan[NF]	4	4185	0.306	0.214	0.33	(−0.46, 1.07)	1.36	(0.63, 2.93)
Hypothetical	2	2586	0.065	0.070	0.00	(−0.07, 0.20)	1.07	(0.93, 1.22)
Real	2	1599	0.696	0.183	0.00	(0.34, 1.05)	2.00	(1.40, 2.87)
High covariates	1	1029	0.658	0.255	–	–	1.93	–
Low covariates	1	570	0.764	0.228	–	–	2.15	–
Window protection	4	7151	−0.378	0.265	0.45	(−1.41, 0.65)	0.69	(0.24, 1.92)
Hypothetical	1	2186	−0.106	0.074	–	–	0.90	–
Real	3	4965	−0.497	0.325	0.46	(−1.60, 0.60)	0.61	(0.20, 1.83)
Florida	2	4154	−0.500	0.510	0.63	(−2.08, 1.09)	0.61	(0.12, 2.96)
Non-Florida	1	811	−0.484	0.232	–	–	0.62	–
High covariates	1	3200	−0.291	0.085	–	–	0.75	–
Low covariates	2	1765	−0.871	0.358	0.46	(−2.02, 0.27)	0.42	(0.13, 1.32)
Car ownership[Hy]	3	1071	0.216	0.410	0.29	(−0.76, 1.19)	1.24	(0.46, 3.31)

Note. k = number of models included in meta-analysis, N = total sample size, $\overline{\beta}$ = sample-size weighted mean log odds ratio (unstandardized logistic regression coefficient), SE = standard error of $\overline{\beta}$, τ = residual random effects standard deviation of β after accounting for sampling error (τ), pred. int. = prediction interval, $\overline{OR}$ = mean odds ratio ($\exp[\overline{\beta}]$).
[Hy] All included models were hypothetical hurricane.
[NF] All included models were non-Florida.

Table A4
Full meta-analysis results for family characteristics

Predictor	k	N	$\overline{\beta}$	$SE_{\overline{\beta}}$	τ	95% pred. int.	$\overline{OR}$	95% pred. int.
Household size	16	19598	−0.067	0.028	0.07	(−0.22, 0.08)	0.94	(0.81, 1.09)
Hypothetical	3	1287	−0.090	0.108	0.10	(−0.38, 0.2)	0.91	(0.69, 1.22)
Real	13	18311	−0.065	0.028	0.07	(−0.21, 0.08)	0.94	(0.81, 1.08)
Florida	8	14131	−0.055	0.032	0.07	(−0.2, 0.09)	0.95	(0.82, 1.09)
Non-Florida	5	4180	−0.098	0.066	0.09	(−0.31, 0.12)	0.91	(0.73, 1.12)
High covariates	8	13839	−0.027	0.017	0.02	(−0.07, 0.02)	0.97	(0.93, 1.02)
Low covariates	5	4472	−0.183	0.088	0.15	(−0.52, 0.15)	0.83	(0.60, 1.16)
Models including number of children	6	5501	−0.198	0.076	0.13	(−0.50, 0.10)	0.82	(0.61, 1.11)
Children in household *(2 definitions)*								
Number of children[R]	6	6572	0.143	0.035	0.00	(0.07, 0.21)	1.15	(1.08, 1.24)
Florida	2	3633	0.140	0.043	0.00	(0.06, 0.23)	1.15	(1.06, 1.25)
Non-Florida	4	2939	0.147	0.058	0.00	(0.03, 0.26)	1.16	(1.03, 1.30)
High covariates	2	3708	0.103	0.037	0.00	(0.03, 0.17)	1.11	(1.03, 1.19)

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Table A4 (*continued*)

