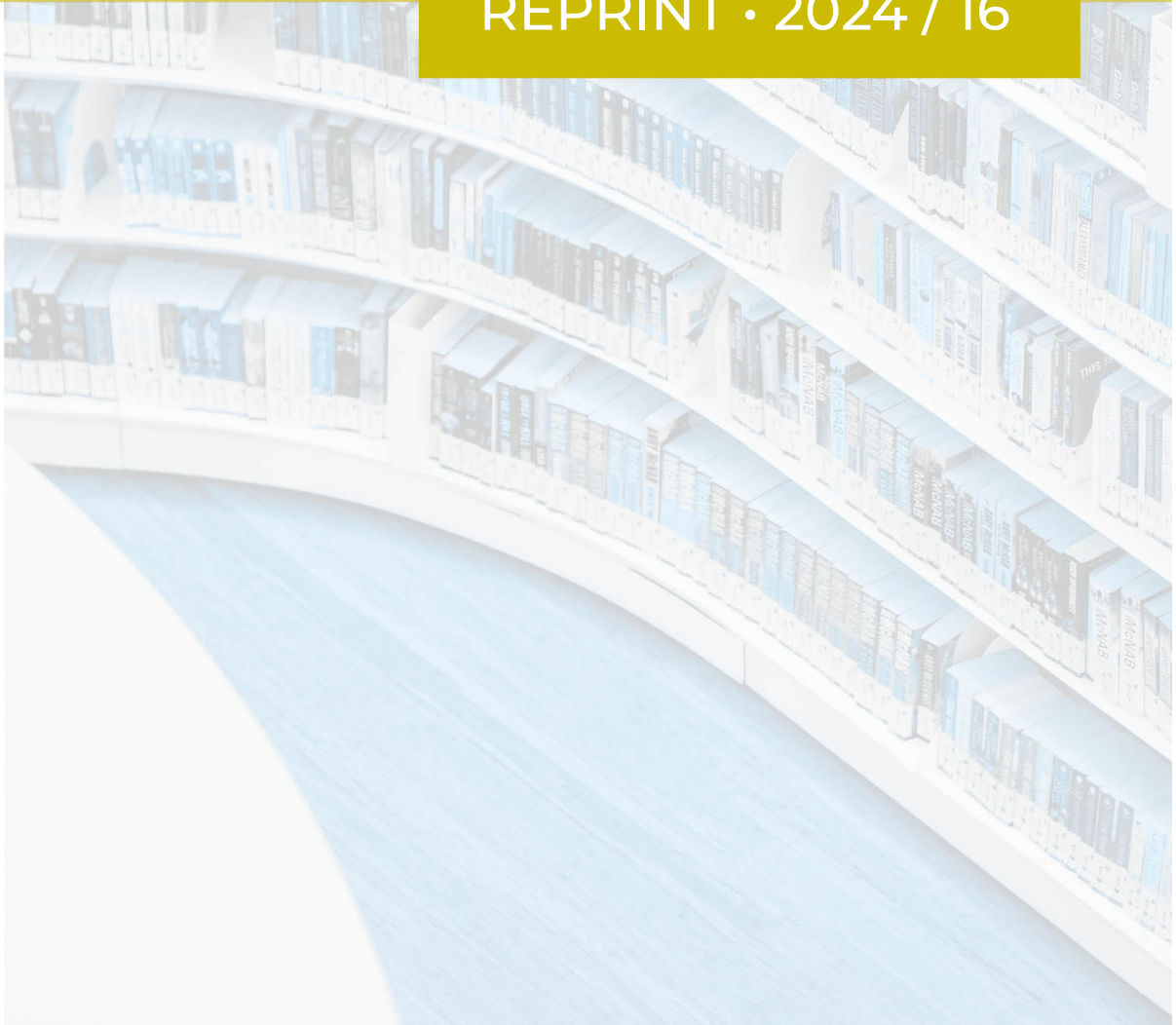


# A SENSE OF RISK: RESPONSES TO CROWDFUNDING RISK DISCLOSURES

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# A sense of risk: Responses to crowdfunding risk disclosures

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## Abstract

**Research Summary:** This paper examines how reward-based crowdfunding backers respond to risk disclosures. Combining theoretical frameworks from financial accounting with the risk perception literature, we adopt an abductive research approach to explore various nuances that influence backers' tolerance for risk information. In addition to identifying the general dynamics in backers' risk interpretation, we highlight the complexities introduced by differences in the disclosure's semantic content, expressed feelings, and the discloser's background attributes. Relying on a hierarchical Bayesian mixture model, we first identify a positive curvilinear relationship between risk information quantity and crowdfunding success. We then demonstrate the influences of *what* is disclosed, *how* it is disclosed, and *who* discloses it, while emphasizing the context-bound specificities of individual project types.

**Managerial Summary:** Our study aids entrepreneurs to effectively communicate risks in reward-based crowdfunding campaigns. We consistently find that entrepreneurs provided substantially less risk information than the optimum amount of information, emphasizing the need for more extensive disclosures. On *what* to disclose, backers favored information on risks that are consequential to them personally and not those that affect the entrepreneur's project. On *how* to disclose, expressed feelings had little influence on how much risk information backers preferred.

However, *who* provides the disclosure was crucial, as trust-enhancing factors increased backers' appetite for risk information. Together, our findings show that, while communicating risks, entrepreneurs should be cognizant that online backers undertake calculative evaluations and have material motivations. Furthermore, our category level results aid entrepreneurs in making practical judgments on context-specific deviations across project types.

#### KEYWORDS

Bayesian analysis, crowdfunding, mandatory risk disclosure, risk perception, textual analysis

## 1 | INTRODUCTION

Crowdfunding has emerged as a crucial financing avenue for ventures that operate beneath the radar of traditional financiers (Mollick, 2014). Here, online backers contribute to distant entrepreneurs drawn by innovative ideas, social participation, and material rewards (Bürger & Kleinert, 2021). Apart from the idea's appeal, backers' decision to contribute is contingent on their assessments of the risks (Belleflamme et al., 2015). Our study is motivated by the case of a reward-based crowdfunding platform Kickstarter, which in September 2012 introduced a section titled "Risks and Challenges" (R&C), mandating every project to provide risk information, responding to the need to reduce backer uncertainty and increase the platform's effectiveness in financing venture projects (Strickler et al., 2012). Yet, given that the transactions are small and the online backers are often likened to consumers (Chan & Parhankangas, 2017), it remains an open question whether such a platform initiative intended to reduce backer uncertainty promotes participation or rather hinders it.

This study undertakes an abductive approach to examine how backers respond to risk disclosures, assimilating the broad-based risk literature (over an overview, see Elshandidy et al., 2018; Siegrist & Árvai, 2020). Using a composite measure of risk information quantity, we find that crowdfunding entrepreneurs provided insufficient risk information, indicating a gap between backers' information demand and what the entrepreneurs communicated. Next, building on research on risk perception and communication, we introduce several qualitative dimensions describing the disclosure and the discloser. First, in accordance with the findings of heterogeneous cognitive responses to different risk issues (e.g., Bao & Datta, 2014; Fischhoff et al., 1978; Linsley et al., 2006), we examine the types of risks discussed. We find that backers responded positively to risk information that has personal consequence but not those that affect the entrepreneur's project. Second, motivated by the emphasis on emotional dimensions in risk judgment (e.g., Lerner & Keltner, 2000; Loewenstein et al., 2001; Slovic et al., 2007), we examine the impact of incidental affects and emotions expressed in the pitch. However, we only find weak relationships, suggesting that backers' responses to risk information were instead more deliberate and cognitive. Lastly, we study if "who communicates the risks" matters by exploring the influence of background project attributes (e.g., Siegrist, 2000; Twyman et al., 2008), and find that trust-enhancing attributes, such as platform endorsement and entrepreneur's experience, increased tolerance to risk information. Together, these findings show that, despite the informal online setting, backers displayed rather reasoned responses to risk information—expecting more extensive information, prioritizing self-interest, and relying on trust indicators to evaluate unverifiable risk information. Furthermore, these findings highlight the cost of obfuscation for entrepreneurs communicating their risks.



As we undertake an abductive research, where we explore a broad landscape of disclosure-response relationships (Locke et al., 2008; Sætre & de Ven, 2021), we use Bayesian analysis, instead of the  $p$ -value null hypothesis significance testing (pNHST) (Kruschke et al., 2012; Zyphur & Oswald, 2015). Unlike the traditional approach, Bayesian analysis informs us on the credibility of the candidate parameter values given the data on hand in the form of probability distributions. It thus provides a probabilistic and intuitive description of the unknown model parameters, suited for the explorative research (Andraszewicz et al., 2015; Kruschke, 2011). Furthermore, Bayesian analysis allows more model flexibility (Anderson et al., 2019; Lohrke et al., 2018). It accommodates complex model structures, which allows us to incorporate hierarchical mixture model structure that accounts for the clustered relationships within the different project types and the random data generating process of the outliers in our large sample (Gelman, 2006; Kruschke & Vanpaemel, 2015).

Furthermore, our study leverages the automated content analysis tools to evaluate extensive textual datasets in a replicable and objective fashion (for an overview, see Loughran & McDonald, 2016, 2020). In response to the challenges in quantifying risk disclosures, we construct an aggregated measure of information quantity, responding to the suggestions of Beretta and Bozzolan (2004), and Shevlin (2004), accounting for variations in information *depth* and *density*. Furthermore, we rely on a machine-learning based topic modeling known as Sentence Latent Dirichlet Allocation (sentLDA) to map the information within the disclosures (Bao & Datta, 2014), and take up standard dictionary-based approach to measure affective and emotional expressions in the entrepreneurs' communications.

Our study makes several contributions to the crowdfunding and the risk disclosure literature. First, we empirically demonstrate wide-ranging dynamics concerning backers' decisions given the entrepreneur's risk disclosure. Integrating psychology and financial accounting research to examine risk information, which are distinct from promotional project descriptions, we extend the crowdfunding literature examining the links between the entrepreneur's communication and backers' decisions (e.g., Allison et al., 2017; Davis et al., 2017; Gafni et al., 2019; Parhankangas & Renko, 2017). Crucially, a peripheral finding that serves as a key contribution is that we identify the main risk issues that early-stage ventures report in a crowdfunding setting, complementing the scholarly works emphasizing the risks associated with crowdfunding (e.g., Cumming, Hornuf, et al., 2020; Moores, 2015).

Secondly, our study contributes to the research on financiers' ability to evaluate firm's risk disclosure (e.g., Elshandidy et al., 2015; Hope et al., 2016; Kravet & Muslu, 2013; Townsend & Campbell, 2004). Risk communication is an extensive literature, which has been examined both in financial accounting, for its capacity to inform and protect financier (Elshandidy et al., 2018; Ryan, 1997, 2012), and in psychology, given the subjective nature of risk assessment (Keller et al., 2012; Siegrist, 2021; Siegrist & Árvai, 2020). However, the two literature streams seldom overlap (*exceptions include* Koonce et al., 2005; Linciano et al., 2018). This study integrates the two domains, documenting the influence of various components in risk communication evaluation, which remain largely overlooked in prior risk disclosure literature. Furthermore, by incorporating several computer-aided textual analysis tools and Bayesian hierarchical estimation, we illustrate their application in evaluating large and segmented, unstructured textual data, and thus, extending the more recent risk disclosure literature adopting content-analysis (e.g., Hope et al., 2016; Malafronte et al., 2016). In addition, our focus on crowdfunding offers new insights to the literature illustrating the intricacies in risk communication in an entrepreneurial financing setting, which is distinctly characterized by inexperienced early-stage ventures and unsophisticated online backers, both with unique risk profiles.

## 2 | BACKGROUND

### 2.1 | Risk disclosures in crowdfunding: The case of Kickstarter

Crowdfunding is a valuable tool for early-stage ventures, reducing spatial constraints and democratizing the process of raising seed capital (Ziegler et al., 2020). In reward-based crowdfunding specifically, entrepreneurs pitch their ideas to online backers for small individual contributions, promising future delivery of a specified reward that is often

a product yet to be made (Belleflamme et al., 2015; Mollick, 2014). As such, backers face young ventures, generally without demonstrable track records, in an online setting, with limited opportunities for interaction to assuage concerns. Furthermore, as the endowments are small and generally one-off, the avenues for post-funding monitoring and accountability are virtually absent (for detailed discussion, see Agrawal et al., 2014; Belleflamme et al., 2015). Thus, inherent to the geographically remote setting with inexperienced ventures, backers' decision to participate is a function of assessments of potential rewards and possible risks.

In such a setting, mediating platforms play a crucial role in devising tools that alleviate backers' apprehensions (Belavina et al., 2020; Strausz, 2017). In order to help facilitate credible communication, the platforms can regulate the type of participants, the nature of the information exchange, and implement tools, such as feedback and certification systems (Belleflamme et al., 2015). While the crowdfunding literature is sizeable, studies focusing on platform design remain few despite their centrality in shaping the exchanges.<sup>1</sup> Exceptions include theoretical examinations by Strausz (2017) and Belavina et al. (2020), which explore mechanisms, such as deferred payment and performance verification, to deter entrepreneurs' potential for misconduct. Also, Burtch et al.'s (2015) study on the impact of privacy control mechanisms on backer participation, and Cumming, Leboeuf, and Schwienbacher's (2020) investigation on the difference in outcome between the "Keep-it-all" model (entrepreneurs receive all pledged amount irrespective of the set campaign goal) and the "All-or-nothing" model (entrepreneurs receive all pledged amount once it reaches the set goal) provide important insights. Similarly, a prominent platform instrument with precedence from the regulatory setup in mainstream finance is the rule of mandatory risk disclosure (Schrand & Elliott, 1998).

With comparable rationales, crowdfunding platforms, like Kickstarter, introduced platform rules compelling participating projects to communicate their risks. In reward-based crowdfunding, such a disclosure policy is especially pertinent as the vulnerabilities are less evident to consumer-like backers anticipating the specified rewards, often in the form of pre-purchasing products or services (Kuppuswamy & Bayus, 2018). Backers' customer-like impulses are likely to blur the risks involved, as they wrongly understand the rewards' conditionality (Strickler et al., 2012). Moreover, unlike traditional settings, *ex-post* legal recourse for backers is distinctly challenging (Moores, 2015). Kickstarter's risk disclosure rule responds to these specific vulnerabilities and participant motivations. However, despite the intention, the consequent response is *ex-ante* uncertain. Risk descriptions concern adverse events that may not occur, but which the entrepreneur seeks to avert, and therefore, could both alleviate and fuel apprehensions. The accuracy or completeness of such forward-looking information is not discernible; thus, the entrepreneur can obfuscate the information despite a platform's mandate (Dobler, 2008; Jorgensen & Kirschenheiter, 2003). Ultimately, what the discloser communicates depends on the their anticipated audience response (Verrecchia, 1983); thus, warranting this study.

Our study complements two recent studies by Cascino et al. (2019), and Madsen and McMullin (2020). The former examines the impact of regulations on consumer protection on the credibility of crowdfunding disclosures. The latter investigates the consequences of the introduction of the "R&C" section on Kickstarter, focusing on the participation decision of entrepreneurs—in terms of their inherent riskiness and their tendency to provide risk information. Our study centers on the backer side of the exchange, focusing on the mechanisms that dictate how backers interpret the ensuing risk information. Understanding both sides of the exchange is equally important to discern the overall impact, as crowdfunding platforms are multi-sided firms that rely on network effects from the participation of entrepreneurs and backers (Belleflamme et al., 2015).

## 2.2 | Risk communication literature

The existing literature on risk communication mainly emerges from two domains—one that concerns economic exchanges among sophisticated actors and the other with broader social settings involving the general public. In the former, owing to the implications for investor protection, risk disclosures are a notable topic of interest, particularly within the finance and accounting research (for overview of the literature, see Elshandidy et al., 2018; Ryan, 1997,



2012). Here, studies argue that disclosures that entail risk information can help facilitate decisions under uncertainty, aiding investors (backers) to formulate firm's (venture's) risk profile and estimate its future value. While firm disclosures, in general, mitigate information asymmetry (Healy & Palepu, 2001), risk disclosures uniquely deal with both value and uncertainty. A distinction that further separates risk disclosures from other communications is the obvious cost of disclosure, which hinders voluntary disclosure and leads to arguments favoring mandatory disclosure regimes (Schrand & Elliott, 1998). Therefore, a substantial body of work in financial accounting is dedicated to investigating their determinants and consequences, across contexts and regulatory specificities (e.g., Al-Hadi et al., 2018; Elshandidy et al., 2015; Malafronte et al., 2016). However, their findings remain inconsistent across markets and regulatory conditions and offer little insight into how such disclosures may translate in crowdfunding contexts (see Elshandidy et al., 2018).<sup>2</sup>

Separate from financial accounting, an extensive literature focuses on the general challenges of risk communication—which treads a fine line between persuasive intent and inadvertent opposite effect (e.g., Keller et al., 2006; Siegrist et al., 2010). These studies derive from the psychology literature, which emphasizes on the subjectivity in individual's risk perception. Instead of the rational choices describing what individuals ought to do, these studies concern with actual observed choices, focusing on the “analytic” and the “experiential” processes that dictate them (Arrow, 1982; Holtgrave & Weber, 1993; Slovic, 1987). For instance, in juxtaposition to the normative view, a prominent early finding in the psychology literature shows that individuals perceive risks from assessments of behavioral dimensions, mainly “dread” and “unknown,” aside from evaluations of probabilities and outcomes (Fischhoff et al., 1978; Slovic, 1987).<sup>34</sup> Following these findings, subsequent research focuses on various processes concerning how risk perception operates and centers on a variety of factors, including cognitive, emotional, and environmental influences (e.g., Lerner & Keltner, 2000; Loewenstein et al., 2001; Slovic et al., 2007).

Accordingly, the two literature streams guide our examination of backers' response to risk information from crowdfunding entrepreneurs. Firstly, the extant divergent findings and arguments in financial accounting literature (Kravet & Muslu, 2013), motivates our central research question that concerns the overall dynamics of backers' interpretation of risk disclosures: what is the relationship between the *quantity of risk information* and the crowdfunding success? Next, we utilize the risk perception literature to guide our further examinations. In accordance with the findings of heterogeneous cognitive responses to different risk issues, mainly in psychometric-based risk literature (e.g., Fischhoff et al., 1978; Slovic, 1987), we investigate the influence of disclosures' *semantic content*, that is, the types of information included in the disclosures. Second, given the prominence of emotional dimensions in risk judgment in non-financial settings (e.g., Lerner & Keltner, 2000; Slovic et al., 2005), we examine the impact of *affects* and *emotions* expressed in the entrepreneur's pitch. Affects describe the broader feelings of “goodness” or “badness” that is experienced when considering a risk factor; whereas, emotions are defined as richer, more complex, feelings that have experiential, cognitive, behavioral, and expressive components, which may be experienced with or without deliberate awareness (Lerner et al., 2015). Lastly, we investigate if the *discloser attributes* influence backers' risk response (e.g., Siegrist, 2000; Twyman et al., 2008).

### 3 | RESEARCH DESIGN

Our study proceeds taking an abductive approach (or more precisely, Inference to the Best Explanation), instead of hypothesizing relationships a priori (see Lipton, 2017; Sætre & de Ven, 2021). As opposed to the traditional hypothetico-deductive inquiry, abduction allows for data-generated insights integrating existing literature for plausible explanation. Moreover, abduction as a research approach is particularly suitable where different theoretical building blocks exists, however, their connections are not yet apparent, as is case in risk disclosure and risk perception literature (Dubois & Gadde, 2002). Therefore, our study aims at understanding the available evidence, to generate ideas about risk information processing in an entrepreneurial financing context. In doing so, we assimilate the insights from the two bodies of work—the financial accounting literature, which details risk communications'

motivations and consequences in financial settings, and risk perception literature, concerning the behavioral and peripheral factors' implications on risk interpretation.

In what follows, we describe the sample data and elaborate on the statistical estimation using Bayesian analysis—arguing its suitability and presenting the model specificities. We then describe the model variables, including the risk disclosure attributes of concern. Next, we describe our findings, followed by an extensive discussion exploring the potential explanations and providing justification for conjectures derived from the observed evidence.

### 3.1 | Data collection

We base our analysis on the risk disclosure data from a leading reward-based crowdfunding platform, Kickstarter. In September 2012, 3 years after its inception in April 2009, Kickstarter introduced a section called “Risks and Challenges” (R&C), making it compulsory for participating entrepreneurs to offer information on various risks they face in their crowdfunding pitches (Strickler et al., 2012). Following the platform's statement, from that point forward, all participating projects must answer the following question: “What are the risks and challenges this project faces, and what qualifies you to overcome them?” We, therefore, use the ensuing disclosures from Kickstarter to study how reward-based crowdfunding backers process risk information.

We collect a sample of Kickstarter campaigns launched after the introduction of the R&C section. We start with Li's (2019) Kickstarter Structured Relational Database. This database provides us with 408,637 campaigns launched between April 2009 and January 2019, and represents 95% of the 432,154 projects that were launched during that period.<sup>5</sup> We obtain a sample with 287,701 observations after removing campaigns that are launched before the introduction of the R&C section, in languages other than English, designated as “canceled,” “suspended,” or “live” during the data collection, and without location or reward details.

Kickstarter data offers several advantages. First, Kickstarter is the largest reward-based crowdfunding platform, which has helped fund over 223,000 campaigns, raising more than USD 6 billion from 21 million backers as of July 2022.<sup>6</sup> As network effects are central in two-sided business models, such as online crowdfunding (Belleflamme et al., 2015), Kickstarter's popularity also indicates its substantial market share, allowing a decent representation of the broader industry. Second, Kickstarter caters to a wide variety of projects, ranging across 15 categories, which allows us to undertake cross-sectional analyses between the different groups. Third, Kickstarter data is easily accessible, comprehensive, and widely used in crowdfunding research (e.g., Courtney et al., 2017; Mollick, 2014), and therefore, the use of the data allows comparisons across findings.

### 3.2 | Statistical analysis: Bayesian estimations

For the analysis, we use Bayesian inference, which enables more detailed model parameter estimates that can be probabilistically described and allows complex model structure that accommodate the idiosyncrasies of our dataset (see Kruschke et al., 2012; Lohrke et al., 2018; Zyphur & Oswald, 2015). Firstly, it allows us to incorporate hierarchical relationships that permit mutually informed estimations of higher-level aggregate parameters and lower-level group-specific parameters (Kruschke & Vanpaemel, 2015).<sup>7</sup> Like most prominent reward-based crowdfunding platforms, Kickstarter caters to a variety of projects, which the platform systematically classifies in 15 categories: “game,” “design,” “technology,” “film & video,” “music,” “publishing,” “fashion,” “food,” “art,” “comics,” “theater,” “photography,” “crafts,” “dance,” and “journalism.” Bayesian analysis permits not only the estimation of group-level relationships within different project types, but also to obtain aggregate estimates that are informed by group-specific parameters and vice-versa, which makes them less prone to endogeneity bias arising from unobserved group characteristics (Ansari et al., 2000; Gelman, 2006).



Moreover, as we deal with a large dataset, a noted challenge is that several campaigns display unrealistic characteristics, such as absurdly high or low goal amounts and inordinately short or long risk disclosures (Yu et al., 2017). Consequently, determining whether a suspected outlying value is caused by an extraneous influence or is a genuine representation of the target becomes a crucial concern (Aguinis et al., 2013). However, instead of deleting or transforming suspected outliers from the data following some arbitrary criterion, as in the conventional practice, Bayesian analysis allows probabilistic mixture models that can account for the aberrant data generating process, while providing robust estimates that are relatively stable (Kruschke, 2014; Smith, 1983).

More crucially, as our study undertakes an explorative abductive research design, Bayesian estimations offers more intuitive output with complete distributional information for the model parameters that we can probabilistically interpret. This is distinct from the traditional pNHST (or frequentist) statistical inference, which focuses on measuring the extremeness of the data under the null hypothesis, suited primarily for the purpose of hypothesis testing (Schervish, 1996).<sup>8</sup> As our research emphasizes on understanding the effect magnitudes, the information in single point estimates from traditional methods is limited, as they overlook the computed values' uncertainty (Wagenmakers, 2007). Bayesian output directly refers to the parameters of interest and provides their distributional information, and therefore, quantifies the uncertainty (McCann & Schwab, 2020). The distributional output, in addition to parameter estimation, also allows probabilistic comparisons of competing models, making it further relevant for this study (see Geweke, 2007; Kruschke, 2011; Wasserman, 2000).<sup>9</sup> However, it is crucial to note that while the traditional pNHST statistical inference leads to deduction based on model falsification, quantifying the risk of error; Bayesian inference instead derives from evaluation of how sensible are the parameter values (or the model), given the available data (Wagenmakers et al., 2008; Zyphur & Oswald, 2015). As such, the comparisons of probabilities, which Bayesian methods accommodate, does not necessarily result in a decision to accept or reject a hypothesis. Instead, it is crucial to interpret the strength of evidence appropriately and to recognize that making a binary decision about any hypothesis in relation to the results from our analysis carries some potential of error.

As such, we use hierarchical Bayesian mixture models to examine the described research questions. In the following section, we detail the model specifications, including the prior assignments and the diagnostics on Monte Carlo Markov Chain (MCMC) sample generating process, which are features distinct to Bayesian analysis. For further information on Bayesian analysis implementation and its comparison to pNHST approach, we refer the readers to Edwards et al. (1963), Kruschke and Liddell (2018), and Wagenmakers et al. (2008). Moreover, detailed discussions on its philosophical foundations and practical contributions can be found in Lindley (2000) and Ntzoufras (2011), respectively.

### 3.3 | Implementation of hierarchical Bayesian mixture model

We implement robust logistic hierarchical Bayesian models, as defined in equations (1) and (2).

$$y_{ij} \sim \text{Bernoulli}(\theta_{ij}), \quad (1)$$

$$\theta_{ij} = \alpha \cdot \frac{1}{2} + (1 - \alpha) \cdot \text{logistic} \left( \beta_{0j} + \sum_{p=1}^P \beta_{pj} X_{p,ij} \right), \quad (2)$$

$$\beta_{p,j} \sim N(\mu_p, \sigma_p) \text{ for } p = 1, \dots, P, \quad (3)$$

where the success  $y_{ij}$  of the  $i$ th crowdfunding project from the  $j$ th category is described with a Bernoulli distribution that has an underlying probability of  $\theta_{ij}$ . The  $\theta_{ij}$  probability value is defined as a logistic function of a linear combination of an intercept and  $P$  predictors, which includes the independent variable (and its quadratic value), and the control variables.<sup>10</sup>

We assume a hierarchical model that incorporates the group-specific variations in the relationship between the explanatory and the explained variables. As shown in equation (2), the intercept and the slope parameters include  $j$  subscripts, indicating that we estimate distinct intercepts and slopes for each of the groups. The resulting estimates assume that the crowdfunding outcome of the  $i$ th project from  $j$ th group is a compromise between the project's individual data and the group-level information. The  $\beta_{0j}$  parameter represents the random effect component for each group. The remaining  $\beta_{pj}$  parameters relate to the deterministic component via the independent and the control variables. Thus, at the lower level, the probability value is defined as a logistic function of a linear combination of the group-specific predictors.

Next, to ensure that the group-level estimates are informed by the aggregate higher-level parameters, we specify that each of the group-specific slope and intercept parameters come from a normal distribution with mean  $\mu_p$  and standard deviation  $\sigma_p$ , as shown in equation (3). The higher-level parameters  $\mu_p$  and  $\sigma_p$  describe the typical coefficient of variable  $p$  for all projects and the variability of those coefficients, respectively. We assign parameter  $\mu_p$  a normally distributed prior with mean zero and standard deviation 2, which is a generic weakly informative prior, emphasizing that the coefficient is near zero unless the data suggests otherwise. Similarly, the noise parameter  $\sigma_p$  is assigned a uniformly distributed prior extending from 0.001 to 1000, which greatly exceeds a realistic value considering the data's scale; thus, minimizing potential bias on the posterior distribution.<sup>1112</sup>

Also shown in Equation (2), we accommodate for the outliers relative to the logistic function by estimating a description of the outliers as prescribed by Kruschke (2014). We define the data as a combination of two processes. The first is the described logistic function of the predictors, and the second is an unrelated function that assigns equal probability to both outcomes (success/failure), resembling a guesswork. Therefore, each project's crowdfunding outcome has a small chance,  $\alpha$ , of being generated by a guess process, that is, the project's success is determined by factors not captured in the model. We assume there is a more prominent chance of  $1 - \alpha$  that the  $\theta_{ij}$  value comes from the defined logistic function. Therefore, the guess parameter  $\alpha$  is assigned a beta distribution prior that is bound between 0 and 1 with shape parameters values of 1 and 9. Since we expect the proportion of random outliers in the data to be small, the assigned prior distribution emphasizes small values of  $\alpha$  and gives values greater than 0.5 very low but non-zero probabilities (Kruschke, 2014).

We then estimate the posterior distribution of parameters for the concerning model using JAGS (Just Another Gibbs Sampler) in R (Plummer, 2012).<sup>13</sup> To generate the posterior samples, 32 chains are initialized at default values in JAGS and are burned in for 500 steps. A total of 70,000 iterations were simulated. We find that, for each of the parameters, the MCMC chains converge well, and the autocorrelation functions showed quick decay, suggesting that the MCMC chains produced stable and representative samples of the posterior distributions. Furthermore, we observe that the Monte Carlo Standard Errors (MCSE) are substantially low, suggesting that the mean of the posteriors of the various concerning parameters are stable. We elaborate on the diagnostic charts for the key model parameters, namely the risk quantity variables, the guess parameter and the intercept parameter in Section A3 of the online appendix (for detailed discussion on evaluation of MCMC chains, see Kruschke, 2014; Lunn et al., 2013).

### 3.4 | Variable description

#### 3.4.1 | Crowdfunding success

Consistent with prior literature (e.g., Buttice et al., 2017; Colombo et al., 2015), we use a binary variable *Funded* as the outcome variable, which indicates whether or not a project succeeded in raising the set funding goal. The benefit of using the success indicator as the outcome variable is that it does not discriminate between the different sized projects. Moreover, as Kickstarter implements an “all-or-nothing” model, the pledged amounts display a bimodal distribution with peaks at 0% and 100% of the funding goal, indicating a substantial distinction between funded and unfunded campaigns.



### 3.4.2 | Quantity measure for risk disclosure

As a central disclosure attribute of interest, we measure the quantity of information in risk disclosures using a composite score made up of three textual attributes—the textual length, the information concreteness and the vocabulary's richness, motivated by Beretta and Bozzolan (2004). The three-dimensional measure accounts for *depth* and *density*, mitigating the two sources of measurement error arising from using textual length as a sole proxy for informational quantity. First, by incorporating concreteness, the index values depth in the information and discounts vagueness, that is, the lack in substance despite the wordiness. Second, the measure's inclusion of lexical richness incorporates the weightage of informative content within the overall disclosure (density)—discounting repetitions, which can misalign the relationship between the text's length and information quantity.<sup>14</sup>

Specifically, to measure concreteness (*Risk Concreteness*), which is a widely studied concept representing clarity in the text, as opposed to abstraction (e.g., Bleasdale, 1987; Elliott et al., 2015), we follow Pan et al. (2018) and take the difference between concrete (i.e., the sum of normalized counts of verbs, numbers, and past-focused words) and abstract (non-concrete) language (i.e., the sum of normalized counts of adjectives, nonspecific quantifiers, and future-focused words) used in the disclosure. We derive the individual items using the LIWC 2022 (Linguistic Inquiry and Word Count) software (Tausczik & Pennebaker, 2010).<sup>15</sup> Next, to measure lexical richness (*Risk Richness*), we use Guiraud's Index.<sup>16</sup> Mathematically, Guiraud's Index is measured as  $V/\sqrt{N}$ , where  $V$  represents the number of types of words in the text and  $N$  represents the total number of words (or tokens). A text with a higher richness score has a greater relative variety of words, and thus, has fewer repetitions (for a similar application, see Malafronte et al., 2016).

The textual length (*Risk Length*) is measured with two parts—the number of sentences and the number of words in the R&C. The sentence count provides a more stable measure in terms of informational quantity, as it is, in general, the smallest integral unit of text that conveys a complete and meaningful idea. The word count performs better in instances where a single lengthy sentence represents multiple ideas and where sentence separators are hard to identify. We take the normalized sum of the two as the textual length component.

Finally, we construct the measure of informational quantity in risk disclosures (*Risk Quantity*) using normalized summations of the three components. We, therefore, consider the three parts to be complementary to each other, that is, the informational quantity of the disclosure is high if all three elements score high. To aid interpretation, in Section A1 of Appendix S1, we provide several examples, including a demonstration of how the composite score penalizes the lack of concreteness and a comparison of disclosures with low and high *Risk Quantity* scores.

### 3.4.3 | Semantic content of risk disclosure

To map the semantic information within each risk disclosure we implement Sentence Latent Dirichlet Allocation (sentLDA) from Bao and Datta (2014) (for examples of application, see Bao & Datta, 2014; Thewissen et al., 2022). sentLDA is an unsupervised learning-based topic modeling that estimates a generalized topic for each document-sentence within a corpus (where each topic is defined as a set of weighted words), which enables discovery and measurement of various semantic themes within the textual risk disclosures. Using the sentLDA.exe file provided by Bao and Datta (2014), we identify 20 topics from the sample risk disclosures, which we group into six risk issues and other topics, classified either as risk management or other statements. Specifically, we categorize the key risk issues in the disclosures as *Production Risk*, *Quality Risk*, *Delay Risk*, *Force Majeure*, *Marketing Risk* and *Financial Risk*. Other topics that concern communication of passion, commitment, updates, know-how, production status and those relating to further information and customer management are grouped as *Risk Management* topics. Furthermore, sentLDA also identified superfluous statements used for rhetorical effects that neither classify as risk or risk management topics. We group these as *Other Statements*. Given the limitations in space, we relegate the concerning details to Section A2 of Appendix S1, which includes further description of sentLDA, its implementation, and a detailed sample

description of the identified topics. Furthermore, to aid interpretation, in Tables A2.1, A2.2, and A2.3 of Appendix S1, we provide lists of 20 highest weighted words, most-common 20 bi-grams, and 100 most-representative sentences, illustrating how each risk topic is represented in the disclosures. In our models, the risk issues are introduced as percentages of the total disclosure sentences.

### 3.4.4 | Expressed feelings in risk disclosures—Affects and emotions

We construct measures of *Positive* and *Negative* affects and emotions: *Anger*, *Disgust*, *Fear*, *Joy*, *Sadness*, *Trust*, *Anticipation*, and *Surprise*, using the standard dictionary-based approach used for emotion and sentiment analysis for textual data. This approach treats a document as a “bag of words” and counts the number of times a word that is linked with a given affect or emotion appears in the document. For this, we rely on the National Research Council Canada (NRC) Word-Emotion Association Lexicon (also called EmoLex), by Mohammad and Turney (2013), which is prominently used for examining relationships between texts and emotions in domains specific to social sciences and organizational research, (for e.g., Choudhury et al., 2019; Vosoughi et al., 2018).<sup>17</sup> We define the expressed affect and emotion as a percentage of the total words in the risk disclosure. To illustrate how expressed feelings manifest in disclosures with low and high *Risk Quantity*, in Section A1 of Appendix S1, we provide examples comparing disclosures with low and high *Positive* affect scores.

### 3.4.5 | Background attributes

Lastly, our data consist of various project-, entrepreneur-, and context-specific variables, which we include in our model. First, to control for the salient attributes of the overall pitch, we include the *Project Description* variable representing the number of sentences in the main project description (“About this project” section). We further incorporate a *Readability* measure of the entire textual pitch based on the Flesch Reading Ease score. The measure is derived from a linear combination of average words per sentence and average syllables per word, and it quantifies the difficulty in reading a document, where a higher score represents greater ease in understanding.

Apart from the textual attributes, we also control for the salient campaign-specific features, such as the goal set by the campaign (*Campaign Goal*), the duration of the project (*Campaign Duration*), and the number of reward options (*Number of Rewards*). These attributes are central features of campaigns launched in reward-based crowdfunding platforms, particularly with “all-or-nothing” models. We also include *Video*, a dummy variable indicating whether the crowdfunding pitch includes a video, another prominent media used by entrepreneurs to present their projects. Furthermore, the models include *Endorsement*, indicating whether the platform endorses the project, and *Experience*, representing the number of prior Kickstarter campaigns launched by the founder (see Courtney et al., 2017; Skirnevskiy et al., 2017).

Moreover, to control for location and time, we introduce the variables *US Project*, *Google Trend* and *Competition*. *US Project* is a location-related variable, which indicates whether the project is from the United States. *Google Trend* represents monthly Google searches of the word “Kickstarter” to proxy for the platform's popularity, which relates to the time-specific variability. Furthermore, to proxy for the extent of competition the project faced, the *Competition* variable represents the number of other campaigns launched while the campaign is live.

All variables are defined in Table 1.

## 3.5 | Descriptive statistics

Table 1 also reports the descriptive statistics of the variables included in our models. Our final sample includes 287,701 campaigns launched by 242,968 distinct entrepreneurs. Among these, 119,260 (41.452%) of the projects



TABLE 1 Variable description.

|                                                                                               | Mean    | SD      | P10    | P25    | Median | P75    | P90    |
|-----------------------------------------------------------------------------------------------|---------|---------|--------|--------|--------|--------|--------|
| Dependent variables                                                                           |         |         |        |        |        |        |        |
| Funded                                                                                        | 0.415   | 0.493   | 0      | 0      | 0      | 1      | 1      |
| Independent variables                                                                         |         |         |        |        |        |        |        |
| Risk words                                                                                    | 115.587 | 102.706 | 33     | 55     | 90     | 145    | 224    |
| Risk sentences                                                                                | 6.231   | 5.361   | 2      | 3      | 5      | 8      | 12     |
| Risk richness                                                                                 | 6.760   | 1.755   | 4.670  | 5.642  | 6.713  | 7.836  | 8.953  |
| measured by Guirand's Index                                                                   |         |         |        |        |        |        |        |
| Risk concreteness                                                                             | −0.139  | 2.365   | −2.649 | −1.432 | −0.216 | 1.089  | 2.483  |
| Measure of concreteness in text based on Pan et al. (2018)                                    |         |         |        |        |        |        |        |
| Risk quantity                                                                                 | 0       | 2.989   | −2.981 | −1.761 | −0.355 | 1.308  | 3.338  |
| Aggregated information quantity measure from RiskSentences, RiskSpecificity, and RiskRichness |         |         |        |        |        |        |        |
| Semantic content <sup>a</sup>                                                                 |         |         |        |        |        |        |        |
| Production risk                                                                               | 8.372   | 17.790  | 0      | 0      | 0      | 9.091  | 33.333 |
| Production-related risks concerns in manufacturing and artistic projects                      |         |         |        |        |        |        |        |
| Quality risk                                                                                  | 14.113  | 21.516  | 0      | 0      | 0      | 25     | 50     |
| Delay risk                                                                                    | 5.922   | 14.032  | 0      | 0      | 0      | 0      | 25     |
| Concerns over potential delays in reward delivery                                             |         |         |        |        |        |        |        |
| Force majeure                                                                                 | 2.271   | 8.577   | 0      | 0      | 0      | 0      | 6.250  |
| Risks that are beyond the entrepreneur's control                                              |         |         |        |        |        |        |        |
| Marketing risk                                                                                | 6.485   | 16.624  | 0      | 0      | 0      | 0      | 25     |
| Challenges in finding community engagement and marketing                                      |         |         |        |        |        |        |        |
| Financial risk                                                                                | 4.957   | 13.349  | 0      | 0      | 0      | 0      | 20     |
| Risk management                                                                               | 39.752  | 28.881  | 0      | 18.182 | 40     | 60     | 76.471 |
| Various statements designed to manage backers' risk concerns                                  |         |         |        |        |        |        |        |
| Other statements                                                                              | 18.128  | 23.437  | 0      | 0      | 11.111 | 28.571 | 50     |
| General non-risk statements                                                                   |         |         |        |        |        |        |        |

(Continues)



TABLE 1 (Continued)

|                                                                                                                                           | Mean   | SD        | P10    | P25    | Median | P75    | P90    |
|-------------------------------------------------------------------------------------------------------------------------------------------|--------|-----------|--------|--------|--------|--------|--------|
| Expressed feelings <sup>a</sup>                                                                                                           |        |           |        |        |        |        |        |
| Positive                                                                                                                                  |        |           |        |        |        |        |        |
| Percentage of “positive” words in the overall project pitch (“About this project” and R&C sections)                                       | 5.473  | 3.169     | 1.724  | 3.448  | 5.263  | 7.246  | 9.314  |
| Negative                                                                                                                                  |        |           |        |        |        |        |        |
| Percentage of “negative” words in the overall project pitch                                                                               | 2.008  | 2.161     | 0      | 0.481  | 1.635  | 2.857  | 4.396  |
| Anger                                                                                                                                     |        |           |        |        |        |        |        |
| Percentage of Words expressing “anger” in the overall project pitch                                                                       | 0.944  | 1.464     | 0      | 0      | 0.483  | 1.449  | 2.564  |
| Anticipation                                                                                                                              |        |           |        |        |        |        |        |
| Percentage of words expressing “anticipation” in the overall project pitch                                                                | 3.610  | 2.641     | 0      | 1.961  | 3.333  | 4.878  | 6.667  |
| Disgust                                                                                                                                   |        |           |        |        |        |        |        |
| Percentage of words expressing “disgust” in the overall project pitch                                                                     | 0.298  | 0.858     | 0      | 0      | 0      | 0      | 1.075  |
| Fear                                                                                                                                      |        |           |        |        |        |        |        |
| Percentage of words expressing “fear” in the overall project pitch                                                                        | 1.449  | 1.875     | 0      | 0      | 1.070  | 2.128  | 3.448  |
| Joy                                                                                                                                       |        |           |        |        |        |        |        |
| Percentage of words expressing “joy” in the overall project pitch                                                                         | 1.972  | 1.929     | 0      | 0      | 1.687  | 2.899  | 4.310  |
| Sadness                                                                                                                                   |        |           |        |        |        |        |        |
| Percentage of words expressing “sadness” in the overall project pitch                                                                     | 0.834  | 1.366     | 0      | 0      | 0      | 1.299  | 2.362  |
| Surprise                                                                                                                                  |        |           |        |        |        |        |        |
| Percentage of words expressing “surprise” in the overall project pitch                                                                    | 0.978  | 1.351     | 0      | 0      | 0.641  | 1.538  | 2.564  |
| Trust                                                                                                                                     |        |           |        |        |        |        |        |
| Percentage of words expressing “trust” in the overall project pitch                                                                       | 2.880  | 2.262     | 0      | 1.370  | 2.660  | 4.082  | 5.634  |
| Control variables                                                                                                                         |        |           |        |        |        |        |        |
| Project description                                                                                                                       |        |           |        |        |        |        |        |
| Number of sentences in the description section of the pitch, which is provided by the entrepreneur under the heading “About this project” | 33.822 | 35.524    | 6      | 11     | 22     | 45     | 76     |
| Readability                                                                                                                               |        |           |        |        |        |        |        |
| Flesch Reading Ease Readability score of the overall project pitch                                                                        | 58.822 | 19.051    | 44.030 | 52.952 | 60.843 | 67.734 | 73.351 |
| Campaign goal <sup>b</sup>                                                                                                                |        |           |        |        |        |        |        |
| The size of the goal in US dollar                                                                                                         | 45,641 | 1,179,383 | 650    | 2000   | 5500   | 15,880 | 45,000 |



TABLE 1 (Continued)

|                               |                                                                                                                                                                         | Mean   | SD     | P10   | P25   | Median | P75    | P90   |
|-------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------|--------|-------|-------|--------|--------|-------|
| Campaign duration             | Number of days for which the project accepted contributions                                                                                                             | 32.757 | 11.214 | 21    | 30    | 30     | 34.140 | 50    |
| Number of reward <sup>b</sup> | Number of reward options on the campaign outcome                                                                                                                        | 7.942  | 6.017  | 2     | 4     | 7      | 10     | 15    |
| Video                         | Takes the value of one if the pitch contains a Video, and zero otherwise                                                                                                | 0.704  | 0.456  | 0     | 0     | 1      | 1      | 1     |
| US project                    | Takes the value of one if the campaign was launched in the US, zero otherwise                                                                                           | 0.718  | 0.450  | 0     | 0     | 1      | 1      | 1     |
| Endorsement                   | Indicates if the campaign was listed as staff pick on the crowdfunding platform                                                                                         | 0.554  | 2.540  | 0     | 0     | 0      | 0      | 1     |
| Experience                    | Number of Kickstarter prior campaigns launched by the founder                                                                                                           | 0.104  | 0.305  | 0     | 0     | 0      | 0      | 1     |
| Competition                   | Number of other campaigns launched on Kickstarter while the campaign is live (in thousands)                                                                             | 5.169  | 2.416  | 2.775 | 3.684 | 4.569  | 6.320  | 8.285 |
| Google trend                  | Measure of popularity of Kickstarter based on monthly Google searches (available at <a href="https://trends.google.com/trends/">https://trends.google.com/trends/</a> ) | 51.377 | 16.626 | 30    | 38    | 54     | 63     | 68    |

<sup>a</sup>In percentage of the total length.