Predictor	k	N	$\overline{\beta}$	$SE_{\overline{\beta}}$	τ	95% pred. int.	$\overline{OR}$	95% pred. int.
Low covariates	4	2864	0.195	0.065	0.00	(0.07, 0.32)	1.22	(1.07, 1.38)
Presence of children (binary)[R]	8	4098	0.171	0.271	0.47	(−0.9, 1.24)	1.19	(0.41, 3.46)
Florida	1	929	1.930	0.748	–	–	6.89	–
Non-Florida	7	3169	−0.345	0.191	0.35	(−1.13, 0.44)	0.71	(0.32, 1.56)
High covariates	2	1086	0.075	0.151	0.00	(−0.22, 0.37)	1.08	(0.8, 1.45)
Low covariates	6	3012	0.205	0.421	0.70	(−1.4, 1.81)	1.23	(0.25, 6.1)
Presence of elderly person[R]	7	10754	−0.133	0.050	0.00	(−0.23, −0.03)	0.88	(0.79, 0.97)
Florida	6	9977	−0.137	0.051	0.00	(−0.24, −0.04)	0.87	(0.79, 0.96)
Non-Florida	1	777	−0.080	0.210	–	–	0.92	–
High covariates	6	9825	−0.011	0.017	0.00	(−0.05, 0.02)	0.99	(0.96, 1.02)
Low covariates	1	929	−1.420	0.550	–	–	0.24	–
Pet ownership	6	5214	−0.227	0.392	0.68	(−1.76, 1.31)	0.80	(0.17, 3.71)
Hypothetical	3	1070	−0.106	0.666	1.00	(−2.45, 2.24)	0.90	(0.09, 9.41)
Real	3	4144	−0.258	0.075	0.03	(−0.41, −0.10)	0.77	(0.66, 0.90)
Florida	1	2679	−0.201	0.081	–	–	0.82	–
Non-Florida	2	1465	−0.362	0.210	0.22	(−0.95, 0.23)	0.70	(0.38, 1.26)
High covariates	2	3574	−0.281	0.156	0.17	(−0.73, 0.17)	0.75	(0.48, 1.19)
Low covariates	1	570	−0.112	0.187	–	–	0.89	–
***Married* (vs. not)**[R,NF]	5	3184	−0.266	0.204	0.30	(−0.98, 0.45)	0.77	(0.38, 1.56)
High covariates	2	871	−0.561	0.248	0.00	(−1.05, −0.07)	0.57	(0.35, 0.93)
Low covariates	3	2313	−0.155	0.246	0.29	(−0.9, 0.59)	0.86	(0.41, 1.81)
Presence of disabled person	3	2130	0.595	0.374	0.48	(−0.60, 1.79)	1.81	(0.55, 6.01)
Hypothetical	1	531	1.079	0.304	–	–	2.94	–
Real[NF]	2	1599	0.434	0.385	0.34	(−0.57, 1.44)	1.54	(0.56, 4.22)
High covariates	1	1029	0.688	0.418	–	–	1.99	–
Low covariates	1	570	−0.026	0.322	–	–	0.97	–

Note. k = number of models included in meta-analysis, N = total sample size, $\overline{\beta}$ = sample-size weighted mean log odds ratio (unstandardized logistic regression coefficient), SE = standard error of $\overline{\beta}$, τ = residual random effects standard deviation of β after accounting for sampling error (τ), pred. int. = prediction interval, $\overline{OR}$ = mean odds ratio ($\exp[\overline{\beta}]$).
[R] All included models were real hurricane.
[NF] All included models were non-Florida.