<sup>b</sup>Natural logarithm of the values are used in the regression analyses.

TABLE 2 Correlation table.

|                                     | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       | (9)       | (10)      | (11)      | (12)      | (13)      | (14)      | (15)      | (16)      | (17)      | (18)      | (19)      | (20)      |
|-------------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| (1) Funded                          |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (2) Risk words                      | 0.071***  |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (3) Risk sentence                   | 0.071***  | 0.907***  |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (4) Risk richness                   | 0.128***  | 0.823***  | 0.751***  |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (5) Risk concreteness               | 0.030***  | -0.003    | 0.020***  | -0.014*** |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (6) Risk quantity                   | 0.100***  | 0.911***  | 0.895***  | 0.854***  | 0.334***  |           |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (7) Production risk                 | -0.022*** | 0.042***  | 0.031***  | 0.040***  | -0.063*** | 0.017***  |           |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (8) Delay risk                      | 0.106***  | -0.063*** | -0.059*** | -0.049*** | -0.014*** | -0.062*** | -0.149*** |           |           |           |           |           |           |           |           |           |           |           |           |           |
| (9) Quality risk                    | 0.058***  | 0.019***  | 0.013***  | 0.049***  | -0.010*** | 0.024***  | -0.115*** | -0.012*** |           |           |           |           |           |           |           |           |           |           |           |           |
| (10) Force majeure                  | -0.021*** | 0.059***  | 0.068***  | 0.060***  | 0.013***  | 0.067***  | -0.010*** | -0.089*** | -0.078*** |           |           |           |           |           |           |           |           |           |           |           |
| (11) Marketing risk                 | -0.158*** | 0.029***  | 0.005***  | 0.017***  | -0.080*** | -0.010*** | -0.068*** | -0.169*** | -0.079*** | -0.038*** |           |           |           |           |           |           |           |           |           |           |
| (12) Financial risk                 | 0         | -0.021*** | -0.027*** | -0.043*** | -0.037*** | -0.043*** | -0.043*** | -0.132*** | -0.100*** | -0.045*** | -0.039*** |           |           |           |           |           |           |           |           |           |
| (13) Risk management                | 0.066***  | 0.084***  | 0.080***  | 0.130***  | 0.093***  | 0.129***  | -0.272*** | -0.278*** | -0.161*** | -0.112*** | -0.242*** | -0.184*** |           |           |           |           |           |           |           |           |
| (14) Other statements               | -0.077*** | -0.119*** | -0.089*** | -0.185*** | 0.025***  | 0.122***  | -0.142*** | -0.227*** | -0.161*** | -0.039*** | -0.121*** | -0.085*** | -0.356*** |           |           |           |           |           |           |           |
| (15) Positive                       | 0         | 0.064***  | 0.054***  | 0.121***  | -0.116*** | 0.041***  | -0.048*** | -0.109*** | 0.065***  | -0.024*** | 0.073***  | 0.029***  | 0.122***  | -0.112*** |           |           |           |           |           |           |
| (16) Negative                       | -0.055*** | -0.070*** | -0.055*** | -0.098*** | -0.077*** | -0.100*** | 0.068***  | 0.056***  | -0.046*** | 0.150***  | 0.003     | -0.043*** | -0.186*** | 0.122***  | -0.058*** |           |           |           |           |           |
| (17) Anger                          | -0.055*** | -0.064*** | -0.053*** | -0.091*** | -0.073*** | -0.094*** | 0.087***  | -0.028*** | -0.072*** | 0.108***  | 0.003*    | 0.071***  | -0.138*** | 0.091***  | 0.032***  | 0.570***  |           |           |           |           |
| (18) Anticipation                   | 0.018***  | -0.060*** | -0.048*** | -0.065*** | -0.102*** | -0.092*** | -0.094*** | 0.135***  | 0.025***  | -0.039*** | -0.064*** | 0.018***  | -0.047*** | 0.040***  | 0.397***  | 0.183***  | 0.069***  |           |           |           |
| (19) Disgust                        | -0.010*** | 0.001     | 0.006***  | 0         | -0.032*** | -0.008*** | 0.015***  | 0.094***  | -0.026*** | 0.140***  | -0.021*** | -0.046*** | -0.066*** | -0.012*** | -0.005*** | 0.414***  | 0.429***  | 0.030***  |           |           |
| (20) Fear                           | -0.059*** | -0.091*** | -0.075*** | -0.128*** | -0.058*** | -0.117*** | 0.061***  | 0.034***  | -0.050*** | 0.127***  | -0.009*** | -0.064*** | -0.153*** | -0.138*** | -0.024*** | 0.792***  | 0.570***  | 0.227***  | 0.401***  |           |
| (21) Joy                            | 0.018***  | 0.016***  | 0.017***  | 0.037***  | -0.050*** | 0.006***  | -0.057*** | -0.114*** | -0.031*** | 0.009***  | -0.001    | 0.086***  | 0.072***  | 0.026***  | 0.599***  | -0.040*** | 0.096***  | 0.411***  | 0         | 0.008***  |
| (22) Sadness                        | -0.015*** | -0.018*** | -0.012*** | -0.018*** | -0.027*** | -0.025*** | 0.023***  | 0.094***  | -0.077*** | 0.127***  | -0.049*** | -0.029*** | -0.056*** | 0.016***  | 0.035***  | 0.529***  | 0.394***  | 0.057***  | 0.503***  | 0.443***  |
| (23) Surprise                       | 0.029***  | -0.003    | 0.001     | 0.010***  | -0.057*** | -0.016*** | -0.014*** | 0.005***  | -0.046*** | 0.040***  | -0.044*** | 0.082***  | -0.011*** | 0.017***  | 0.312***  | 0.090***  | 0.228***  | 0.365***  | 0.131***  | 0.111***  |
| (24) Trust                          | 0.008***  | 0.063***  | 0.054***  | 0.105***  | -0.083*** | 0.047***  | -0.015*** | -0.137*** | 0.009***  | -0.001    | 0.068***  | 0.086***  | 0.093***  | -0.079*** | 0.576***  | -0.044*** | 0.075***  | 0.270***  | 0.007***  | -0.018*** |
| (25) Project description            | 0.163***  | 0.267***  | 0.270***  | 0.326***  | 0.006***  | 0.290***  | -0.045*** | 0.065***  | 0.093***  | -0.007*** | -0.085*** | -0.071*** | 0.087***  | -0.086*** | 0.052***  | -0.026*** | -0.052*** | 0.024***  | 0.009***  | -0.032*** |
| (26) Readability                    | -0.005*** | -0.053*** | 0.033***  | -0.052*** | 0.031***  | -0.013*** | -0.028*** | 0.049***  | 0.013***  | 0.019***  | -0.089*** | -0.031*** | -0.038*** | 0.089***  | -0.059*** | 0.018***  | 0.019***  | 0.031***  | 0.010***  | 0.020***  |
| (27) Campaign goal <sup>a</sup>     | -0.228*** | 0.196***  | 0.174***  | 0.223***  | -0.020*** | 0.191***  | -0.020*** | -0.077*** | 0.042***  | -0.010*** | 0.128***  | -0.033*** | 0.057***  | -0.078*** | 0.110***  | -0.032*** | -0.027*** | -0.008*** | -0.020*** | -0.023*** |
| (28) Duration                       | -0.155*** | 0.014***  | 0.010***  | 0.001     | -0.016*** | 0.003*    | -0.006*** | -0.062*** | -0.013*** | 0.003     | 0.053***  | 0.012***  | 0.009***  | 0.012***  | 0.029***  | -0.007*** | 0.003     | -0.007*** | -0.006*** | -0.002    |
| (29) Number of rewards <sup>a</sup> | 0.338***  | 0.220***  | 0.208***  | 0.307***  | 0.001     | 0.246***  | -0.022*** | 0.109***  | 0.084***  | -0.020*** | -0.137*** | -0.046*** | 0.085***  | -0.107*** | 0.037***  | -0.062*** | -0.069*** | 0.022***  | -0.002    | -0.065*** |
| (30) Video                          | 0.226***  | 0.179***  | 0.172***  | 0.248***  | 0.009***  | 0.203***  | 0.005***  | 0.025***  | 0.048***  | -0.016*** | -0.104*** | -0.023*** | 0.098***  | -0.084*** | 0.067***  | -0.039*** | -0.034*** | 0.019***  | -0.010*** | -0.037*** |
| (31) US project                     | 0.016***  | -0.004*   | 0.033***  | 0.006***  | 0.007***  | 0.014***  | -0.001    | -0.009*** | -0.039*** | 0.014***  | 0.021***  | 0.012***  | -0.019*** | 0.029***  | 0.031***  | 0.001     | 0.023***  | 0.014***  | -0.001    | -0.003    |
| (32) Experience                     | 0.152***  | 0.019***  | 0.022***  | 0.013***  | 0.033***  | 0.029***  | -0.044*** | 0.077***  | 0.050***  | -0.013*** | -0.055*** | -0.024*** | 0.020***  | -0.034*** | -0.021*** | -0.013*** | -0.030*** | 0.022***  | 0.002     | -0.018*** |
| (33) Endorsement                    | 0.274***  | 0.085***  | 0.074***  | 0.124***  | 0.010***  | 0.097***  | -0.023*** | 0.034***  | 0.027***  | -0.004*** | -0.050*** | -0.021*** | 0.056***  | -0.051*** | 0.015***  | -0.030*** | -0.036*** | -0.001    | -0.004*** | -0.034*** |
| (34) Competing campaigns            | -0.172*** | -0.026*** | -0.024*** | -0.059*** | -0.020*** | -0.043*** | 0.009***  | -0.061*** | -0.032*** | 0.024***  | 0.069***  | 0.011***  | -0.030*** | 0.041***  | 0.004***  | 0.009***  | 0.018***  | -0.021*** | 0.004***  | 0.010***  |
| (35) Google trend                   | -0.078*** | 0         | 0.002     | -0.021*** | -0.023*** | -0.014*** | 0.061***  | -0.032*** | -0.069*** | 0.043***  | 0.017***  | 0.007***  | -0.044*** | 0.047***  | -0.018*** | 0.020***  | 0.040***  | -0.034*** | 0.012***  | 0.018***  |



|                                     | (21)     | (22)      | (23)      | (24)      | (25)      | (26)      | (27)      | (28)      | (29)      | (30)      | (31)      | (32)      | (33)      | (34)     |
|-------------------------------------|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|----------|
| (22) Sadness                        | 0.106*** |           |           |           |           |           |           |           |           |           |           |           |           |          |
| (23) Surprise                       | 0.480*** | 0.164***  |           |           |           |           |           |           |           |           |           |           |           |          |
| (24) Trust                          | 0.525*** | -0.014*** | 0.334***  |           |           |           |           |           |           |           |           |           |           |          |
| (25) Project description            | -0.001   | -0.025*** | 0.001     | 0.043***  |           |           |           |           |           |           |           |           |           |          |
| (26) Readability                    | 0.010*** | 0.014***  | 0.015***  | -0.036*** | 0.098***  |           |           |           |           |           |           |           |           |          |
| (27) Campaign goal <sup>a</sup>     | 0.005*** | -0.053*** | -0.025*** | 0.085***  | 0.209***  | -0.098*** |           |           |           |           |           |           |           |          |
| (28) Duration                       | 0.011*** | -0.012*** | -0.006*** | 0.026***  | -0.002    | -0.039*** | 0.221***  |           |           |           |           |           |           |          |
| (29) Number of rewards <sup>a</sup> | 0.012*** | -0.027*** | 0.016***  | 0.031***  | 0.372***  | 0.014***  | 0.159***  | -0.025*** |           |           |           |           |           |          |
| (30) Video                          | 0.026*** | -0.017*** | 0.015***  | 0.054***  | 0.247***  | -0.022*** | 0.193***  | -0.010*** | 0.381***  |           |           |           |           |          |
| (31) US project                     | 0.039*** | 0.013***  | 0.020***  | 0.019***  | -0.036*** | 0.088***  | 0.018***  | -0.006*** | 0.018***  | 0.032***  |           |           |           |          |
| (32) Experience                     | -0.001   | -0.002    | 0.008***  | -0.007*** | 0.068***  | 0.026***  | -0.099*** | -0.102*** | 0.045***  | -0.007*** | 0.038***  |           |           |          |
| (33) Endorsement                    | 0.008*** | -0.018*** | 0.009***  | 0.015***  | 0.179***  | -0.037*** | 0.115***  | -0.033*** | 0.231***  | 0.175***  | -0.007*** | 0.034***  |           |          |
| (34) Competing campaigns            | 0.004**  | 0.003*    | -0.003    | 0.007***  | -0.064*** | -0.036*** | 0.143***  | 0.725***  | -0.085*** | -0.093*** | 0.011***  | -0.101*** | -0.011*** |          |
| (35) Google trend                   | 0        | 0.033***  | 0.013***  | -0.011*** | -0.077*** | -0.011*** | -0.009*** | 0.009***  | -0.019*** | -0.046*** | 0.097***  | -0.088*** | 0.014***  | 0.467*** |

Note: \*, \*\*, and \*\*\* denote statistical significance at the 10 percent, 5 percent, and 1 percent levels (two-tailed), respectively.

<sup>a</sup>Natural logarithmic values.

were successfully funded, which is comparable to the success rates reported in the literature (e.g., Buttice et al., 2017; Chan & Parhankangas, 2017; Courtney et al., 2017).<sup>18</sup> There were also a considerable variability among the campaigns in terms of the target amount. Approximately half of the projects had a target capital of USD 5500 or lower, while 10% of the projects have set the goal above USD 45,000.<sup>19</sup> A typical campaign offered approximately eight reward options and had a campaign duration of a little over a month. Furthermore, 70.402% of the campaigns included a video pitch, and 71.847% of projects were based in the United States.

Concerning risk disclosures, the average number of sentences in the R&C section was approximately six (6.231 sentences), which approximately equals one-fifth of the average project descriptions (33.822 sentences). While there were projects without a single risk sentence (618 observations), the most extensive risk disclosure were 423 sentences long. Among the various risk topics, on average, *Delay Risk* was the most prominent (14.113%), whereas, *Force Majeure* was the least discussed (2.271%). The other risk topics, *Production Risk*, *Quality Risk*, *Marketing Risk*, and *Financial Risk* average, respectively, accounted for 8.372%, 5.922%, 6.485%, and 4.957% of the risk disclosure sentences. The mean percentage of words expressing *Positive* and *Negative* affects were 5.473% and 2.008%, respectively. Furthermore, 10.370% of the projects were endorsed by Kickstarter, and over three-quarters of the projects were launched by founders without prior experience in raising funds on the platform.

We also report the correlations (Pearson's) between the various variables in Table 2 and do not find any exceptional level of correlation among the control variables.

## 4 | RESULTS

### 4.1 | Model selection

In the first part of our analysis, we examine the baseline relationship between the amount of information in risk disclosures with crowdfunding outcome by comparing models with different functional relationships, as reported in Table 3. We compare models assuming a linear, a curvilinear, a cubic, and a quartic relationship between *Risk Quantity* and *Funded* relying on different model comparison metrics.

In Panel A, we report the two deviance-based metrics, Deviance Information Criterion (DIC), which resembles a generalized version of Akaike's criterion, along with Penalized Expected Deviance (PED), an alternative measure robust to discrete model parameters (Lunn et al., 2013; Plummer, 2008). We also report Watanabe-Akaike (Widely Available) Information Criterion (WAIC), a fully Bayesian extension (Vehtari et al., 2017; Watanabe & Opper, 2010). We find substantially lower scores for the curvilinear model opposed to the linear, suggesting a greater model fit for the former. Comparing the curvilinear model with the cubic and quartic models, we generally find marginal decrease in the measures, suggesting some model contribution from introducing the additional variables.

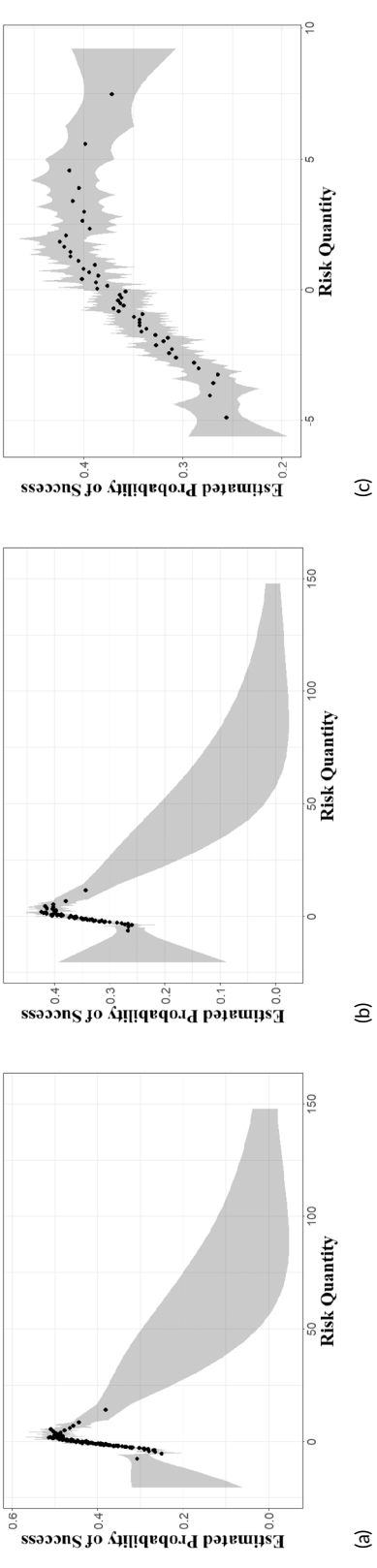
In Panel B, we report the Bayes factors, which represents the posterior odds in favor of one model over another (Kass & Raftery, 1995). As the linear model is nested within the curvilinear model, we obtain the Bayes factor by the Savage-Dickey density ratio (Dickey & Lientz, 1970; Wagenmakers et al., 2010).<sup>20</sup> We report corresponding Bayes factors at various reasonable non-committal prior values for the parameter of interest, given their influence on the Bayes factor (see Liu & Aitkin, 2008). We find consistent and substantive evidence in favor of the curvilinear model as opposed to linear.<sup>21</sup> Whereas, when comparing the cubic with the curvilinear model or the quartic with the cubic model, the evidence in support of the more complex models is generally limited to "anecdotal evidence" as described by Andraszewicz et al. (2015), and only when the priors are more informed.

Given the slim evidence separating the curvilinear, cubic, and quartic models, in Panel C, we graphically examine the data, plotting the relationship between *Risk Quantity* and *Success* with binned scatter plots, following Starr and Goldfarb's (2020) guidelines (also see Cattaneo et al., 2019).<sup>22</sup> Figure (a) from Table 3 derives from the entire sample observations, where we observe an inverted U-shaped spanning between the 1st and the 99th percentile; but at the extreme high and low values of *Risk Quantity*, there are aberrations. At the extremities, there are wide confidence



TABLE 3 Model comparison.

| Panel A: Deviance-based analysis      |                                   |                                  |                                  |                       |
|---------------------------------------|-----------------------------------|----------------------------------|----------------------------------|-----------------------|
|                                       | Linear model (m = 1)              | Curvilinear model (m = 2)        | Cubic model (m = 3)              | Quartic model (m = 4) |
| DIC                                   | 274461.387                        | 273787.508                       | 273742.554                       | 273700.425            |
| PED                                   | 274651.169                        | 273992.933                       | 274004.109                       | 273945.998            |
| WAIC                                  | 274481.668                        | 273812.696                       | 273774.723                       | 273742.937            |
| Panel B: Bayes' factor-based analysis |                                   |                                  |                                  |                       |
| Priors                                | BF <sub>21</sub>                  | BF <sub>32</sub>                 | BF <sub>43</sub>                 |                       |
| N(0,2) Actual prior                   | 1212.801 (Extreme evidence for 2) | 1.376 (Anecdotal evidence for 3) | 1.715 (Anecdotal evidence for 4) |                       |
| N(0,1) Informative prior              | 4569.578 (Extreme evidence for 2) | 2.21 (Anecdotal evidence for 3)  | 1.252 (Anecdotal evidence for 4) |                       |
| N(0,10) Diffused prior                | 384.309 (Extreme evidence for 2)  | 0.286 (Moderate evidence for 2)  | 1.840 (Anecdotal evidence for 4) |                       |
| Panel C: Binned-scatter plots         |                                   |                                  |                                  |                       |



Note: This table reports metrics and graphs in relation to the model selection procedure detailed in Section 4.1. Panel A reports the Deviance Information Criterion (DIC), Penalized Expected Deviance (PED) and Watanabe-Akaike (Widely Available) Information Criterion (WAIC) corresponding to the models assuming linear, quadratic, cubic and quartic relationships between Risk Quantity and Funded. Panel B reports the Savage-Dikey density ratio-based Bayes Factors comparing adjacent models, with interpretations from Jeffreys' (1961) classification scheme. Panel C presents binned scatter plots showing non-parametric estimates of Funded probability against Risk Quantity (a) with the raw data, (b) introducing adjustments for model control variables, and (c) removing observations outside the 1st and the 99th percentiles.



TABLE 4 Impact of risk quantity on crowdfunding success.

| Higher-level $\mu_f$ parameters  |                   |
|----------------------------------|-------------------|
| Dependent variable: Funded       |                   |
| Variables                        | Pr( $\beta > 0$ ) |
| Risk quantity                    | 1                 |
| Risk quantity <sup>2</sup>       | 0                 |
| Project description              | 1                 |
| Project description <sup>2</sup> | 0                 |
| Readability                      | 0                 |
| Campaign goal                    | 0                 |
| Duration                         | 0                 |
| Number of rewards                | 1                 |
| Video                            | 1                 |
| US project                       | 1                 |
| Experience                       | 1                 |
| Endorsement                      | 1                 |
| Competition                      | 0.01              |
| Google trend                     | 0                 |
| Constant                         | 1                 |
| Guess ( $\alpha$ )               | 1                 |

TABLE 4 (Continued)

Figure (a): Posterior distribution of parameters concerning risk quantity

Risk Quantity

Risk Quantity<sup>2</sup>

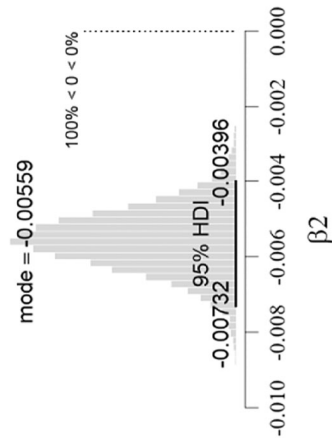
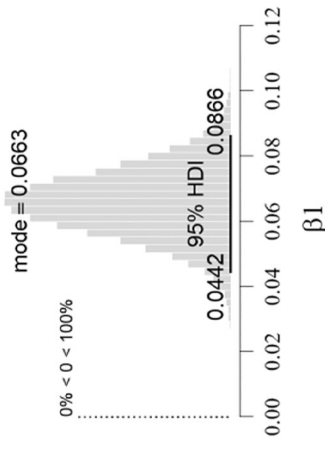
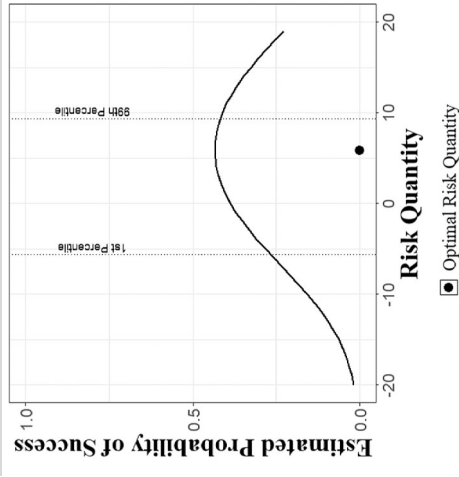


Figure (b): Estimated curvilinear relationship between risk quantity and crowdfunding success



Note: This table reports the posterior means of the higher-level parameters from the hierarchical Bayesian mixture model describing the common relationships across project types. Apart from the posterior means, the table provides 95% Highest Density Intervals (HDI) in parentheses, and the probability of the estimated coefficient being greater than zero. The model and the variables are detailed in Sections 3.3 and 3.4. Figure (a) presents the posterior distributions of the higher-level parameters for Risk Quantity and Risk Quantity<sup>2</sup> with 95% HDI and the mode of the distribution indicated. Figure (b) illustrates the aggregate relationship between Risk Quantity and project's success probability based on the estimated posterior means (with other continuous variables held constant at their mean values and the categorical variables held at the modal values). The vertical lines indicate the Risk Quantity at the 1st and the 99th sample percentiles, and the dot indicates the Risk Quantity value at which the success probability peaks.



TABLE 5 Impact of risk quantity on Crowdfunding success (by category).

| Group-level $\beta$ parameters |                                   |                                   |
|--------------------------------|-----------------------------------|-----------------------------------|
| Dependent Variable: Funded     |                                   |                                   |
| Categories                     | Risk Quantity                     | Risk Quantity <sup>2</sup>        |
|                                | Mean $\beta$<br>(95% <i>HDI</i> ) | Mean $\beta$<br>(95% <i>HDI</i> ) |
| Art                            | 0.043<br>(0.029,0.057)            | -0.003<br>(-0.005,-0.002)         |
| Comics                         | 0.077<br>(0.052,0.102)            | -0.008<br>(-0.013,-0.005)         |
| Crafts                         | 0.097<br>(0.069,0.124)            | -0.01<br>(-0.014,-0.006)          |
| Dance                          | 0.049<br>(0.015,0.085)            | -0.003<br>(-0.007,0.001)          |
| Design                         | 0.082<br>(0.068,0.096)            | -0.008<br>(-0.01,-0.006)          |
| Fashion                        | 0.107<br>(0.089,0.123)            | -0.007<br>(-0.009,-0.005)         |
| Film & video                   | 0.038<br>(0.027,0.049)            | -0.005<br>(-0.006,-0.004)         |
| Food                           | 0.069<br>(0.052,0.085)            | -0.006<br>(-0.008,-0.004)         |
| Games                          | 0.142<br>(0.128,0.157)            | -0.007<br>(-0.009,-0.005)         |
| Journalism                     | 0.055<br>(0.020,0.090)            | -0.003<br>(-0.006,0)              |
| Music                          | 0.012<br>(0.001,0.023)            | -0.003<br>(-0.004,-0.001)         |
| Photography                    | 0.057<br>(0.033,0.080)            | -0.004<br>(-0.006,-0.001)         |
|                                | Pr ( $\beta>0$ )                  | Pr ( $\beta>0$ )                  |
|                                | 1                                 | 0                                 |
|                                | 1                                 | 0                                 |
|                                | 1                                 | 0                                 |
|                                | 0.996                             | 0.046                             |
|                                | 1                                 | 0                                 |
|                                | 1                                 | 0                                 |
|                                | 1                                 | 0                                 |
|                                | 1                                 | 0                                 |
|                                | 1                                 | 0                                 |
|                                | 0.999                             | 0.036                             |
|                                | 0.982                             | 0                                 |
|                                | 1                                 | 0.003                             |

TABLE 5 (Continued)

| Group-level $\beta$ parameters |                          |                    |                                                |
|--------------------------------|--------------------------|--------------------|------------------------------------------------|
| Dependent Variable: Funded     |                          |                    |                                                |
| Categories                     | Risk Quantity            |                    | Risk Quantity <sup>2</sup>                     |
|                                | Mean $\beta$<br>(95%HDl) | Pr ( $\beta > 0$ ) | Mean $\beta$<br>(95%HDl)<br>Pr ( $\beta > 0$ ) |
| Publishing                     | 0.053<br>(0.040,0.066)   | 1                  | -0.005<br>(-0.007,-0.004)<br>0                 |
| Technology                     | 0.081<br>(0.064,0.097)   | 1                  | -0.007<br>(-0.009,-0.005)<br>0                 |
| Theater                        | 0.025<br>(0.002,0.048)   | 0.981              | -0.004<br>(-0.007,-0.002)<br>0.001             |

Figure (a): Estimated curvilinear relationship between risk quantity and crowdfunding success

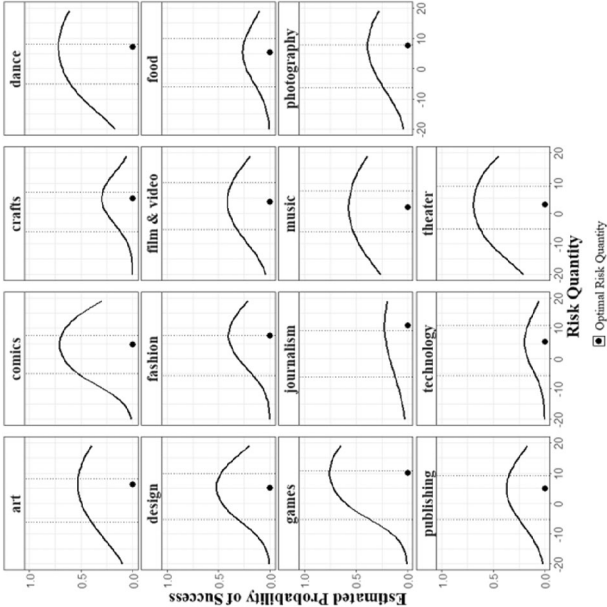
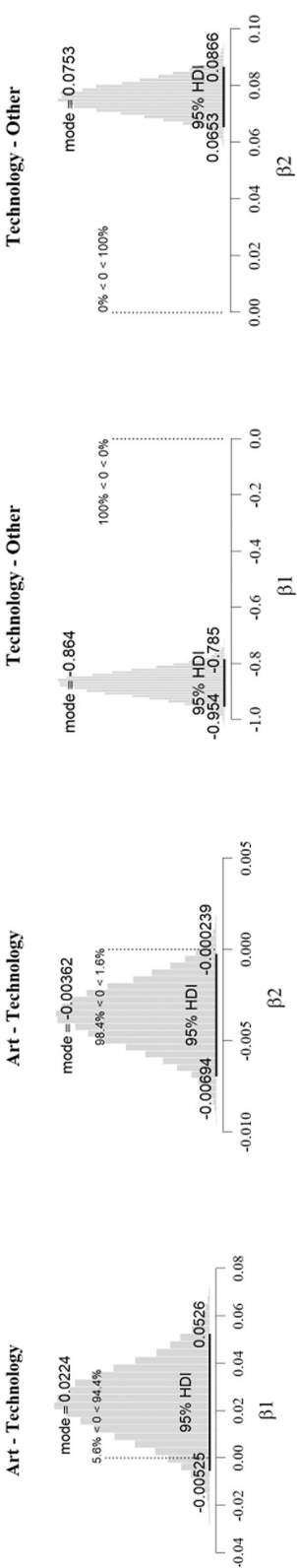




TABLE 5 (Continued)

Figure (b): Sample difference in posterior distribution of parameters concerning risk quantity



Note: This table reports posterior means of category-level parameters for the risk quantity variables from the hierarchical Bayesian model. Apart from the posterior means, the table provides 95% Highest Density Intervals (HDI) in parentheses, and the probability of the estimated coefficient being greater than zero. The model and variables are detailed in Sections 4.2 and 3. Figure (a) illustrates the category-specific relationships between Risk Quantity and project's success probability, based on the estimated posterior means (with other continuous variables held constant at their category-mean values and the categorical variables held at the category-modal values). The vertical lines indicate Risk Quantity at the 1st and the 99th category percentiles, and the dot indicates the Risk Quantity value at which the success probability peaks. Figure (b) illustrates the distribution of the credible differences in parameter estimates between categories "Art" and "Technology," and all other categories.



bands and large distance between the successive points, suggesting high outcome variability and data sparsity. At the lower end, interestingly, the projects with the least risk information performed better than projects at the 1st percentile.<sup>23</sup> Nevertheless, in Figure (b) in Table 3, when the estimated *Funded* probabilities account for the model control variables, the general pattern remains consistent. To further examine the persistence of these aberrant relationships, in Figure (c) from Table 3, we examine the binned scattered plot dropping observations outside the 1st and the 99th percentile. The diverging trends at the extremes are no longer present, suggesting a curvilinear model for the predominant dataspace.

Therefore, as per the visual and the statistical evaluations, the predominant underlying relationship between *Risk Quantity* and *Success* appears to have been curvilinear, at least within the main range of observed dataspace.<sup>24</sup> We next report detailed Bayesian estimation results with the quadratic variable of *Risk Quantity* included in all models. For consistency and to account for a potential non-linear relationship with the control variable *Project Description*, we also include a corresponding quadratic term. To account for the outlying dynamics, we incorporate a mixture model, including a *guess* parameter that models a random data generation process, as described in Section 3.3.

## 4.2 | Curvilinear relationship between risk quantity and crowdfunding success

In Table 4, we provide the aggregate estimates from the hierarchical model, and in Table 5 we report category-specific parameter estimates. As Bayesian analysis provides coefficient estimates described as probabilistic posterior distributions, the tables provide the mean, the 95% Highest Density Interval (HDI), and the probability describing  $\Pr(\beta_j > 0|D)$  from the sampled posterior distributions.<sup>25</sup>

Firstly, for the guess parameter “ $\alpha$ ,” we find the posterior mean to be 1.3%, while the 95% HDI and  $\Pr(\beta_j > 0|D)$  indicate that the coefficient value is most certainly greater than zero. Therefore, the model estimates that 1.3% of the crowdfunding outcomes in our Kickstarter sample were generated by a random process unrelated to the defined logistic model. We provide further diagnostics concerning the  $\alpha$  parameter in Section A3 of Appendix S1.

For all control variables, the posterior estimates are substantially different from zero, and the estimated signs and magnitudes corroborate with prior literature (see Courtney et al., 2017; Gafni et al., 2019). We also find there was a quadratic relationship between the project descriptions' length and crowdfunding campaign's outcome, with the optimal number of sentences of 102 sentences (at the 95th percentile). Similarly, more readable crowdfunding pitches were less likely to be successful, suggesting backers demanded a degree of sophistication in the project descriptions. The project size was inversely related to the funding probability, as higher targets were more challenging to reach. Campaign attributes, such as the number of rewards and having a video presentation, had positive and substantial influences on the outcome. Furthermore, the funding success was inversely tied to the number of competing campaigns and the contemporaneous popularity of the platform, suggesting that projects were likelier to succeed in the platform's earlier period than in the latter.

On our study's central explanatory variable, *Risk Quantity*, we find that the posterior distribution for the linear parameter is entirely above 0, and for the quadratic, it is below 0, thus adding to the strong evidence for a positive curvilinear relationship. Precisely, we find the mean values of the coefficients for the slope and the curvature parameters were 0.066 and  $-0.006$ , with 95% HDIs spanning between 0.044 and 0.097, and  $-0.007$  and  $-0.004$ , respectively.<sup>26</sup> The sampled posterior distributions of the two parameters are shown in Figure (a) from Table 4, and the estimated positive curvilinear relationship is shown in Figure (b) from Table 4.<sup>27</sup> Given the estimates, a central finding is that the amount of risk information in Kickstarter campaigns was substantially lower than the optimal, indicating a general under-reporting in comparison to backers' information demand. To illustrate, we find that the optimal *Risk Quantity* that maximized the probability of success was 5.910, which is notably higher than the sample mean, and indeed is close to the 96th percentile of the sample *Risk Quantity*.<sup>28</sup> Among typical projects, the percentage difference in success probabilities between those with the mean quantity of risk information and the optimum was 12.131%.<sup>29</sup>

In Table 5, we detail the category-specific estimates. While we find the curvilinear relationship consistent across all groups, we observe substantial heterogeneity as illustrated in Figure (a) from Table 5.<sup>30</sup> Among the categories, *games*, *fashion*, and *crafts* had the highest estimates for the slope parameter. Whereas, the curvature parameter was especially high for *crafts*, *comics*, and *fashion*. Therefore, there were substantial inter-group differences in the initial positive effects and the optimal level of disclosures. The *games*, *dance*, and *comics* projects benefitted the most from the disclosures, as having adequate risk information increased the campaign's success probability to up to 0.754, 0.718, and 0.707, respectively. In contrast, the risk information's impact on funding success was low for *technology*, *journalism*, and *food* projects (maximum probability of success: 0.199, 0.220, and 0.265, respectively). Second, we find that backers' tolerance for risk information was highest for *journalism*, *games*, and *fashion* projects (optimal *Risk Quantity*: 10.969, 10.165, and 7.604, respectively) and lowest for *music*, *theater*, and *film & video* (optimal *Risk Quantity*: 2.237, 3.079, and 3.964, respectively). Yet, the observed average *Risk Quantities* were notably less than the optimal quantity for all groups (mean *Risk Quantity*: -0.476, 0.249, and 0.167, respectively), suggesting that under-reporting was pervasive.

Bayesian estimates also permit direct comparisons between the different parameter posterior distributions, enabling us to highlight some of the across-category differences in Figure (b) from Table 5. Specifically, we compare the *art* and *technology*, given their distinctive characteristics and prominence in Kickstarter. Overall, these figures illustrate significant differences in backers' response to risk information across project categories, however, the positive curvilinear shape persists.

### 4.3 | Effects of qualitative and peripheral attributes

Next, we explore the influences arising from the variability in the semantic content within disclosures, in the emotions expressed in the entire funding appeal, and in the underlying background attributes. In essence, we investigate the impacts of *what* risks are disclosed, *how* are they disclosed and *who* provides the disclosure.

#### 4.3.1 | Disclosure's semantic content

Table 6 reports the description of the parameter estimates for interactions between the semantic topic variables, as described in Section 4.3.3, and *Risk Quantity*. Figure (a) from Table 6 illustrates these interactions. For each topic, we plot two curvilinear relationships between *Risk Quantity* and funding success: (i) with the topic variable at the sample mean, and (ii) at the mean plus one *sd*. Accordingly, the *dots* on the vertical axis indicate the consequent change in the success probability, and the horizontal *dots* indicate the shift in the optimal *Risk Quantity*.

The *dots* on the vertical axis show that more information on *Delay* and *Quality* improved the probability of success (*Delay*: 13.485% from 0.415 to 0.472; *Quality*: 11.398%, from 0.410 to 0.457), as opposed to *Production* and *Marketing* topics (*Production*: -5.105%, from 0.418 to 0.397; *Marketing*: -17.662%, from 0.416 to 0.342). Additionally, for non-risk topics, we find that having more *Risk Management* sentences positively influenced the funding outcome by 15.593% (from 0.482 to 0.417), while including *Other Statements* had the opposite effect (by -13.977%, from 0.416 to 0.358). Overall, while we observe heterogeneous relationships across risk types, backers responded positively to reward-related risks and adversely to entrepreneur's project-related risks.

From the changes in optimal *Risk Quantity*, we find that, generally, with a lengthy discussion on a specific risk topic, backers' tolerance to the entire risk information was lower. This effect was particularly sizeable for *Marketing*. The optimal *Risk Quantity* was 6.545 when the disclosure had a typical-length discussion on marketing issues, but the optimum dropped to 3.367 when increasing the topic by one *sd*. Therefore, we find that if a specific topic was overemphasized, backers' demand for risk information declined. Conversely, when a certain topic was inadequate, backers sought more information in general, suggesting that backers preferred more balanced disclosures.