Table A5
Full meta-analysis results for sociodemographic characteristics

Predictor	k	N	$\overline{\beta}$	$SE_{\overline{\beta}}$	τ	95% pred. int.	$\overline{OR}$	95% pred. int.
Female (vs. male)	20	19096	0.254	0.056	0.15	(−0.06, 0.57)	1.29	(0.94, 1.77)
Hypothetical	5	3873	0.079	0.071	0.00	(−0.06, 0.22)	1.08	(0.94, 1.24)
Real	15	15223	0.299	0.067	0.16	(−0.04, 0.64)	1.35	(0.96, 1.90)
Florida	5	9048	0.329	0.093	0.16	(−0.03, 0.69)	1.39	(0.97, 1.99)
Non-Florida	10	6175	0.254	0.094	0.19	(−0.16, 0.67)	1.29	(0.85, 1.95)
High covariates	10	11903	0.318	0.091	0.20	(−0.12, 0.76)	1.37	(0.89, 2.13)
Low covariates	5	3320	0.228	0.094	0.00	(0.04, 0.41)	1.26	(1.04, 1.51)
***Age** (2 definitions)*								
Continuous (20 years)	12	8370	−0.502	0.275	0.47	(−1.60, 0.60)	0.61	(0.20, 1.82)
Hypothetical	3	2942	−0.138	0.498	0.64	(−1.80, 1.40)	0.87	(0.17, 4.06)
Real[NF]	9	5428	−0.699	0.377	0.49	(−2.00, 0.60)	0.50	(0.14, 1.82)
High covariates	4	2212	−0.115	0.24	0.36	(−1.00, 0.80)	0.89	(0.37, 2.23)
Low covariates	5	3216	−1.101	0.622	0.58	(−2.80, 0.60)	0.33	(0.06, 1.82)
Ordinal age categories	5	1611	−0.058	0.071	0.10	(−0.30, 0.18)	0.94	(0.74, 1.20)
Hypothetical	3	1070	−0.004	0.085	0.08	(−0.24, 0.23)	1.00	(0.79, 1.26)
Real[NF,L]	2	541	−0.164	0.088	0.00	(−0.34, 0.01)	0.85	(0.71, 1.01)
***Income** (2 definitions)*								
Continuous ($20,000)	10	12432	0.051	0.168	0.00	(−0.20, 0.40)	1.05	(0.82, 1.49)
Hypothetical	1	400	−0.4	0.2	–	–	0.67	–
Real	9	12032	0.066	0.174	0.00	(−0.20, 0.40)	1.07	(0.82, 1.49)
Florida	6	9977	0.011	0.089	0.00	(−0.20, 0.20)	1.01	(0.82, 1.22)
Non-Florida	3	2055	0.33	0.923	0.05	(−1.40, 2.20)	1.39	(0.25, 9.03)
High covariates	7	10505	0.155	0.172	0.00	(−0.20, 0.40)	1.17	(0.82, 1.49)
Low covariates	2	1527	−0.548	0.692	0.00	(−2.00, 0.80)	0.58	(0.14, 2.23)
Ordinal income categories	7	4731	−0.031	0.045	0.08	(−0.21, 0.15)	0.97	(0.81, 1.16)
Hypothetical	4	3081	−0.008	0.030	0.03	(−0.10, 0.08)	0.99	(0.91, 1.08)
Real[NF,H]	3	1650	−0.074	0.088	0.12	(−0.37, 0.22)	0.93	(0.69, 1.25)
***Education** (2 definitions)*								
Years of education (5 years)	9	12182	0.009	0.131	0.27	(−0.60, 0.60)	1.01	(0.55, 1.82)
Hypothetical	1	400	0.85	0.35	–	–	2.34	–
Real	8	11782	−0.02	0.123	0.24	(−0.55, 0.50)	0.98	(0.58, 1.65)
Florida	5	9048	−0.09	0.158	0.28	(−0.70, 0.55)	0.91	(0.5, 1.73)
Non-Florida	3	2734	0.214	0.188	0.00	(−0.15, 0.60)	1.24	(0.86, 1.82)
High covariates	7	10505	−0.04	0.141	0.26	(−0.60, 0.55)	0.96	(0.55, 1.73)
Low covariates	1	1277	0.15	0.2	–	–	1.16	–
Ordinal education categories	6	2768	−0.009	0.082	0.15	(−0.35, 0.33)	0.99	(0.71, 1.39)

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Table A5 (*continued*)

Predictor	k	N	$\overline{\beta}$	$SE_{\overline{\beta}}$	τ	95% pred. int.	$\overline{OR}$	95% pred. int.
Hypothetical	4	1427	−0.112	0.088	0.12	(−0.40, 0.17)	0.89	(0.67, 1.19)
Real[NF,H]	2	1341	0.101	0.051	0.03	(−0.02, 0.22)	1.11	(0.98, 1.25)
Non-Hispanic Black (vs. Non-Hispanic White)	9	12173	−0.447	0.179	0.39	(−1.28, 0.39)	0.64	(0.28, 1.48)
Hypothetical	1	400	0.323	1.075	–	–	1.38	–
Real	8	11773	−0.474	0.183	0.39	(−1.32, 0.38)	0.62	(0.27, 1.46)
Florida	6	9977	−0.424	0.203	0.38	(−1.27, 0.42)	0.65	(0.28, 1.52)
Non-Florida	2	1796	−0.749	0.168	0.15	(−1.19, −0.31)	0.47	(0.31, 0.73)
High covariates	6	9825	−0.456	0.242	0.48	(−1.50, 0.59)	0.63	(0.22, 1.81)
Low covariates	2	1948	−0.563	0.176	0.00	(−0.91, −0.22)	0.57	(0.40, 0.80)
Hispanic (vs. White)[R]	7	10754	0.072	0.165	0.29	(−0.59, 0.73)	1.08	(0.55, 2.08)
Florida	6	9977	0.004	0.124	0.10	(−0.30, 0.31)	1.00	(0.74, 1.37)
Non-Florida	1	777	0.950	0.250	–	–	2.59	–
High covariates	6	9825	0.076	0.196	0.35	(−0.70, 0.86)	1.08	(0.50, 2.35)
Low covariates	1	929	0.030	0.018	–	–	1.03	–

Note. k = number of models included in meta-analysis, N = total sample size, $\overline{\beta}$ = sample-size weighted mean log odds ratio (unstandardized logistic regression coefficient), SE = standard error of $\overline{\beta}$, τ = residual random effects standard deviation of β after accounting for sampling error (τ), pred. int. = prediction interval, $\overline{OR}$ = mean odds ratio ($\exp[\overline{\beta}]$).

[R] All included models were real hurricane.

[NF] All included models were non-Florida.

[H] All included models included a high number of predictor covariates.

[L] All included models included a low number of predictor covariates.

References

Adeola, F. O. (2009). Katrina cataclysm: Does duration of residency and prior experience affect impacts, evacuation, and adaptation behavior among survivors? *Environment and Behavior, 41*(4), 459–489. https://doi.org/10.1177/0013916508316651

Albarracín, D., Johnson, B. T., Fishbein, M., & Muellerleile, P. A. (2001). Theories of reasoned action and planned behavior as models of condom use: A meta-analysis. *Psychological Bulletin, 127*(1), 142–161. https://doi.org/10.1037/0033-2909.127.1.142

Bakbergenuly, I., Hoaglin, D. C., & Kulinskaya, E. (2019). *Simulation study of estimating between-study variance and overall effect in meta-analysis of odds-ratios*, Article 07154. ArXiv Preprint ArXiv:1902.

Baker, E. J. (1991). Hurricane evacuation behavior. *International Journal of Mass Emergencies and Disasters, 9*(2), 287–310.

Bamberg, S., & Möser, G. (2007). Twenty years after hines, hungerford, and tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. *Journal of Environmental Psychology*. https://doi.org/10.1016/j.jenvp.2006.12.002

Bateman, J. M., & Edwards, B. (2002). Gender and evacuation: A closer look at why women are more likely to evacuate for hurricanes. *Natural Hazards Review, 3*(3), 107–117. https://doi.org/10.1061/(ASCE)1527-6988(2002)3:3(107)

Bowser, G. C., & Cutter, S. L. (2015). Stay or go? Examining decision making and behavior in hurricane evacuations. *Environment: Science and Policy for Sustainable Development, 57*(6), 28–41. https://doi.org/10.1080/00139157.2015.1089145

Brackenridge, S., Zottarelli, L. K., Rider, E., & Carlsen-Landy, B. (2012). Dimensions of the human–animal bond and evacuation decisions among pet owners during Hurricane Ike. *Anthrozoös, 25*(2), 229–238. https://doi.org/10.2752/175303712X13316289505503

Burnside, R. (2006). Leaving the big easy: An examination of the hurricane evacuation behavior of new Orleans residents before hurricane Katrina. *Journal of Public Management and Social Policy, 12*(2), 49–61.

Chakraborty, J., Tobin, G. A., & Montz, B. E. (2005). Population evacuation: Assessing spatial variability in geophysical risk and social vulnerability to natural hazards. *Natural Hazards Review, 6*(1), 23–33. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:1(23)

Chinn, S. (2000). A simple method for converting an odds ratio to effect size for use in meta-analysis. *Statistics in Medicine, 19*(22), 3127–3131.