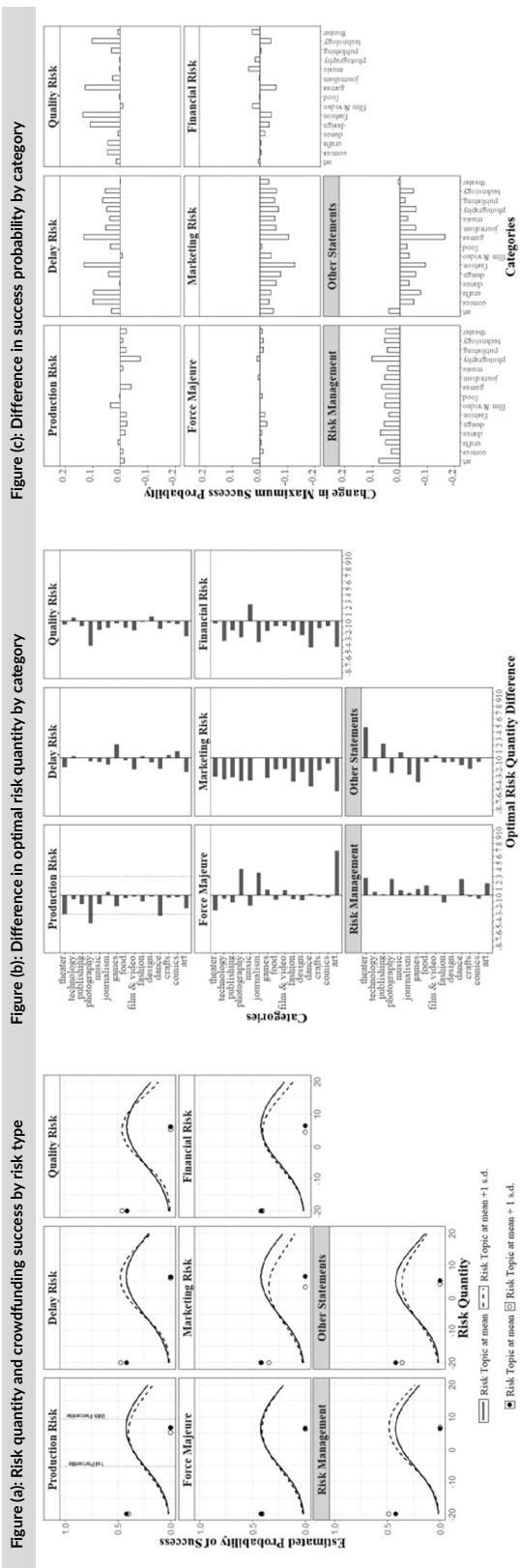


TABLE 6 Interactions with semantic content.

| Higher-level $\mu_p$ parameters        |                                                                            |                                                                            |                                                                             |                                                                          |                                                                           |       |       |       |       |
|----------------------------------------|----------------------------------------------------------------------------|----------------------------------------------------------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------------------------|-------|-------|-------|-------|
| Dependent variable: Funded             |                                                                            |                                                                            |                                                                             |                                                                          |                                                                           |       |       |       |       |
|                                        | Model 1<br>Production risk<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ ) | Model 2<br>Delay risk<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ )      | Model 3<br>Quality risk<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ )     | Model 4<br>Force majeure<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ ) | Model 5<br>Marketing risk<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ ) |       |       |       |       |
| Risk quantity                          | 0.081<br>(0.056, 0.106)                                                    | 0.062<br>(0.044, 0.079)                                                    | 0.063<br>(0.046, 0.08)                                                      | 0.078<br>(0.054, 0.103)                                                  | 0.086<br>(0.061, 0.111)                                                   | 1     | 1     | 1     | 1     |
| Risk quantity <sup>2</sup>             | −0.006<br>(−0.007, −0.004)                                                 | −0.005<br>(−0.006, −0.003)                                                 | −0.005<br>(−0.006, −0.003)                                                  | −0.006<br>(−0.008, −0.004)                                               | −0.005<br>(−0.007, −0.004)                                                | 0     | 0     | 0     | 0     |
| Risk type                              | 0<br>(−0.002, 0.006)                                                       | 0.009<br>(0.006, −0.006)                                                   | 0.012<br>(0.007, −0.653)                                                    | 0<br>(−0.003, −0.003)                                                    | −0.008<br>(−0.012, 1.242)                                                 | 1     | 0.373 | 0     | 0     |
| Risk quantity × risk type              | −0.0008<br>(−0.0014, −0.0002)                                              | 0.0008<br>(0.0001, 0.0014)                                                 | 0.0014<br>(−0.00002, 0.0028)                                                | −0.0012<br>(−0.0021, −0.0003)                                            | −0.0021<br>(−0.0027, −0.0014)                                             | 0.983 | 0.006 | 0     | 0     |
| Risk quantity <sup>2</sup> × risk type | −0.00001<br>(−0.00006, 0.00005)                                            | −0.00008<br>(−0.00013, −0.00002)                                           | −0.00021<br>(−0.00034, −0.00009)                                            | 0.00006<br>(−0.00005, 0.00016)                                           | −0.00002<br>(−0.00009, 0.00005)                                           | 0.422 | 0.875 | 0.312 | 0.312 |
| Controls                               | Yes                                                                        | Yes                                                                        | Yes                                                                         | Yes                                                                      | Yes                                                                       |       |       |       |       |
| Higher-level $\mu_p$ parameters        |                                                                            |                                                                            |                                                                             |                                                                          |                                                                           |       |       |       |       |
| Dependent variable: Funded             |                                                                            |                                                                            |                                                                             |                                                                          |                                                                           |       |       |       |       |
|                                        | Model 6<br>Financial risk<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ )  | Model 7<br>Risk management<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ ) | Model 8<br>Other statements<br>Mean $\beta$ (95% HDI)<br>Pr ( $\beta > 0$ ) |                                                                          |                                                                           |       |       |       |       |
| Risk quantity                          | 0.079<br>(0.054, 0.106)                                                    | 0.055<br>(0.029, 0.083)                                                    | 0.088<br>(0.059, 0.118)                                                     | 1                                                                        | 1                                                                         | 1     | 1     | 1     | 1     |
| Risk quantity <sup>2</sup>             | −0.005<br>(−0.007, −0.004)                                                 | −0.005<br>(−0.007, −0.003)                                                 | −0.008<br>(−0.01, −0.006)                                                   | 0                                                                        | 0                                                                         | 0     | 0     | 0     | 0     |
| Risk type                              | 0.004<br>(0.001, 0.983)                                                    | 0.007<br>(0.006, 0.232)                                                    | −0.007<br>(−0.009, −0.005)                                                  | 0.99                                                                     | 1                                                                         | 0     | 0     | 0     | 0     |
| Risk quantity × risk type              | −0.0011<br>(−0.0019, 0)                                                    | 0.0005<br>(0.0003, 0.0008)                                                 | −0.0009<br>(−0.0015, −0.0003)                                               | 0.022                                                                    | 1                                                                         | 0.004 | 0.004 | 0.004 | 0.004 |
| Risk quantity <sup>2</sup> × risk type | −0.00007<br>(−0.00018, 0.00003)                                            | −0.00002<br>(−0.00006, 0.00001)                                            | 0.00004<br>(−0.00001, 0.00001)                                              | 0.069                                                                    | 0.096                                                                     | 0.946 | 0.946 | 0.946 | 0.946 |
| Controls                               | Yes                                                                        | Yes                                                                        | Yes                                                                         |                                                                          |                                                                           |       |       |       |       |

(Continues)

TABLE 6 (Continued)



Note: This table reports posterior means of higher-level parameters from hierarchical Bayesian mixture models describing the interactions between Risk Quantity and semantic content variables in describing crowdfunding success. The estimated coefficients for the control variables, which although are included in the model, are not reported. In addition to the posterior means, the table provides 95% Highest Density Intervals (HDI) in parentheses, and the probability of the estimated coefficient being greater than zero. The model and variables are detailed in Sections 3.3 and 3.4. Figure (a) illustrates the aggregate relationship between Risk Quantity and project's success probability, given the proportion of individual risk type is held at the mean and at the mean plus one standard deviation. The probability estimates are based on the estimated posterior means with other continuous variables held constant at their means and the categorical variables held at the modes. The dots indicate the optimal Risk Quantity and the maximum success probability. Figure (b) presents the category-specific differences in the optimal Risk Quantity when the proportion of each risk type increases from the category-mean by one standard deviation. Figure (c) presents the category-specific differences in the estimated maximum probability of success when the proportion of each risk type increases from the category-mean by one standard deviation.



TABLE 7 Interactions with expressed feelings.

| Higher-level $\mu_p$ parameters      |                              |                             |                            |                              |                              |                    |                    |                    |                    |                    |
|--------------------------------------|------------------------------|-----------------------------|----------------------------|------------------------------|------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Dependent Variable: Funded           |                              |                             |                            |                              |                              |                    |                    |                    |                    |                    |
|                                      | Model 1<br>Positive          | Model 2<br>Negative         | Model 3<br>Anger           | Model 4<br>Anticipation      | Model 5<br>Disgust           |                    |                    |                    |                    |                    |
|                                      | Mean $\beta$ (95% HDI)       | Mean $\beta$ (95% HDI)      | Mean $\beta$ (95% HDI)     | Mean $\beta$ (95% HDI)       | Mean $\beta$ (95% HDI)       | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) |
| Risk quantity                        | 0.099<br>(0.076, 0.124)      | 0.078<br>(0.058, 0.097)     | 0.069<br>(0.047, 0.091)    | 0.071<br>(0.052, 0.09)       | 0.073<br>(0.054, 0.093)      | 1                  | 1                  | 1                  | 1                  | 1                  |
| Risk quantity <sup>2</sup>           | −0.006<br>(−0.008, −0.003)   | −0.006<br>(−0.009, −0.004)  | −0.006<br>(−0.009, −0.004) | −0.005<br>(−0.008, −0.003)   | −0.006<br>(−0.008, −0.004)   | 0                  | 0                  | 0                  | 0                  | 0                  |
| Feeling                              | −0.09<br>(−0.138, −0.043)    | −0.134<br>(−0.19, −0.077)   | −0.062<br>(−0.148, 0.028)  | −0.171<br>(−0.213, −0.13)    | 0.096<br>(0.024, 0.166)      | 0                  | 0.075              | 0                  | 0.993              | 0.993              |
| Risk quantity × feeling              | −0.003<br>(−0.006, −0.001)   | −0.002<br>(−0.008, 0.003)   | 0.003<br>(−0.001, 0.01)    | 0.001<br>(−0.004, 0.006)     | 0.001<br>(−0.014, 0.016)     | 0.001              | 0.936              | 0.614              | 0.544              | 0.544              |
| Risk quantity <sup>2</sup> × feeling | −0.0001<br>(−0.0004, 0.0002) | 0.0001<br>(−0.0006, 0.0007) | 0<br>(−0.0011, 0.0011)     | −0.0002<br>(−0.0007, 0.0003) | −0.0009<br>(−0.0025, 0.0006) | 0.292              | 0.603              | 0.204              | 0.108              | 0.108              |
| Controls                             | Yes                          | Yes                         | Yes                        | Yes                          | Yes                          |                    |                    |                    |                    |                    |

| Higher-level $\mu_p$ parameters      |                              |                              |                             |                              |                              |                    |                    |                    |                    |                    |
|--------------------------------------|------------------------------|------------------------------|-----------------------------|------------------------------|------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Dependent Variable: Funded           |                              |                              |                             |                              |                              |                    |                    |                    |                    |                    |
|                                      | Model 6<br>Fear              | Model 7<br>Joy               | Model 8<br>Sadness          | Model 9<br>Surprise          | Model 10<br>Trust            |                    |                    |                    |                    |                    |
|                                      | Mean $\beta$ (95% HDI)       | Mean $\beta$ (95% HDI)       | Mean $\beta$ (95% HDI)      | Mean $\beta$ (95% HDI)       | Mean $\beta$ (95% HDI)       | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) | Pr ( $\beta > 0$ ) |
| Risk quantity                        | 0.067<br>(0.049, 0.086)      | 0.073<br>(0.048, 0.098)      | 0.081<br>(0.064, 0.1)       | 0.074<br>(0.05, 0.097)       | 0.099<br>(0.073, 0.128)      | 1                  | 1                  | 1                  | 1                  | 1                  |
| Risk quantity <sup>2</sup>           | −0.006<br>(−0.008, −0.004)   | −0.006<br>(−0.008, −0.004)   | −0.007<br>(−0.009, −0.005)  | −0.006<br>(−0.008, −0.004)   | −0.006<br>(−0.008, −0.003)   | 0                  | 0                  | 0                  | 0                  | 0                  |
| Feeling                              | −0.052<br>(−0.12, 0.017)     | 0.065<br>(0.007, 0.125)      | 0.045<br>(−0.018, 0.115)    | −0.053<br>(−0.098, −0.008)   | 0.16<br>(0.103, 0.221)       | 0.063              | 0.918              | 0.011              | 1                  | 1                  |
| Risk quantity × feeling              | 0.005<br>(−0.003, 0.013)     | 0<br>(−0.004, 0.004)         | −0.006<br>(−0.014, 0.002)   | 0<br>(−0.006, 0.005)         | −0.006<br>(−0.012, 0)        | 0.891              | 0.546              | 0.458              | 0.018              | 0.018              |
| Risk quantity <sup>2</sup> × feeling | −0.0002<br>(−0.0009, 0.0006) | −0.0001<br>(−0.0007, 0.0005) | 0.0004<br>(−0.0004, 0.0013) | −0.0002<br>(−0.0015, 0.0009) | −0.0001<br>(−0.0005, 0.0003) | 0.342              | 0.389              | 0.337              | 0.322              | 0.322              |
| Controls                             | Yes                          | Yes                          | Yes                         | Yes                          | Yes                          |                    |                    |                    |                    |                    |

(Continues)

TABLE 7 (Continued)

Figure (a): Risk quantity and crowdfunding success by expressed feeling

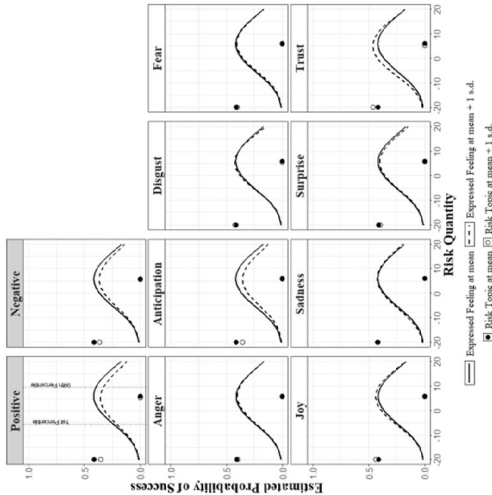


Figure (b): Difference in optimal risk quantity by category

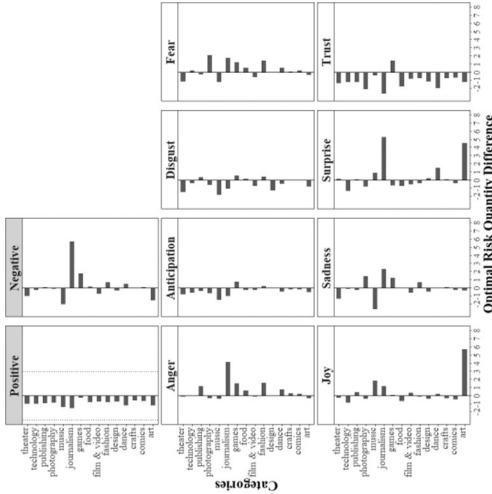
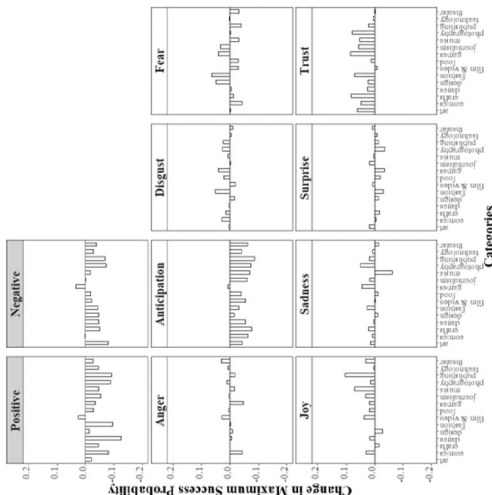


Figure (c): Difference in success probability by category



Note: This table reports posterior means of higher-level parameters from the hierarchical Bayesian mixture model describing the interactions between Risk Quantity and expressed feelings variables in describing crowdfunding success. The estimated coefficients for the control variables, which although included in the model, are not reported. In addition to the posterior means, the table provides 95% Highest Density Intervals (HDI) in parentheses, and the probability of the estimated coefficient being greater than zero. The model and variables are detailed in Sections 3.3 and 3.4. Figure (a) illustrates the aggregate relationship between Risk Quantity and project's success probability, given the feelings variable is held at the mean and at the mean plus one standard deviation. The probability estimates are based on the estimated posterior means with other continuous variables held constant at their mean values and the categorical variables held at the modal values. The dots indicate the optimal Risk Quantity and the maximum success probability. Figure (b) presents the category-specific differences in optimal Risk Quantity when the expressed feeling increases from the category-mean by one standard deviation. Figure (c) presents the category-specific differences in estimated maximum probability of success when the expressed feeling increases from the category-mean by one standard deviation.



Furthermore, uniquely, we find a positive effect for *Risk Management*; that is, having more information showing the entrepreneur's ability to manage risks increased backers' tolerance to the overall risk information, albeit by a small margin (from 6.353 to 6.888 *Risk Quantity*).

Figure (b,c) from Table 6 illustrates these relationships at the category level. The group-level results mostly corroborate the aggregate relationships. For topics, *Force Majeure* and *Financial*, which displayed low aggregate associations, we find greater variability across groups. In Figure (b) from Table 6, in certain contexts, backers did in turn demand more overall risk information. For instance, when *Force Majeure* risks are discussed, which are issues beyond the entrepreneur's control, backers demanded more information, particularly among *art*, *photography*, and *journalism* projects.

#### 4.3.2 | Expression of feelings

Next, we examine the effects of expressed *feelings* (*affects* and *emotions*), as shown in Table 7. Firstly, from Figure (a) from Table 7, the horizontal dots indicate shifts in optimal *Risk Quantity* with an increase in expressed feelings in the overall pitch by one *sd* from the mean. The shifts are negligible and generally negative, with the exceptions of *Anger* and *Fear*. These minimal moderating effects suggest that changing the expressed feelings in the pitch barely impacted backers' tolerance for risk information. However, we do observe some notable direct effects on the funding outcome, as indicated by the vertical dots. Increases in *Positive* and *Negative* reduced the probability of crowdfunding success by 14.47% (from 0.414 to 0.354) and 11.50% (from 0.414 to 0.366), respectively. Moreover, among the expressed emotions, *Anticipation*, which represents the use of words, such as “caution,” “unknown,” and “anxiety,” had a strong negative effect (−14.56%, from 0.414 to 0.354). In contrast, *Trust*, which indicates the use of words, such as “management,” “organization,” and “scientific,” had a notable positive effect (10.88%, from 0.414 to 0.459).

At the category level, as shown in Figure (b) from Table 7, the effects of expressed feelings on the estimated optimal *Risk Quantity* were generally weak even at the group level. However, we do observe noteworthy patterns, suggesting that articulation of certain emotions was effective in some contexts. In particular, categories *journalism* and *art* display notable exceptions. For example, when a *journalism* project increased words expressing anger by one *sd* from the mean, the optimal *Risk Quantity* increased from 12.631 to 16.823 (also see *Negative* and *Surprise*). Among *art* projects, *Joy* and *Surprise* were associated with distinctly large shifts. Furthermore, in Figure (c) from Table 7, concerning the direct relationship with success probability, the results are largely consistent across categories for variables that showed strong aggregate associations (*Positive*, *Negative*, *Anticipation*, and *Trust*) and more varied when the aggregate associations were low (*Anger*, *Disgust*, *Fear*, *Sadness*, and *Surprise*).<sup>31</sup>

#### 4.3.3 | Background attributes

Lastly, we look at the influence of the project's attributes on the relationship between *Risk Quantity* and *Success*, as shown in Table 8. Among the different background variables, as shown in Figure (a) from Table 8, we observe substantial influences of *Project Campaign Goal*, *Number of Rewards*, *Video*, *Experience*, and *Endorsement*, as indicated by the dots on the horizontal axis. Distinctly, *Experience* and *Endorsement*, the two attributes that enhance project credibility, were associated with greater demand for risk information. The optimal *Risk Quantity* was 14.076 for projects with one *sd* higher *Experience* and 8.671 for endorsed projects, compared to 6.378 for a typical project. In contrast, *Project Description*, *Video*, *Campaign Goal*, and *Number of Rewards* reduced the optimal disclosure quantity. The negative interactions with *Project Description* and *Video* indicate that backers favor less risk information when the overall amount of information to process is greater. Also, the lower optimal disclosure quantities for higher *Campaign Goals* and *Number of Rewards* suggest that backers' apprehension of risk increases as the stakes get higher. The direct



TABLE 8 Interactions with background attributes.