Cutter, S. L., Mitchell, J. T., & Scott, M. S. (2000). Revealing the vulnerability of people and places: A case study of georgetown county, South Carolina. *Annals of the Association of American Geographers, 90*(4), 713–737. https://doi.org/10.1111/0004-5608.00219

Dahlke, J. A., & Wiernik, B. M. (2019). *psychmeta: Psychometric meta-analysis toolkit (2.3.2) [R package]* (Original work published 2017) https://cran.r-project.org/package=psychmeta.

Dahlke, J. A., & Wiernik, B. M. (2019). *psychmeta*: An R package for psychometric meta-analysis. *Applied Psychological Measurement, 43*(5), 415–416. https://doi.org/10.1177/0146621618795933

Drabek, T. E. (1969). Social processes in disaster: Family evacuation. *Social Problems, 16*(3), 336–349.

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science, 2*(2), 156–168. https://doi.org/10.1177/2515245919847202

Fussell, E., Sastry, N., & VanLandingham, M. (2010). Race, socioeconomic status, and return migration to new Orleans after hurricane Katrina. *Population and Environment, 31*(1), 20–42. https://doi.org/10.1007/s11111-009-0092-2

Fu, H., Wilmot, C. G., & Baker, E. J. (2006). Sequential logit dynamic travel demand model and its transferability. *Transportation Research Record: Journal of the Transportation Research Board, 1977*(1), 17–26. https://doi.org/10.1177/0361198106197700103

Gladwin, H., & Peacock, W. G. (1997). Warning and evacuation: A night for hard houses. In *Hurricane Andrew: Ethnicity, gender and the sociology of disasters* (pp. 52–74). Routledge. Issue July.

Hasan, S., Mesa-Arango, R., Ukkusuri, S., & Murray-Tuite, P. (2012). Transferability of hurricane evacuation choice model: Joint model estimation combining multiple data sources. *Journal of Transportation Engineering, 142*(2), 548–556. https://doi.org/10.1061/(ASCE)TE.1943-5436

Hasan, S., Ukkusuri, S., Gladwin, H., & Murray-Tuite, P. (2011). Behavioral model to understand household-level hurricane evacuation decision making. *Journal of Transportation Engineering, 137*(5), 341–348. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000223

Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Academic Press.

Horney, J. A., MacDonald, P. D. M., Van Willigen, M., Berke, P. R., & Kaufman, J. S. (2010). Individual actual or perceived property flood risk: Did it predict evacuation from hurricane Isabel in North Carolina, 2003? *Risk Analysis, 30*(3), 501–511. https://doi.org/10.1111/j.1539-6924.2009.01341.x

Horney, J. A., MacDonald, P. D., Van Willigen, M., & Kaufman, J. S. (2012). The importance of effect measure modification when using demographic variables to predict evacuation. *Risk, Hazards & Crisis in Public Policy, 3*(1), 1–19.

Huang, S. (2014). *Households' evacuation decision in response to hurricanes Katrina and Rita [PhD thesis]*. Texas A&M University.

Huang, S., Lindell, M. K., & Prater, C. S. (2016). Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. *Environment and Behavior, 48*(8), 991–1029. https://doi.org/10.1177/0013916515578485

Huddy, L., & Feldman, S. (2006). Worlds apart: Blacks and whites react to hurricane Katrina. *Du Bois Review: Social Science Research on Race, 3*(1), 97–113. https://doi.org/10.1017/S1742058X06060073

Hunter, J. E., & Schmidt, F. L. (2000). Fixed effects vs. Random effects meta-analysis models: Implications for cumulative research knowledge. *International Journal of Selection and Assessment, 8*(4), 275–292. https://doi.org/10.1111/1468-2389.00156

IntHout, J., Ioannidis, J. P. A., Rovers, M. M., & Goeman, J. J. (2016). Plea for routinely presenting prediction intervals in meta-analysis. *BMJ Open, 6*(7), Article e010247.

Kaniasty, K., & Norris, F. H. (1995). In search of altruistic community: Patterns of social support mobilization following Hurricane Hugo. *American Journal of Community Psychology, 23*(4), 447–477.