| Higher-level $\mu_p$ parameters         |                                               |                    |                                       |                    |                                         |                    |                                       |                    |                                             |                    |                                        |
|-----------------------------------------|-----------------------------------------------|--------------------|---------------------------------------|--------------------|-----------------------------------------|--------------------|---------------------------------------|--------------------|---------------------------------------------|--------------------|----------------------------------------|
| Dependent variable: Funded              |                                               |                    |                                       |                    |                                         |                    |                                       |                    |                                             |                    |                                        |
|                                         | Model 1                                       |                    | Model 2                               |                    | Model 3                                 |                    | Model 4                               |                    | Model 5                                     |                    | Pr ( $\beta > 0$ )                     |
|                                         | Project description<br>Mean $\beta$ (95% HDI) | Pr ( $\beta > 0$ ) | Readability<br>Mean $\beta$ (95% HDI) | Pr ( $\beta > 0$ ) | Campaign goal<br>Mean $\beta$ (95% HDI) | Pr ( $\beta > 0$ ) | Duration<br>Mean $\beta$ (95% HDI)    | Pr ( $\beta > 0$ ) | Number of rewards<br>Mean $\beta$ (95% HDI) | Pr ( $\beta > 0$ ) |                                        |
| Risk quantity                           | 0.109<br>(0.082, 0.135)                       | 1                  | 0.094<br>(0.056, 0.132)               | 1                  | 0.14<br>(0.077, 0.201)                  | 1                  | 0.073<br>(0.045, 0.1)                 | 1                  | 0.087<br>(0.037, 0.135)                     | 1                  | 0.999                                  |
| Risk quantity <sup>2</sup>              | −0.006<br>(−0.008, −0.004)                    | 0                  | −0.007<br>(−0.01, −0.004)             | 0                  | 0.002<br>(−0.002, 0.005)                | 0.84               | −0.005<br>(−0.007, −0.003)            | 0                  | −0.003<br>(−0.006, −0.001)                  | 0                  | 0.002                                  |
| Background                              | 0.005<br>(0.003, 0.007)                       | 1                  | −0.011<br>(−0.015, −0.006)            | 0                  | −0.691<br>(−0.737, −0.643)              | 0                  | −0.01<br>(−0.018, −0.003)             | 0.006              | 1.166<br>(1.037, 1.29)                      | 0.006              | 1                                      |
| Risk quantity × background              | −0.0012<br>(−0.0014, −0.0009)                 | 0                  | −0.0004<br>(−0.0008, 0)               | 0.036              | −0.008<br>(−0.0156, −0.0001)            | 0.023              | 0                                     | 0.454              | −0.0065<br>(−0.0276, 0.0133)                | 0.454              | 0.249                                  |
| Risk quantity <sup>2</sup> × background | 0.00004<br>(0.00002, 0.00005)                 | 1                  | 0.00001<br>(−0.00003, 0.00005)        | 0.646              | −0.00086<br>(−0.00125, −0.00045)        | 0                  | −0.00003<br>(−0.00011, 0.00004)       | 0.189              | −0.00127<br>(−0.00221, −0.00026)            | 0.189              | 0.004                                  |
| Controls                                | Yes                                           | Yes                | Yes                                   | Yes                | Yes                                     | Yes                | Yes                                   | Yes                | Yes                                         | Yes                | Yes                                    |
| Higher-level $\mu_p$ parameters         |                                               |                    |                                       |                    |                                         |                    |                                       |                    |                                             |                    |                                        |
| Dependent variable: Funded              |                                               |                    |                                       |                    |                                         |                    |                                       |                    |                                             |                    |                                        |
|                                         | Model 6                                       |                    | Model 7                               |                    | Model 8                                 |                    | Model 9                               |                    | Model 10                                    |                    | Google trend<br>Mean $\beta$ (95% HDI) |
|                                         | Video<br>Mean $\beta$ (95% HDI)               | Pr ( $\beta > 0$ ) | US project<br>Mean $\beta$ (95% HDI)  | Pr ( $\beta > 0$ ) | Experience<br>Mean $\beta$ (95% HDI)    | Pr ( $\beta > 0$ ) | Endorsement<br>Mean $\beta$ (95% HDI) | Pr ( $\beta > 0$ ) | Competition<br>Mean $\beta$ (95% HDI)       | Pr ( $\beta > 0$ ) |                                        |
| Risk quantity                           | 0.068<br>(0.044, 0.091)                       | 1                  | 0.075<br>(0.051, 0.098)               | 1                  | 0.066<br>(0.045, 0.086)                 | 1                  | 0.077<br>(0.055, 0.1)                 | 1                  | 0.052<br>(0.025, 0.078)                     | 0.999              | 0.036<br>(0.002, 0.069)                |
| Risk quantity <sup>2</sup>              | −0.004<br>(−0.006, −0.002)                    | 0                  | −0.006<br>(−0.008, −0.004)            | 0                  | −0.006<br>(−0.008, −0.005)              | 0                  | −0.007<br>(−0.009, −0.005)            | 0                  | −0.005<br>(−0.006, −0.003)                  | 0                  | −0.004<br>(−0.007, −0.002)             |
| Background                              | 0.9<br>(0.769, 1.026)                         | 1                  | 0.126<br>(0.033, 0.219)               | 0.994              | 0.219<br>(0.138, 0.299)                 | 1                  | 1.951<br>(1.753, 2.15)                | 1                  | −0.035<br>(−0.063, −0.009)                  | 0.006              | −0.009<br>(−0.013, −0.006)             |
| Risk quantity × background              | 0.0072<br>(−0.0061, 0.0221)                   | 0.857              | −0.0039<br>(−0.015, 0.0064)           | 0.234              | 0.017<br>(0.0055, 0.028)                | 0.997              | −0.0568<br>(−0.077, −0.0379)          | 0                  | 0.0041<br>(0.0009, 0.0072)                  | 0.994              | 0.007<br>(0.0003, 0.011)               |
| Risk quantity <sup>2</sup> × background | −0.0022<br>(−0.00457, 0.00003)                | 0.028              | −0.0011<br>(−0.0015, 0.00127)         | 0.441              | 0.00067<br>(−0.00095, 0.00225)          | 0.822              | 0.00548<br>(0.00313, 0.00688)         | 1                  | −0.00031<br>(−0.00072, 0.00009)             | 0.058              | −0.0004<br>(−0.00008, 0)               |
| Controls                                | Yes                                           | Yes                | Yes                                   | Yes                | Yes                                     | Yes                | Yes                                   | Yes                | Yes                                         | Yes                | Yes                                    |



TABLE 8 (Continued)

Figure (a): Risk quantity and crowdfunding success by background attribute

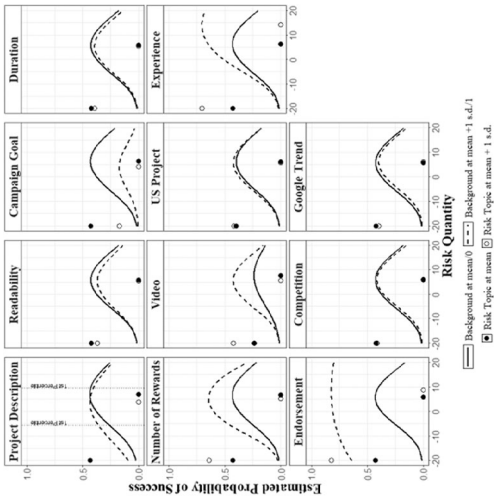


Figure (b): Difference in optimal risk quantity by category

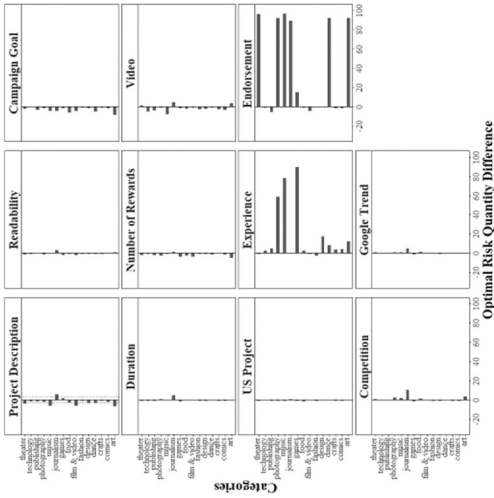
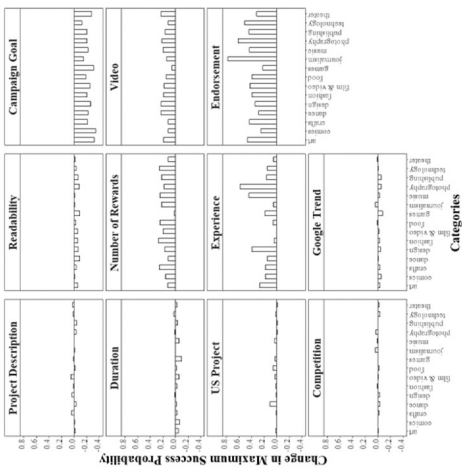


Figure (c): Difference in success probability by category



Note: This table reports posterior means from the hierarchical Bayesian mixture model describing the interaction between Risk Quantity and project background variables in describing crowdfunding success. The estimated coefficients for the control variables, which although included in the model, are not reported. Apart from the posterior means, the table provides 95% Highest Density Intervals (HDI) in parentheses, and the probability of the estimated coefficient being greater than zero. The model and variables are detailed in Sections 3.3 and 3.4. Figures (a) illustrates the aggregate relationship between Risk Quantity and project's success probability, given the background variable is held at the mean (0 for categorical variables) and at the mean plus one standard deviation (1 for categorical variables). The probability estimates are based on the estimated posterior means with other continuous variables held constant at their mean values and the categorical variables held at the modal values. The dots indicate the optimal Risk Quantity and the maximum success probability. Figure (b) presents the category-specific differences in optimal Risk Quantity when the background variable increases from the category-mean by one standard deviation. Figure (c) presents the category-specific differences in estimated maximum probability of success when the background variable increases from the category-mean by one standard deviation.

effect of the variables on success probability indicated by the vertical *dots* reflects the descriptions in Section 4.2, as the background attributes perform as the control variables in our main model.<sup>32</sup>

In Figure (b) from Table 8, which illustrates the category-specific shifts in the optimal *Risk Quantity*, we observe some crucial patterns. Firstly, the large influence of *Experience* and *Endorsement* on backers' tolerance to risk information appears specific to certain categories. The impact of *Experience* is larger for *photography*, *music*, and *games* projects, and for *Endorsement*, it is especially high for *theater*, *photography*, *music*, *journalism*, *dance*, and *art* projects. Moreover, in Figure (c) from Table 8, which illustrates the variables' impact on success probability, we similarly find large differences in the effect magnitudes across categories for the two variables, highlighting context-specific variability in their effectiveness.

## 5 | DISCUSSION

### 5.1 | Curvilinear relationship

A finding consistent throughout our analysis, at the aggregate and the category level, is that backers in our sample of Kickstarter campaigns responded positively to risk information. As context, there are three competing concerning arguments in the financial accounting literature: (i) boilerplate, (ii) divergence, and (iii) convergence, as labeled by Kravet and Muslu (2013). The boilerplate argument argues that risk disclosures are uninformative since disclosers would hide such detrimental information, and therefore, are ineffective (Abraham & Shrivs, 2014; Pérignon & Smith, 2010). The divergence argument emphasizes the inherent negative nature of the information, arguing an adverse response (Filzen, 2015; Kravet & Muslu, 2013). In contrast, the convergence argument states that risk disclosures encourage favorable response (Elbannan & Elbannan, 2015; Elshandidy & Neri, 2015). The latter argument derives from individuals' aversion to conditions of ambiguity—a subjective feeling of lack of relevant information (Frisch & Baron, 1988).<sup>3334</sup> Communicating relevant information through risk disclosures, although negative in nature, reduces the audience's sense of ambiguity, motivating confidence in the discloser, leading to participation. Our finding corroborates with the convergence explanation, showing that in reward-based crowdfunding, backers were generally receptive to risk information.

However, instead of a constant and monotonic relationship, we find that there is a non-linear quadratic association with an inflection point at which the relationship between the amount of risk information and funding outcome inverts. For this, we note two plausible explanations. The first explanation relates to the divergence argument: Given the inherent negative nature of risk information, at some point, the marginal decrease in the perception of ambiguity reduces to an extent that it is superseded by apprehensions from the additional adverse risk information (Kravet & Muslu, 2013). However, a number of peripheral findings suggest a second reason. For instance, for *Project Description*, which is unlike risk disclosure and concern positive and promotional information, we still find a similar curvilinear relationship. Similarly, in our analysis of background attributes' effects, our results show that for campaigns with longer pitches or with videos, backers favored less risk information. Also, our analysis of semantic content showed that, as the emphasis on a specific topic grew, backers' tolerance to the overall risk information decreased. Together, these findings indicate that backers were rather susceptible to information overload, explaining their aversion when the amount of information exceeded a threshold (Chapman et al., 2019; Hirshleifer & Teoh, 2003).

From the observed curvilinear relationship, we derive a key finding, that is, crowdfunding entrepreneurs underreported their private risk information. Such inhibitions to disclose risks are a known phenomenon among small ventures, given the greater costs and limited governance-related checks (Linsley & Shrivs, 2005; Miihkinen, 2012). However, the entrepreneur's caution to communicate risk is not entirely unfounded, as backers do eventually exhibit aversion to extensive amounts of risk information. The non-linear relationship may be specific to crowdfunding backers, exhibiting their readiness to shift to non-participation given the low-stake, informal setting (see Easley & O'Hara, 2009). However, the non-linear relationship also reflects early theoretical works, such as Diamond and Verrecchia (1991), which argue that



with increasing disclosure there is a decline in investors' risk-bearing capacity, and therefore, the maximum benefit of the disclosure is realized short of full disclosure. Therefore, despite the consistent evidence for under-reporting of risk information, entrepreneurs should nevertheless take caution not to report too much information.

## 5.2 | The role of trust attributes

From the analysis of the interactions with background attributes, a key finding we observe is that *Endorsement* and *Experience* were the only two attributes that increased backers' tolerance to risk information—by a significant margin. The two attributes are among several that backers rely on, such as the inclusion of a video or pitch readability, which together indicates the entrepreneur's effort and competence (Colombo, 2021; Vismara, 2018). However, in crowdfunding, such cues incur little cost for entrepreneurs as they are easy to replicate, leading to trust concerns (Steigenberger & Wilhelm, 2018). In that regard, the role of platform endorsement and crowdfunding experience is rather unique, as they are hard to imitate for disingenuous entrepreneurs, and therefore, motivate trust (Courtney et al., 2017; Li & Martin, 2019; Liang et al., 2019). In fact, in accordance with the trust literature, *Experience* and *Endorsement*, respectively, align with two key sources of trust—relation-based, that is trust established through past interactions, and institution-based, that is trust in a third party or institutions (McKnight et al., 1998; Zucker, 1986). Therefore, the increase in backers' tolerance to risk information with *Endorsement* and *Experience* suggests backers accepted more risk information when they considered the project as trustworthy.

The implication of trust in backers' response to risk information is evident in another finding of our study. When entrepreneurs communicated information on their ability and commitment to manage risks through *Risk Management* topics, the chances of funding success and backers' tolerance to risk information increased. These sentences include claims of the entrepreneur's commitment and passion, which aid in displaying integrity, and descriptions of know-how and production status, which indicates competence. Both integrity and competence are considered two central antecedents of trust (McKnight et al., 2002; Rousseau et al., 1998).

The significance of trust-building attributes in backers' reaction to risk information resonates with prior literature emphasizing the role of trust in perceptions and acceptance of risk (see Renn & Levine, 1991; Siegrist, 2021; Slovic, 1993). The notion that trust is intertwined with people's risk perceptions has stimulated wide-ranging research, including in organizational research, in contexts ranging from strategic alliance to employee performance (Colquitt et al., 2007; Das & Teng, 2001). Here, trust is understood as the intention to accept vulnerability based on positive expectations of others (Rousseau et al., 1998), and hence, as a mechanism that enables people to act in complex environments, like risk evaluation (Siegrist, 2021). Moreover, trust's influence on risk acceptance is argued as especially relevant in settings with information constraints (Siegrist & Cvetkovich, 2000). In the online crowdfunding setting, informational challenges between backers and entrepreneurs are substantial, implying the significance of trust in the backers' evaluation of risk information (Agrawal et al., 2014; Belleflamme et al., 2015).

## 5.3 | Demand for consequential information

From our analysis of the semantic topics discussed within risk disclosures, we find that among the various issues, *Delay* and *Quality* were positively related to the funding outcome; whereas, for topics *Marketing*, *Production*, and *Financial*, the relationships were negative. In this regard, the psychometric studies in risk perception—a prominent research domain focusing on why people view specific issues to be riskier than others, provide some crucial guidance (e.g., Fischhoff et al., 1978; Slovic, 1987; for an overview, see Siegrist & Árvai, 2020). These studies typically proceed by rating hazardous activities on several attributes, such as familiarity, effect's immediacy, knowledge, and severity of consequences, which are then associated with the resulting risk perception.

From the different underlying attributes, an explanation that distinguishes the two topics, *Delay* and *Quality*, from the others is that these risks specifically are of consequence to backers (see Herriges et al., 2010; Zawojcka

et al., 2019). For instance, other risk features like “control,” that is, the ability of the backer to influence the risk outcome, while may offer other reasonable explanations, they fail to explain why backers favored information on product-specific risks, like *Delay* and *Quality*, but not on venture-specific risks. *Delay* and *Quality* topics concern the timely delivery and quality of the promised reward, which are of consequence to the backers directly, unlike *Marketing*, *Production*, or *Financial* risks, which concern the entrepreneur's interest.

Moreover, other findings, such as an increase in backers' aversion to risk information when the stakes were higher (*Number of Reward* and *Campaign Size*) in the background attribute-related analyses, further support the explanation that the severity of the personal cost is a crucial criterion influencing backers' reaction to risk information.

## 5.4 | (Un)emotional response

In addition to the analytic view centering on the inherent risk attributes, risk perception is also known to arise from emotional channels, leading to the “risk as feelings” literature (Loewenstein et al., 2001; Slovic, 2010). In accordance, we examine the impact of incidental affects and emotions on backers' disclosure response.<sup>35</sup> First, on the affect variables, *Positive* and *Negative*, which indicate the overall polarity of the words used in the pitch, we find adverse relationships for both. This finding is interesting, as there are two main competing arguments: Isen and Patrick' (1983) mood maintenance hypothesis holds that positive affect induces risk-averse behavior, while negative affect leads to risk-seeking behavior; whereas others, such as the affect infusion model proposed by Forgas (1995) and the affect heuristic-based evidence suggest the opposite effect, arguing greater tolerance to risk amidst positive affect (Finucane et al., 2000; Johnson & Tversky, 1983; for an overview, see Grable & Roszkowski, 2008). Our findings instead align with experimental findings, such as Drichoutis and Nayga Jr (2013), and Williams et al. (2003), which show that both positive and negative affects lead to aversion toward risks. These studies argue that in situations that are cognitively demanding and where the possible loss becomes significant, stronger affect (or mood) prompts an increase in patience during risk assessment, leading to conservative risk-taking behavior (Arkes et al., 1988; Kim & Kanfer, 2009). Correspondingly, our findings show that crowdfunding backers, amidst a financial contribution decision, demonstrated more deliberate and cautious responses to risk information, despite prompts of positive or negative affects.

Moreover, our findings, or the lack thereof, on the moderating effects of expressed emotions lead to a similar explanation. Particularly, for Ekman's (1992) six fundamental emotions, the evidence for effects on backers' response to risk information, at the aggregate level, was minimal, and at the category level, was inconsistent. These findings align with the emphasis on context in understanding the role of emotions in risk perception. For example, in prior research, emotions' significance in risk evaluation is found to reduce when time allowance and financial considerations are introduced (Hu et al., 2015; Treffers et al., 2012). Individual attributes—such as emotional intelligence, are also shown to be contributing factors (Yip & Côté, 2013). Furthermore, the effect of emotions may be contingent on cognitive appraisals, such as certainty, pleasantness, control, anticipated effort, and responsibility (e.g., Lerner & Keltner, 2000; Smith & Ellsworth, 1985). For instance, Lerner and Keltner (2001) show that individuals' appraisals of certainty and control moderate the effects of fear and anger on optimism in risk evaluation. Therefore, in our crowdfunding setting where backers lack control over the risk outcome and are prone to the entrepreneur's responsibility, we similarly find limited impacts of incidental emotions on how backers responded to risk information.

Overall, our analyses show that crowdfunding backers in Kickstarter favored greater risk information, albeit, with an aversion to too much information. Importantly, amidst the challenges of evaluating risk disclosures from distant early-stage ventures, backers relied on assessments of entrepreneurs' trustworthiness, preferred information that had personal consequences, and displayed limited sway from expressions of feelings in the entrepreneur's pitch. Recognizing the broader implications of these findings requires acknowledging the distinctiveness of the crowdfunding setting. Unlike traditional financing settings, reward-based crowdfunding involves consumer-like online backers who lack the incentive for due diligence given the low stakes (Ahlers et al., 2015). The access to



finance that crowdfunding extends to early-stage ventures comes at the price of absent monitoring and accountability mechanisms (Moore, 2015). In contrast, mainstream financing settings constitute professional investors with relevant knowledge and resources, protected by regulatory structures for accountability. As such, prior literature that is predominantly set in mainstream settings, consistently highlights the importance of regulatory conditions and firm characteristics, such as corporate governance, for the efficacy of risk disclosures (e.g., Elshandidy & Neri, 2015; Malafronte et al., 2016). Absent such cues and having distinct profiles, our findings detail how crowdfunding backers navigate risk information, which is inherently negative, forward-looking, and unverifiable (Dobler, 2008).

Moreover, the patterns of backers' responses to risk communications we observe are telling of reward-based crowdfunding backers' motivations and efforts in making their contribution decisions. The tendency to process risks is broadly attributed to two types of judgments—cost–benefit and ethical considerations (Böhm & Pfister, 2000). We find that backers display deliberate and calculative reactions to risk information, focusing on self-interest over supporting entrepreneurs to overcome their business risks. Moreover, backers' reliance on trust-inducing factors indicates their general skepticism and caution against entrepreneurs' capacity to manage the risks they reveal. These findings in fact counter the typical description of reward-based crowdfunding backers as unsophisticated supporters with motivations other than material gain (Bürger & Kleinert, 2021; Gerber & Hui, 2013). In contrast to the common view that often cites social and altruistic motivations of crowdfunding backers, we find that backers' evaluations of risk information were in fact reasoned.

## 6 | CONCLUSION

Crowdfunding is touted as a “bridge” for early-stage ventures before they can access more traditional financing sources. Acknowledging its potential to support small businesses, authorities have introduced various regulations to support its development (e.g., Jumpstart Our Business Startups (JOBS) Act 2012, USA; Regulation on European Crowdfunding Service Providers (ESCP) for business 2020, EU). Thus, given the importance of risk judgments in participation decisions, mandatory risk disclosure rules could be an essential tool for platforms to help promote backers' security, reduce ambiguity, and encourage participation. In this study, we investigate its implications by examining how backers respond to consequent risk communications.

### 6.1 | Academic contributions

Our study, thus, makes several contributions. First, we contribute to the crowdfunding literature by conducting a nuanced study on crowdfunding risk disclosures. We expand on the work on crowdfunding communications, which, given the limited avenue for direct inter-personal exchange, has been a crucial research topic (e.g., Allison et al., 2017; Anglin et al., 2018; Parhankangas & Renko, 2017; Steigenberger & Wilhelm, 2018). However, unlike the prior literature's focus on project descriptions, we contribute by examining risk disclosures that serve a distinct role in entrepreneurs' communications. Second, in light of the platform's role in mitigating informational challenges, this study informs our understanding of a risk disclosure rule's implications—if and how backers respond to the ensuing information (see Agrawal et al., 2014; Belleflamme et al., 2015). Third, we adopt an unsupervised topic modeling tool, sentLDA, for knowledge extraction from the textual disclosures. This way, we provide empirical evidence detailing the types of risks faced and reported by early-stage crowdfunding ventures (Bao & Datta, 2014). Furthermore, incorporating hierarchical Bayesian models, our results introduce new insights pertaining to specific project types, which are often ignored in crowdfunding research despite the project variability in large platforms like Kickstarter.