Kuha, J., & Mills, C. (2017). On group comparisons with logistic regression models. *Sociological Methods & Research, 49*(2), 498–525. https://doi.org/10.1177/0049124117747306

Lazo, J. K., Waldman, D. M., Morrow, B. H., & Thacher, J. A. (2010). Household evacuation decision making and the benefits of improved hurricane forecasting: Developing a framework for assessment. *Weather and Forecasting, 25*(1), 207–219. https://doi.org/10.1175/2009WAF2222310.1

Lindell, M. K., Lu, J., & Prater, C. S. (2005). Household decision making and evacuation in response to Hurricane Lili. *Natural Hazards Review, 13*(4), 283–296. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000074

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. SAGE publications, Inc.

Lowe, S. R., Rhodes, J. E., Zwiebach, L., & Chan, C. S. (2009). The impact of pet loss on the perceived social support and psychological distress of hurricane survivors. *Journal of Traumatic Stress, 22*(3), 244–247. https://doi.org/10.1002/jts.20403

Meyer, R., Broad, K., Orlove, B., & Petrovic, N. (2013). Dynamic simulation as an approach to understanding hurricane risk response: Insights from the stormview lab. *Risk Analysis, 33*(8), 1532–1552. https://doi.org/10.1111/j.1539-6924.2012.01935.x

Mozumder, P., & Vásquez, W. F. (2018). Understanding hurricane evacuation decisions under contingent scenarios: A stated preference approach. *Environmental and Resource Economics, 71*(2), 407–425. https://doi.org/10.1007/s10640-017-0163-2

NOAA. (2005). *U.S. Mainland hurricane strikes by state, 1851-2004*. National Hurricane Center https://www.nhc.noaa.gov/paststate.shtml.

Ones, D. S., Viswesvaran, C., & Schmidt, F. L. (2017). Realizing the full potential of psychometric meta-analysis for a cumulative science and practice of human resource management. *Human Resource Management Review, 27*(1), 201–215.

Perry, R. W., & Lindell, M. K. (1997). Aged citizens in the warning phase of disasters: Re-examining the evidence. *The International Journal of Aging and Human Development, 44*(4), 257–267. https://doi.org/10.2190/RT3X-6MEJ-24AQ-03PT

Petrolia, D. R., & Bhattacharjee, S. (2010). Why don't coastal residents choose to evacuate for hurricanes? *Coastal Management, 38*(2), 97–112. https://doi.org/10.1080/08920751003605365

Putka, D. J., Le, H., McCloy, R. A., & Diaz, T. (2008). Ill-structured measurement designs in organizational research: Implications for estimating interrater reliability. *Journal of Applied Psychology, 93*(5), 959–981. https://doi.org/10.1037/0021-9010.93.5.959

R Core Team. (2020). *R: A language and environment for statistical computing (4.0.2)* [Computer software]. R Foundation for Statistical Computing http://www.r-project.org/.

Riad, J. K., Norris, F. H., & Ruback, R. B. (1999). Predicting evacuation in two major disasters: Risk perception, social influence, and access to resources. *Journal of Applied Social Psychology, 29*(5), 918–934. https://doi.org/10.1111/j.1559-1816.1999.tb00132.x

Rosenkoetter, M. M., Covan, E. K., Cobb, B. K., Bunting, S., & Weinrich, M. (2007). Perceptions of older adults regarding evacuation in the event of a natural disaster. *Public Health Nursing, 24*(2), 160–168. https://doi.org/10.1111/j.1525-1446.2007.00620.x

Sarwar, M. T., Anastasopoulos, P. C., Ukkusuri, S. V., Murray-Tuite, P., & Mannering, F. L. (2018). A statistical analysis of the dynamics of household hurricane-evacuation decisions. *Transportation, 45*(1), 51–70. https://doi.org/10.1007/s11116-016-9722-6

Schmidt, F. L., & Hunter, J. E. (2015). *Methods of meta-analysis: Correcting error and bias in research findings* (3rd ed.). Sage. https://doi.org/10.4135/9781483398105

Sigelman, L., & Welch, S. (1994). *Black Americans' views of racial inequality: The dream deferred*. CUP Archive.

Smith, S. K., & McCarty, C. (2009). Fleeing the storm(s): An examination of evacuation behavior during Florida's 2004 hurricane season. *Demography, 46*(1), 127–145. https://doi.org/10.1353/dem.0.0048

Sorensen, J. H. (2000). Hazard warning systems: Review of 20 years of progress. *Natural Hazards Review, 1*(2), 119–125. https://doi.org/10.1061/(ASCE)1527-6988(2000)1:2(119)

Soto, C. J. (2020). *Do links between personality and life outcomes generalize? Testing the robustness of trait–outcome associations across gender, age, ethnicity, and analytic approaches. Social psychological and personality science*. Advance online publication. https://doi.org/10.1177/1948550619900572

Stein, R. M., Dueñas-Osorio, L., & Subramanian, D. (2010). Who evacuates when hurricanes approach? The role of risk , information , and location. *91*(3).

Tanim, S. H., & Tobin, G. A. (2018). Social factors and evacuation vulnerability: An application in Pinellas County, Florida. *Papers in Applied Geography, 4*(2), 123–136. https://doi.org/10.1080/23754931.2016.1266020

Thiede, B. C., & Brown, D. L. (2013). Hurricane Katrina: Who stayed and why? *Population Research and Policy Review, 32*(6), 803–824. https://doi.org/10.1007/s11113-013-9302-9

Tinsley, C. H., Dillon, R. L., & Cronin, M. A. (2012). How near-miss events amplify or attenuate risky decision making. *Management Science, 58*(9), 1596–1613. https://doi.org/10.1287/mnsc.1120.1517

Van Willigen, M., Edwards, T., Edwards, B., & Hessee, S. (2002). Riding out the storm: Experiences of the physically disabled during hurricanes Bonnie, Dennis, and Floyd. *Natural Hazards Review, 3*(3), 98–106. https://doi.org/10.1061/(ASCE)1527-6988(2002)3:3(98)

Van Willigen, M., Edwards, B., Lormand, S., & Wilson, K. (2005). Comparative assessment of impacts and recovery from hurricane floyd among student and community households. *Natural Hazards Review, 6*(4), 180–190. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:4(180)

Viechtbauer, W. (2005). Bias and efficiency of meta-analytic variance estimators in the random-effects model. *Journal of Educational and Behavioral Statistics, 30*(3), 261–293. https://doi.org/10.3102/10769986030003261

Viechtbauer, W. (2010). Conducting meta-analyses in *R* with the **metafor** package. *Journal of Statistical Software, 36*(3). https://doi.org/10.18637/jss.v036.i03

Viechtbauer, W. (2019). *metafor: Meta-analysis package for R (2.1-0* [Computer software] https://CRAN.R-project.org/package=metafor.

Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin, 132*(2), 249–268. https://doi.org/10.1037/0033-2909.132.2.249

Whitehead, J. C., Edwards, B., Van Willigen, M., Maiolo, J. R., Wilson, K., & Smith, K. T. (2000). Heading for higher ground: Factors affecting real and hypothetical hurricane evacuation behavior. *Environmental Hazards, 2*(4), 133–142. https://doi.org/10.1016/S1464-2867(01)00013-4

Whitehead, J. C., Edwards, B., Van Willigen, M., Maiolo, J. R., Wilson, K., & Smith, K. T. (2001). Heading for higher ground: Factors affecting real and hypothetical hurricane evacuation behavior. *Environmental Hazards, 2*(4), 133–142. https://doi.org/10.3763/ehaz.2000.0219

Whitener, E. M. (1990). Confusion of confidence intervals and credibility intervals in meta-analysis. *Journal of Applied Psychology, 75*(3), 315–321. https://doi.org/10.1037/0021-9010.75.3.315

Wiernik, B. M., & Dahlke, J. A. (2020). Obtaining unbiased results in meta-analysis: The importance of correcting for statistical artefacts. *Advances in Methods and Practices in Psychological Science, 3*(1), 94–123. https://doi.org/10.1177/2515245919885611

Wiernik, B. M., Kostal, J. W., Wilmot, M. P., Dilchert, S., & Ones, D. S. (2017). Empirical benchmarks for interpreting effect size variability in meta-analysis. *Industrial and Organizational Psychology, 10*(3), 472–479.

Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for travel demand simulation for hurricane evacuation. *Transportation Research Part C: Emerging Technologies, 42*, 44–59. https://doi.org/10.1016/j.trc.2014.02.015