This study also contributes to the risk disclosure literature, in which the empirical findings on outsiders' response to risk disclosures remain inconclusive, although it is a fervent area of research (see Elshandidy

et al., 2018). We believe a reason for this lack of consensus is the common assumption of constant marginal effects. We accommodate the contradicting arguments by considering a non-linear and hierarchical model structure, and accordingly, respond to a general call for attention to context-specific boundaries in organizational research (Pierce & Aguinis, 2013; Lewis & Smith, 2014). Also, we acknowledge the appeals for a more nuanced outlook on evaluating risk information (Beretta & Bozzolan, 2004; Shevlin, 2004), and illustrate the assimilation of various computer-aided tools to accommodate qualitative features, including semantic variability, in examining textual disclosures. In this manner, our study also advances the literature adopting automated content analysis in financial accounting (e.g., Hope et al., 2016; Malafronte et al., 2016). In addition, given that the extant risk reporting literature is limited to corporate settings, our examination concerning early-stage ventures and unsophisticated online backers contributes to the entrepreneurship literature, highlighting the specifics of respective risk communication.

Crucially, our study contributes by incorporating advances in risk studies in psychology to expand on how crowdfunding backers interpret risk information. Given the limitations of conventional expected-utility-based assessments, studies in psychology have been instrumental in understanding attitudes toward risks (see Keller et al., 2012; Siegrist, 2021; Slovic, 1987). In line with the appeals to examine the implications of financial regulations through the behavioral lens (Hirshleifer & Teoh, 2017), our study adds to prior literature by incorporating these insights in evaluating a regulatory tool in a crowdfunding setting. As crowdfunding backers largely constitute common online participants, behavioral dimensions make up a crucial area of study within crowdfunding research (e.g., Allison et al., 2017; Anglin et al., 2018; Davis et al., 2017; Mahmood et al., 2019; Parhankangas & Renko, 2017). We join this body of research by drawing upon studies on risk perception in psychology to demonstrate some of the complexities in how crowdfunding backers respond to risk information.

## 6.2 | Limitations and avenues for future research

Incorporating various content analysis tools, in conjunction with hierarchical modeling, our study produces a rich set of insights on the context-related factors influencing risk interpretation in crowdfunding. As such, the abductively derived findings from our work provide important theoretical implications. They serve as a preliminary step toward more specific analyses, possibly through other methods, such as experiments or surveys. Future research could, therefore, address some of the limitations of our study, such as those concerning measurement challenges when dealing with large textual datasets (see Loughran & McDonald, 2016, 2020). For instance, while our study examines emotional expressions used within the pitch, direct measurements of integral emotions and cognitive appraisals that backers associate with the disclosed risks could expand on our findings. Moreover, the evidence on behavioral influences in risk assessments emphasizes that a potent area for future research may lie in related methodological advances in the psychology literature, for instance, those related to neurobiology (e.g., Gianotti et al., 2009), extending our understanding of financiers' response to risk information.

Moreover, our study's exploration of backers' response to risk information should not be equated to the efficacy of the mechanisms they display in evaluating risks. Future studies are recommended to investigate how backers' assessments of risk information correspond with projects' eventual outcomes, specifically whether these manners of response indeed contribute to more efficient and accurate risk assessments. Furthermore, in evaluating the platform implications of a risk disclosure rule, what the entrepreneurs choose to report and withhold is also essential to be understood (e.g., Madsen & McMullin, 2020). Altogether, this study identifies the specific risk issues that crowdfunding entrepreneurs communicate, which leads to new questions concerning the links between entrepreneur's underlying riskiness and what they choose to disclose.



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## ENDNOTES

- <sup>1</sup> Prior studies in crowdfunding explore various topics, including the timing and trajectory of backers' contributions (Kuppuswamy & Bayus, 2018), the influence of socio-economic background, such as gender and race (Johnson et al., 2018; Younkin & Kuppuswamy, 2018), signals used in crowdfunding and other determinants of crowdfunding success (Courtney et al., 2017), backers and entrepreneurs' incentives to participate (Bürger & Kleinert, 2021), and the impact of crowdfunding on macro-level factors, such as industry's growth, innovation and investment (Gamble et al., 2017; Stevenson et al., 2019).
- <sup>2</sup> For instance, while both Kravet and Muslu (2013) and Campbell et al. (2014) evidence investors' sensitivity to risk information, they observe unfavorable outcomes for the disclosing firms. In contrast, other studies either document a favorable response (e.g., Elbannan & Elbannan, 2015; Linsmeier et al., 2002) or report investors' indifference to risk information (e.g., Pérignon & Smith, 2010).
- <sup>3</sup> Valuation models within accounting and finance that take the decision theory perspective often define risk in terms of the variance of expected returns, cash flows, or earnings or the covariance of these measures with the market (Jorgensen & Kirschenheiter, 2003).
- <sup>4</sup> The implications of "dread" and "unknown" in risk assessment are well-documented, including in financial settings. For instance, in an experimental setting, Koonce et al. (2005) study 40 participants and find that these behavioral factors shape risk judgments of financial items, over and above what is explained by conventional variables of probability and outcome. An earlier study on subjective risk assessments of various financial and health & safety risks by Holtgrave and Weber (1993) similarly documents the explanatory capacity of the two behavioral factors (also see Luce & Weber, 1986).
- <sup>5</sup> We obtain the total number of projects launched during that period from <https://www.kickstarter.com/help/stats> using the Wayback Machine (available at <http://archive.org/web/>) to revert to the saved snapshot of the site on Jan 30, 2019).
- <sup>6</sup> See <https://www.kickstarter.com/help/stats>
- <sup>7</sup> Hierarchical structure can also be implemented in models that are evaluated using pNHST, but the mutually informed nature of the higher-level and group-specific parameters is mainly realized using multiple levels of random-effects or residuals specific to clusters. In Bayesian models, the shrinkage towards the parameters at different tiers instead is achieved through priors expressed in the model, making implementation of complex model structures more straightforward and flexible (for further discussion, see Gelman, 2006; Kruschke & Vanpaemel, 2015).
- <sup>8</sup> There are criticisms of pNHST approach in this regard. One of the key reasons is attributed to misinterpretations of  $p$ -value, which are often wrongly described as an error probability for rejection of the hypothesis or as the posterior probability that the hypothesis is true, leading to issues of overstating the evidence against the null hypothesis (Haller & Krauss, 2002; Wagenmakers, 2007). Moreover,  $p$ -values are not able to quantify the evidence in favor of a null hypothesis (Gallistel, 2009; Rouder et al., 2009), and further, its values are dependent on the sampling plan (Berger & Wolpert, 1988). Given these limitations and the potential for more intuitive and informative inferences, adoption of Bayesian analysis is repeatedly advocated by scholars, including in organizational and entrepreneurship research (e.g., Anderson et al., 2019; Lohrke et al., 2018; Maula & Stam, 2020).
- <sup>9</sup> The task of direct model comparison and selection is rather challenged with the traditional pNHST methods, as the tests using classical tools, such as chi-square, Akaike information criterion, and Bayesian information criterion, are directed towards testing the evidence against the null hypothesis (that the models are equal) (Andraszewicz et al., 2015). This limitation directly relates to the inability of  $p$ -values to quantify evidence in favor of the null (Gallistel, 2009; Rouder et al., 2009). In contrast, probabilistic output from Bayesian analysis allows a direct test of two (or more) models. Also, in relation to accounting for model complexity, classical methods have difficulty incorporating "Occam's razor," the notion

that if two models perform equally, the simpler model is preferred. Bayes factors do this automatically without relying on ad hoc penalties for model complexity, as in the former case (Jefferys & Berger, 1992; Spiegelhalter & Smith, 1982).

- <sup>10</sup> For more efficient MCMC sampling, in the model implementation, the predictor variables are standardized such that they are mean-centered and have a standard deviation of one as per the recommendations in Kruschke (2014).
- <sup>11</sup> In Bayesian inference, uncertainty in the parameter values is quantified in the form of probability distributions. Accordingly, to initiate the estimation process, we must first specify this uncertainty before observing the data, which is referred as priors. The transition from prior  $p(\theta)$  to posterior  $p(\theta/D)$  is then given by Bayes' rule:  $P(\theta/D) = \frac{P(D/\theta) \cdot P(\theta)}{P(D)}$ , where  $P(D/\theta)$  represents the likelihood that the data could be generated with parameter  $\theta$  and  $P(D)$  is the overall probability of the data.
- <sup>12</sup> A crucial element when conducting Bayesian analysis is determining the priors to be used (Kass & Wasserman, 1996; Suppes, 2007). While these prior distributions can be *informative* or *empirical* (based on previous findings or observed data, respectively), as we seek to apply conservative priors, we use *generic weakly informative* priors (Ghosh, 2011). Nonetheless, to understand the impact of having a different prior on the posterior distributions, we implement a set of alternatives to compare the results with our original priors. We selected alternative priors  $N(0,10)$  and  $N(0,1)$  for the parameters concerning *Risk Quantity*. The  $N(0,10)$  alternative is much more diffused than the original prior, suggesting a lack of knowledge concerning the parameters; whereas,  $N(0,1)$  is a more informative prior, suggesting no relationship. Furthermore, for the noise parameter, we examined the differences in estimate with priors set at more restrictive uniform distribution  $U(0.001,10)$  and Gamma distribution  $G(1,0.2)$ . Owing to the considerable sample size, we find the influence of the priors to be almost non-existent. These results are available in Table A6 of the online appendix.
- <sup>13</sup> Another crucial part of Bayesian estimation is the sampling methodology, generally known as Markov chain Monte Carlo (MCMC). MCMC techniques, such as Gibbs sampling or the Metropolis–Hastings algorithm, allows direct sampling from the posterior distribution of interest, circumventing the need for closed form analytic solutions (see Gamerman & Lopes, 2006; Gilks et al., 1995).
- <sup>14</sup> Our information quantity measure diverges from Beretta and Bozzolan (2004) in terms of operationalization. They formulate their index using items that require manual coding, which is in fact a criticism of the index put forth by Shevlin (2004). Since our dataset is substantially large and not feasible for manual coding, we adopt well-documented automated content-analysis-based items that closely overlap with Beretta and Bozzolan's (2004) conceptualization.
- <sup>15</sup> LIWC is a prominently used language analysis tool for examining the relationship between used words and linguistic variables. The software package analyzes written or spoken text based on the “bag of words” approach, grouping the constituting words into predefined linguistic categories. The word lists for each category are generated by collecting a set of words based on theory and conceptual dimensions—using English dictionaries and psychological measures, which are assessed by independent judges and are shown to be internally reliable and externally valid (see Pennebaker et al., 2007). For examples of usage in prior crowdfunding literature, see Buttice et al. (2017) and Parhankangas and Renko (2017).
- <sup>16</sup> Guiraud's Index is a transformation of Type/Token Ratio (TTR), which is measured as  $V/N$  (Guiraud, 1954). Although TTR is a more straightforward measure, it is found to produce erratic outcomes when the number of tokens vary substantially between the texts to be compared, as it is in our case. In an evaluation of various lexical variety measures, Van Hout and Vermeer (2007) find Guiraud Index to perform best.
- <sup>17</sup> The NRC lexicons includes a comprehensive list of English words (14,000 words) with binary ratings linking each word to positive/negative classifications and to Plutchik's (1980) eight fundamental emotions (1 if the word is related to a given emotion; 0 otherwise), which includes Ekman's (1992) six basic emotions.
- <sup>18</sup> The slight discrepancy from the success rate reported by Kickstarter (<https://www.kickstarter.com/help/stats>) is due to the exclusion of “canceled” and “suspended” campaigns.
- <sup>19</sup> In terms of other indicators of crowdfunding outcome, in our sample, the amount pledged to a project ranges from zero to USD 20 million, with an average of USD 11,967, which is roughly 65% of the average goal amount of USD 45,641.
- <sup>20</sup> For discussion on the deviance-based approach to model comparison and Bayes factor, we refer the readers to Lunn et al. (2013).
- <sup>21</sup> From Jeffreys' (1961) classification scheme, Bayes factor above 100 can be interpreted as extreme evidence in support of a model in comparison to another (see Andraszewicz et al., 2015).
- <sup>22</sup> The presented plots are created using the *binsreg* package in R by Cattaneo et al. (2019). The plots are based on estimated optimal number of bins, as supported by the package, based on integrated mean squared error using the quantile-spaced partitioning scheme. The illustrated 95% confidence bands shown in gray are derived from cubic B-spline estimates with three smoothness constraints.



- <sup>23</sup> On manual inspection, we find that the disclosures with the least information include short phrases, such as: “To be decided” and “Not enough funding,” whereas disclosures at the first percentile include at least a full sentence, such as “The project might be released at a later date” and “Finding a good produce might be my only problem.”
- <sup>24</sup> Another mode of conducting model comparisons involves directly computing the posterior model probabilities over a space of models by means of MCMC sampling. However, a practical challenge in such computations is that the chain for the model index can be highly autocorrelated, especially when the evidence for one is much stronger than the other; therefore, making it difficult to obtain accurate and stable posterior probabilities. To overcome this, we follow Carlin and Chib (1995) and use “pseudopriors” on limited random samples of 1000 observations and obtain posterior model probabilities (for details on implementation, see Kruschke, 2014). We find that despite the substantially smaller sample size, we consistently find that the probability assigned to the curvilinear model, as opposed to the linear, is over 90%. We provide a sample of these results in Figure A4.1 in Section A4 of Appendix S1.
- <sup>25</sup> The 95% HDI is a summary of the distribution that specifies an interval that includes 95% of the posterior such that every point inside the interval has a higher probability density (i.e., credibility) than any point outside the interval.
- <sup>26</sup> The observed curvilinear relationship is consistent when simply taking the *Risk Sentence*, *Risk Word*, *Risk Richness*, or *Risk Concreteness* individually as the independent variable. These results are available in Table A5 of the Appendix S1.
- <sup>27</sup> The estimates are based on the mean of the posteriors for the higher-level parameters.
- <sup>28</sup> In terms of the component variables of *Risk Quantity*, when keeping the disclosure richness and concreteness at the sample means and taking the average word count per sentence, the optimal risk *Sentences* translate to 21.855 sentences, which lies at the 98th percentile. Similarly, the optimal level of *Richness* and *Concreteness* is 17.045 (> 99th percentile) and 13.72 (> 99th percentile), respectively. It should be noted, however, given the high correlation between the variables (especially *Sentences*, *Words*, and *Richness*), substantial deviations among the component variables are rather uncommon.
- <sup>29</sup> In logistic models, an explanatory variable's marginal effect is contingent on the concurrent values of the other covariates. Henceforth, the reported aggregate relationships are derived with other independent continuous variables held at their sample means and the dummy variables kept at their modal values.
- <sup>30</sup> All illustrated category-specific relationships are derived with the independent continuous variables held at their category-specific means and the dummy variables kept at their modal values.
- <sup>31</sup> For instance, for *Joy*, which represents the use of words like “delight,” “gratitude,” and “passion,” the category-level relationships were particularly large for some categories, such as *publishing* (28.73%, from 0.359 to 0.463) and *publishing* (12.106%, from 0.563 to 0.631), although the aggregate effect was low. Also, expressing anger with words like “awful,” “condemn,” and “fraudulent,” increased the probability of success from 0.395 to 0.425 (7.584%) and 0.688 to 0.720 (4.60%) for *film & video* and *theater*, respectively, but decreased from 0.705 to 0.622 (−6.079%) and 0.727 to 0.681 (−6.312%) for *comics* and *games*, respectively. Similarly, the use of *Fear* words, such as “afraid,” “hopeless,” and “seriousness,” was favorable for *design*, *fashion*, *games*, and *journalism*, but not for other project types.
- <sup>32</sup> For example, an increase in founder's experience by one *sd* from the mean, increased the project's maximum probability of success by 63.69% (from 0.431 to 0.705). Moreover, a typical project with platform endorsement had a 92.363% greater chance of getting funded in comparison to those without (from 0.427 to 0.821). In contrast, an increase in the project's funding goal by one *sd* decreased the success probability by 60% (from 0.427 to 0.170).
- <sup>33</sup> Formally, ambiguity is often defined as uncertainty concerning the probability distribution or the outcome generating process itself (see Keren & Gerritsen, 1999).
- <sup>34</sup> A particularly robust prediction resulting from incorporating ambiguity aversion is a lower stock market participation (compared to what is predicted by the expected utility models). For instance, in empirical studies, Antoniou et al. (2015) and Dimmock et al. (2016) find inverse relationships between ambiguity and participation of households in the securities market. Decision making under ambiguity is also argued to explain other empirical aberrations, such as equity premium puzzle and home bias in portfolio choice. As such, implications of ambiguity aversion have been a prolific area of research with applications ranging from corporate finance to macroeconomics (for an overview, see Guidolin & Rinaldi, 2013).
- <sup>35</sup> On the scope of feelings on risk assessment, scholars distinguish between integral and incidental emotions. Integral feelings are experienced as one considers a risk stimulus; whereas, incidental feelings are unrelated to the risk itself, such as the anger experienced from missing the train carried over to an office meeting (Lerner et al., 2015).

## REFERENCES

- Abraham, S., & Shrivs, P. J. (2014). Improving the relevance of risk factor disclosure in corporate annual reports. *The British Accounting Review*, 46(1), 91–107.
- Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy*, 14(1), 63–97.

- Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, 16(2), 270–301.
- Ahlers, G. K. C., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, 39(4), 955–980.
- Al-Hadi, A., Al-Yahyaee, K. H., Hussain, S. M., & Taylor, G. (2018). Market risk disclosures, corporate governance structure and political connections: Evidence from GCC firms. *Applied Economics Letters*, 25(19), 1346–1350.
- Allison, T. H., Davis, B. C., Webb, J. W., & Short, J. C. (2017). Persuasion in crowdfunding: An elaboration likelihood model of crowdfunding performance. *Journal of Business Venturing*, 32(6), 707–725.
- Anderson, B. S., Wennberg, K., & McMullen, J. S. (2019). Enhancing quantitative theory-testing entrepreneurship research. *Journal of Business Venturing*, 34(5), 105928.
- Andraszewicz, S., et al. (2015). An introduction to Bayesian hypothesis testing for management research. *Journal of Management*, 41(2), 521–543.
- Anglin, A. H., Wolfe, M. T., Short, J. C., McKenny, A. F., & Pidduck, R. J. (2018). Narcissistic rhetoric and crowdfunding performance: A social role theory perspective. *Journal of Business Venturing*, 33(6), 780–812.
- Ansari, A., Jedidi, K., & Jagpal, S. (2000). A hierarchical Bayesian methodology for treating heterogeneity in structural equation models. *Marketing Science*, 19(4), 328–347.
- Antoniou, C., Harris, R. D. F., & Zhang, R. (2015). Ambiguity aversion and stock market participation: An empirical analysis. *Journal of Banking & Finance*, 58, 57–70.
- Arkes, H. R., Herren, L. T., & Isen, A. M. (1988). The role of potential loss in the influence of affect on risk-taking behavior. *Organizational Behavior and Human Decision Processes*, 42(2), 181–193.
- Arrow, K. (1982). Risk perception in psychology and economics. *Economic Inquiry*, 20(1), 1–9.
- Bao, Y., & Datta, A. (2014). Simultaneously discovering and quantifying risk types from textual risk disclosures. *Management Science*, 60(6), 1371–1391.
- Belavina, E., Marinesi, S., & Tsoukalas, G. (2020). Rethinking crowdfunding platform design: Mechanisms to deter misconduct and improve efficiency. *Management Science*, 66(11), 4980–4997.
- Belleflamme, P., Omrani, N., & Peitz, M. (2015). The economics of crowdfunding platforms. *Information Economics and Policy*, 33, 11–28.
- Beretta, S., & Bozzolan, S. (2004). A framework for the analysis of firm risk communication. *The International Journal of Accounting*, 39(3), 265–288.
- Berger, J. O., & Wolpert, R. L. (1988). *The likelihood principle* (2nd ed.). Institute of Mathematical Statistics.
- Bleasdale, F. A. (1987). Concreteness-dependent associative priming: Separate lexical organization for concrete and abstract words. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 13(4), 582.
- Böhm, G., & Pfister, H.-R. (2000). Action tendencies and characteristics of environmental risks. *Acta Psychologica*, 104(3), 317–337.
- Bürger, T., & Kleinert, S. (2021). Crowdfunding cultural and commercial entrepreneurs: An empirical study on motivation in distinct backer communities. *Small Business Economics*, 57(2), 667–683.
- Burtch, G., Ghose, A., & Wattal, S. (2015). The hidden cost of accommodating crowdfunder privacy preferences: A randomized field experiment. *Management Science*, 61(5), 949–962.
- Buttice, V., Colombo, M. G., & Wright, M. (2017). Serial crowdfunding, social capital, and project success. *Entrepreneurship Theory and Practice*, 41(2), 183–207.
- Campbell, J. L., Chen, H., Dhaliwal, D. S., Lu, H., & Steele, L. B. (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, 19(1), 396–455.
- Carlin, B. P., & Chib, S. (1995). Bayesian model choice via Markov chain Monte Carlo methods. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(3), 473–484.
- Cascino, S., Correia, M., & Tamayo, A. (2019). Does consumer protection enhance disclosure credibility in reward crowdfunding? *Journal of Accounting Research*, 57(5), 1247–1302.
- Cattaneo, M. D., Crump, R. K., Farrell, M. H., & Feng, Y. (2019). On binscatter. University of Michigan. Working paper.
- Chan, C. S., & Parhankangas, A. (2017). Crowdfunding innovative ideas: How incremental and radical innovativeness influence funding outcomes. *Entrepreneurship Theory and Practice*, 41(2), 237–263.
- Chapman, K. L., Reiter, N., White, H. D., & Williams, C. D. (2019). Information overload and disclosure smoothing. *Review of Accounting Studies*, 24, 1486–1522.
- Choudhury, P., Wang, D., Carlson, N. A., & Khanna, T. (2019). Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles. *Strategic Management Journal*, 40(11), 1705–1732.
- Colombo, M., Franzoni, C., & Rossi-Lamastra, C. (2015). Internal social capital and the attraction of early contributions in crowdfunding. *Entrepreneurship Theory and Practice*, 39(1), 75–100.
- Colombo, O. (2021). The use of signals in new-venture financing: A review and research agenda. *Journal of Management*, 47(1), 237–259.



- Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology*, 92(4), 909.
- Courtney, C., Dutta, S., & Li, Y. (2017). Resolving information asymmetry: Signaling, endorsement, and crowdfunding success. *Entrepreneurship Theory and Practice*, 41(2), 265–290.
- Cumming, D. J., Hornuf, L., Karami, M., & Schweizer, D. (2020). Disentangling crowdfunding from fraudfunding. Max Planck Institute for Innovation & Competition research paper (16–09). [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2828919](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2828919)
- Cumming, D. J., Leboeuf, G., & Schwienbacher, A. (2020). Crowdfunding models: Keep-it-all vs. all-or-nothing. *Financial Management*, 49(2), 331–360.
- Das, T. K., & Teng, B.-S. (2001). Trust, control, and risk in strategic alliances: An integrated framework. *Organization Studies*, 22(2), 251–283.
- Davis, B. C., Hmieleski, K. M., Webb, J. W., & Coombs, J. E. (2017). Funders' positive affective reactions to entrepreneurs' crowdfunding pitches: The influence of perceived product creativity and entrepreneurial passion. *Journal of Business Venturing*, 32(1), 90–106.
- Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance*, 46(4), 1325–1359.
- Dickey, J. M., & Lientz, B. P. (1970). The weighted likelihood ratio, sharp hypotheses about chances, the order of a Markov chain. *The Annals of Mathematical Statistics*, 41, 214–226.
- Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2016). Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics*, 119(3), 559–577.
- Dobler, M. (2008). Incentives for risk reporting—A discretionary disclosure and cheap talk approach. *The International Journal of Accounting*, 43(2), 184–206.
- Drichoutis, A. C., & Nayga, R. M., Jr. (2013). Eliciting risk and time preferences under induced mood states. *The Journal of Socio-Economics*, 45, 18–27.
- Dubois, A., & Gadde, L.-E. (2002). Systematic combining: An abductive approach to case research. *Journal of Business Research*, 55(7), 553–560.
- Easley, D., & O'Hara, M. (2009). Ambiguity and nonparticipation: The role of regulation. *The Review of Financial Studies*, 22(5), 1817–1843.
- Edwards, W., Lindman, H., & Savage, L. J. (1963). Bayesian statistical inference for psychological research. *Psychological Review*, 70(3), 193–242.
- Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion*, 6(3–4), 169–200.
- Elbannan, M. A., & Elbannan, M. A. (2015). Economic consequences of bank disclosure in the financial statements before and during the financial crisis: Evidence from Egypt. *Journal of Accounting, Auditing & Finance*, 30(2), 181–217.
- Elliott, W. B., Rennekamp, K. M., & White, B. J. (2015). Does concrete language in disclosures increase willingness to invest? *Review of Accounting Studies*, 20(2), 839–865.
- Elshandidy, T., Fraser, I., & Hussainey, K. (2015). What drives mandatory and voluntary risk reporting variations across Germany, UK and US? *The British Accounting Review*, 47(4), 376–394.
- Elshandidy, T., & Neri, L. (2015). Corporate governance, risk disclosure practices, and market liquidity: Comparative evidence from the UK and Italy. *Corporate Governance: An International Review*, 23(4), 331–356.
- Elshandidy, T., Shrives, P. J., Bamber, M., & Abraham, S. (2018). Risk reporting: A review of the literature and implications for future research. *Journal of Accounting Literature*, 40, 54–82.
- Filzen, J. J. (2015). The information content of risk factor disclosures in quarterly reports. *Accounting Horizons*, 29(4), 887–916.
- Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, 13(1), 1–17.
- Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy Sciences*, 9(2), 127–152.
- Forgas, J. P. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, 117(1), 39.
- Frisch, D., & Baron, J. (1988). Ambiguity and rationality. *Journal of Behavioral Decision Making*, 1(3), 149–157.
- Gafni, H., Marom, D., & Sade, O. (2019). Are the life and death of an early-stage venture indeed in the power of the tongue? Lessons from online crowdfunding pitches. *Strategic Entrepreneurship Journal*, 13(1), 3–23.
- Gallistel, C. R. (2009). The importance of proving the null. *Psychological Review*, 116(2), 439.
- Gamble, J. R., Brennan, M., & McAdam, R. (2017). A rewarding experience? Exploring how crowdfunding is affecting music industry business models. *Journal of Business Research*, 70, 25–36.
- Gamerman, D., & Lopes, H. F. (2006). *Markov chain Monte Carlo: Stochastic simulation for Bayesian inference*. Chapman & Hall/CRC.
- Gelman, A. (2006). Multilevel (hierarchical) modeling: What it can and cannot do. *Technometrics*, 48(3), 432–435.

- Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction*, 20(6), 32.
- Geweke, J. (2007). Bayesian model comparison and validation. *American Economic Review*, 97(2), 60–64.
- Ghosh, M. (2011). Objective priors: An introduction for frequentists. *Statistical Science*, 26(2), 187–202.
- Gianotti, L. R. R., Knoch, D., Faber, P. L., Lehmann, D., Pascual-Marqui, R. D., Diezi, C., Schoch, C., Eisenegger, C., & Fehr, E. (2009). Tonic activity level in the right prefrontal cortex predicts individuals' risk taking. *Psychological Science*, 20(1), 33–38.
- Gilks, W. R., Richardson, S., & Spiegelhalter, D. (1995). *Markov chain Monte Carlo in practice*. Chapman & Hall/CRC.
- Grable, J. E., & Roszkowski, M. J. (2008). The influence of mood on the willingness to take financial risks. *Journal of Risk Research*, 11(7), 905–923.
- Guidolin, M., & Rinaldi, F. (2013). Ambiguity in asset pricing and portfolio choice: A review of the literature. *Theory and Decision*, 74(2), 183–217.
- Guiraud, P. (1954). *The statistical characters of the vocabulary: Method test*. University Presses of France.
- Haller, H., & Krauss, S. (2002). Misinterpretations of significance: A problem students share with their teachers. *Methods of Psychological Research*, 7(1), 1–20.
- Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1–3), 405–440.
- Herriges, J., Kling, C., Liu, C.-C., & Tobias, J. (2010). What are the consequences of consequentiality? *Journal of Environmental Economics and Management*, 59(1), 67–81.
- Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1–3), 337–386.
- Hirshleifer, D., & Teoh, S. H. (2017). How psychological bias shapes accounting and financial regulation. *Behavioural Public Policy*, 1(1), 87–105.
- Holtgrave, D. R., & Weber, E. U. (1993). Dimensions of risk perception for financial and health risks. *Risk Analysis*, 13(5), 553–558.
- Hope, O.-K., Hu, D., & Lu, H. (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies*, 21(4), 1005–1045.
- Hu, Y., Wang, D., Pang, K., Xu, G., & Guo, J. (2015). The effect of emotion and time pressure on risk decision-making. *Journal of Risk Research*, 18(5), 637–650.
- Isen, A. M., & Patrick, R. (1983). The effect of positive feelings on risk taking: When the chips are down. *Organizational Behavior and Human Performance*, 31(2), 194–202.
- Jefferys, W. H., & Berger, J. O. (1992). Ockham's razor and Bayesian analysis. *American Scientist*, 80(1), 64–72.
- Jeffreys, H. (1961). *Theory of probability* (3rd ed.). Oxford University Press.
- Johnson, E. J., & Tversky, A. (1983). Affect, generalization, and the perception of risk. *Journal of Personality and Social Psychology*, 45(1), 20–31.
- Johnson, M. A., Stevenson, R. M., & Letwin, C. R. (2018). A woman's place is in the... startup! Crowdfunder judgments, implicit bias, and the stereotype content model. *Journal of Business Venturing*, 33(6), 813–831.
- Jorgensen, B. N., & Kirschenheiter, M. T. (2003). Discretionary risk disclosures. *The Accounting Review*, 78(2), 449–469.
- Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, 90(430), 773–795.
- Kass, R. E., & Wasserman, L. (1996). The selection of prior distributions by formal rules. *Journal of the American Statistical Association*, 91(435), 1343–1370.
- Keller, C., Bostrom, A., Kuttischreuter, M., Savadori, L., Spence, A., & White, M. (2012). Bringing appraisal theory to environmental risk perception: A review of conceptual approaches of the past 40 years and suggestions for future research. *Journal of Risk Research*, 15(3), 237–256.
- Keller, C., Siegrist, M., & Gutscher, H. (2006). The role of the affect and availability heuristics in risk communication. *Risk Analysis*, 26(3), 631–639.
- Keren, G., & Gerritsen, L. E. M. (1999). On the robustness and possible accounts of ambiguity aversion. *Acta Psychologica*, 103(1–2), 149–172.
- Kim, M. Y., & Kanfer, R. (2009). The joint influence of mood and a cognitively demanding task on risk-taking. *Motivation and Emotion*, 33, 362–372.
- Koonce, L., McAnally, M. L., & Mercer, M. (2005). How do investors judge the risk of financial items? *The Accounting Review*, 80(1), 221–241.
- Kravit, T., & Muslu, V. (2013). Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies*, 18(4), 1088–1122.
- Kruschke, J. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. Academic Press.
- Kruschke, J. K. (2011). Bayesian assessment of null values via parameter estimation and model comparison. *Perspectives on Psychological Science*, 6(3), 299–312.



- Kruschke, J. K., Aguinis, H., & Joo, H. (2012). The time has come: Bayesian methods for data analysis in the organizational sciences. *Organizational Research Methods*, 15(4), 722–752.
- Kruschke, J. K., & Liddell, T. M. (2018). The Bayesian new statistics: Hypothesis testing, estimation, meta-analysis, and power analysis from a Bayesian perspective. *Psychonomic Bulletin & Review*, 25(1), 178–206.
- Kruschke, J. K., & Vanpaemel, W. (2015). Bayesian estimation in hierarchical models. In J. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), *The Oxford handbook of computational and mathematical psychology*. Oxford University Press.
- Kuppuswamy, V., & Bayus, B. L. (2018). Crowdfunding creative ideas: The dynamics of project backers. In D. Cumming & L. Hornuf (Eds.), *The economics of crowdfunding* (pp. 151–182). Springer International Publishing.
- Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & Emotion*, 14(4), 473–493.
- Lerner, J. S., & Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology*, 81(1), 146–159.
- Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. *Annual Review of Psychology*, 66, 799–823.
- Lewis, M. W., & Smith, W. K. (2014). Paradox as a metatheoretical perspective: Sharpening the focus and widening the scope. *The Journal of Applied Behavioral Science*, 50(2), 127–149.
- Li, E., & Martin, J. S. (2019). Capital formation and financial intermediation: The role of entrepreneur reputation formation. *Journal of Corporate Finance*, 59, 185–201.
- Li, G.-C. (2019). Kickstarter structured relational database. Harvard Dataverse. <https://doi.org/10.7910/DVN/EOYBXM>
- Liang, T.-P., Wu, S. P.-J., & Huang, C. (2019). Why funders invest in crowdfunding projects: Role of trust from the dual-process perspective. *Information & Management*, 56(1), 70–84.
- Linciano, N., Lucarelli, C., Gentile, M., & Soccorso, P. (2018). How financial information disclosure affects risk perception. Evidence from Italian investors' behaviour. *The European Journal of Finance*, 24(15), 1311–1332.
- Lindley, D. V. (2000). The philosophy of statistics. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 49(3), 293–337.
- Linsley, P. M., & Shrives, P. J. (2005). Examining risk reporting in UK public companies. *The Journal of Risk Finance*, 6(4), 292–305.
- Linsley, P. M., Shrives, P. J., & Crumpton, M. (2006). Risk disclosure: An exploratory study of UK and Canadian banks. *Journal of Banking Regulation*, 7(3–4), 268–282.
- Linsmeier, T. J., Thornton, D. B., Venkatachalam, M., & Welker, M. (2002). The effect of mandated market risk disclosures on trading volume sensitivity to interest rate, exchange rate, and commodity price movements. *The Accounting Review*, 77(2), 343–377.
- Lipton, P. (2017). Inference to the best explanation. In *A companion to the philosophy of science* (pp. 184–193). Wiley Online Library.
- Liu, C. C., & Aitkin, M. (2008). Bayes factors: Prior sensitivity and model generalizability. *Journal of Mathematical Psychology*, 52(6), 362–375.
- Locke, K., Golden-Biddle, K., & Feldman, M. S. (2008). Perspective—Making doubt generative: Rethinking the role of doubt in the research process. *Organization Science*, 19(6), 907–918.
- Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, 127(2), 267.
- Lohrke, F. T., Carson, C. M., & Lockamy, A. (2018). Bayesian analysis in entrepreneurship decision-making research: Review and future directions. *Management Decision*, 56(5), 972–986.
- Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54(4), 1187–1230.
- Loughran, T., & McDonald, B. (2020). Textual analysis in finance. *Annual Review of Financial Economics*, 12(1), 357–375.
- Luce, R. D., & Weber, E. U. (1986). An axiomatic theory of conjoint, expected risk. *Journal of Mathematical Psychology*, 30(2), 188–205.
- Lunn, D., Jackson, C., Best, N., Thomas, A., & Spiegelhalter, D. (2013). *The BUGS book – A practical introduction to Bayesian analysis*. Chapman & Hall/CRC.
- Madsen, J. M., & McMullin, J. L. (2020). Economic consequences of risk disclosures: Evidence from crowdfunding. *The Accounting Review*, 95(4), 331–363.
- Mahmood, A., Luffarelli, J., & Mukesh, M. (2019). What's in a logo? The impact of complex visual cues in equity crowdfunding. *Journal of Business Venturing*, 34(1), 41–62.
- Malafronte, I., Porzio, C., & Starita, M. G. (2016). The nature and determinants of disclosure practices in the insurance industry: Evidence from European insurers. *International Review of Financial Analysis*, 45, 367–382.
- Maula, M., & Stam, W. (2020). *Enhancing rigor in quantitative entrepreneurship research*. SAGE Publications Sage.
- McCann, B. T., & Schwab, A. (2020). Bayesian analysis in strategic management research: Time to update your priors. *Strategic Management Review*, 4(1), 75–106.

- McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334–359.
- McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *The Academy of Management Review*, 23(3), 473–490.
- Miihkinen, A. (2012). What drives quality of firm risk disclosure?: The impact of a national disclosure standard and reporting incentives under IFRS. *The International Journal of Accounting*, 47(4), 437–468.
- Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–Emotion association lexicon. *Computational Intelligence*, 29(3), 436–465.
- Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, 29(1), 1–16.
- Moore, C. (2015). Kickstart my lawsuit: Fraud and justice in rewards-based crowdfunding. *UCDL Rev*, 49, 383.
- Ntzoufras, I. (2011). *Bayesian modeling using WinBUGS*. John Wiley & Sons.
- Pan, L., McNamara, G., Lee, J. J., Halebian, J., & Devers, C. E. (2018). Give it to us straight (most of the time): Top managers' use of concrete language and its effect on investor reactions. *Strategic Management Journal*, 39(8), 2204–2225.
- Parhankangas, A., & Renko, M. (2017). Linguistic style and crowdfunding success among social and commercial entrepreneurs. *Journal of Business Venturing*, 32(2), 215–236.
- Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2007). *Linguistic inquiry and word count: LIWC [Computer software]*. LIWC.
- Pérignon, C., & Smith, D. R. (2010). The level and quality of value-at-risk disclosure by commercial banks. *Journal of Banking & Finance*, 34(2), 362–377.
- Pierce, J. R., & Aguinis, H. (2013). The too-much-of-a-good-thing effect in management. *Journal of Management*, 39(2), 313–338.
- Plummer, M. (2008). Penalized loss functions for Bayesian model comparison. *Biostatistics*, 9(3), 523–539.
- Plummer, M. (2012). JAGS Version 3.3.0 user manual. [Computer software manual]. (October 1, 2012).
- Plutchik, R. (1980). A general psychoevolutionary theory of emotion. In R. Plutchik & H. Kellerman (Eds.), *Theories of emotion* (pp. 3–33). Academic Press.
- Renn, O., & Levine, D. (1991). Credibility and trust in risk communication. In *Communicating risks to the public* (pp. 175–217). Springer.
- Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, 16(2), 225–237.
- Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *The Academy of Management Review*, 23(3), 393–404.
- Ryan, S. G. (1997). A survey of research relating accounting numbers to systematic equity risk, with implications for risk disclosure policy and future research. *Accounting Horizons*, 11(2), 82.
- Ryan, S. G. (2012). Risk reporting quality: Implications of academic research for financial reporting policy. *Accounting and Business Research*, 42(3), 295–324.
- Sætre, A. S., & de Ven, A. (2021). Generating theory by abduction. *Academy of Management Review*, 46(4), 684–701.
- Schervish, M. J. (1996). P values: What they are and what they are not. *The American Statistician*, 50(3), 203–206.
- Schrand, C. M., & Elliott, J. A. (1998). Risk and financial reporting: A summary of the discussion at the 1997 AAA/FASB conference. *Accounting Horizons*, 12(3), 271.
- Shevlin, T. (2004). Discussion of 'A framework for the analysis of firm risk communication'. *The International Journal of Accounting*, 39(3), 297–302.
- Siegrist, M. (2000). The influence of trust and perceptions of risks and benefits on the acceptance of gene technology. *Risk Analysis*, 20(2), 195–204.
- Siegrist, M. (2021). Trust and risk perception: A critical review of the literature. *Risk Analysis*, 41(3), 480–490.
- Siegrist, M., & Árvai, J. (2020). Risk perception: Reflections on 40 years of research. *Risk Analysis*, 40(S1), 2191–2206.
- Siegrist, M., & Cvetkovich, G. (2000). Perception of hazards: The role of social trust and knowledge. *Risk Analysis*, 20(5), 713–720.
- Siegrist, M., Earle, T. C., & Gutscher, H. (2010). *Trust in risk management: Uncertainty and scepticism in the public mind*. Earthscan.
- Skirnevskiy, V., Bendig, D., & Brettel, M. (2017). The influence of internal social capital on serial creators' success in crowdfunding. *Entrepreneurship Theory and Practice*, 41(2), 209–236.
- Slovic, P. (1987). Perception of risk. *Science*, 236(4799), 280–285.
- Slovic, P. (1993). Perceived risk, trust, and democracy. *Risk Analysis*, 13(6), 675–682.
- Slovic, P. (2010). *The feeling of risk: New perspectives on risk perception*. Routledge.
- Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research*, 177(3), 1333–1352.
- Slovic, P., Peters, E., Finucane, M. L., & MacGregor, D. G. (2005). Affect, risk, and decision making. *Health Psychology*, 24(4S), S35.



- Smith, A. F. M. (1983). Bayesian approaches to outliers and robustness. In J. P. Florens, M. Mouchart, J. P. Raoult, L. Simar, & A. F. M. Smith (Eds.), *Specifying statistical models* (pp. 13–35). Springer.
- Smith, C. A., & Ellsworth, P. C. (1985). Patterns of cognitive appraisal in emotion. *Journal of Personality and Social Psychology*, 48(4), 813–838.
- Spiegelhalter, D. J., & Smith, A. F. M. (1982). Bayes factors for linear and log-linear models with vague prior information. *Journal of the Royal Statistical Society: Series B (Methodological)*, 44(3), 377–387.
- Starr, E., & Goldfarb, B. (2020). Binned scatterplots: A simple tool to make research easier and better. *Strategic Management Journal*, 41(12), 2261–2274.
- Steigenberger, N., & Wilhelm, H. (2018). Extending signaling theory to rhetorical signals: Evidence from crowdfunding. *Organization Science*, 29(3), 529–546.
- Stevenson, R. M., Kuratko, D. F., & Eutsler, J. (2019). Unleashing main street entrepreneurship: Crowdfunding, venture capital, and the democratization of new venture investments. *Small Business Economics*, 52(2), 375–393.
- Strausz, R. (2017). A theory of crowdfunding: A mechanism design approach with demand uncertainty and moral hazard. *American Economic Review*, 107(6), 1430–1476.
- Strickler, Y., Chen, P., & Adler, C. (2012). Kickstarter is not a store. Kickstarter Blog. <https://www.kickstarter.com/blog/kickstarter-is-not-a-store>
- Suppes, P. (2007). Where do Bayesian priors come from? *Synthese*, 156(3), 441–471.
- Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1), 24–54.
- Thewissen, J., Shrestha, P., Torsin, W., & Pastwa, A. M. (2022). Unpacking the black box of ICO white papers: A topic modeling approach. *Journal of Corporate Finance*, 75, 102225.
- Townsend, E., & Campbell, S. (2004). Psychological determinants of willingness to taste and purchase genetically modified food. *Risk Analysis: An International Journal*, 24(5), 1385–1393.
- Treffer, T., Koellinger, P., & Picot, A. O. (2012). In the mood for risk? A random-assignment experiment addressing the effects of moods on risk preferences. ERIM Report Series Reference No. ERS-2012-014-ORG.
- Twyman, M., Harvey, N., & Harries, C. (2008). Trust in motives, trust in competence: Separate factors determining the effectiveness of risk communication. *Judgment and Decision Making*, 3(1), 111.
- Van Hout, R., & Vermeer, A. (2007). Comparing measures of lexical richness. In *Modelling and assessing vocabulary knowledge* (pp. 93–115). Cambridge University Press.
- Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, 27, 1413–1432.
- Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of Accounting and Economics*, 5, 179–194.
- Vismara, S. (2018). Signaling to overcome inefficiencies in crowdfunding markets. In D. Cumming & L. Hornuf (Eds.), *The economics of crowdfunding*. Palgrave Macmillan. [https://doi.org/10.1007/978-3-319-66119-3\\_3](https://doi.org/10.1007/978-3-319-66119-3_3)
- Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, 359(6380), 1146–1151.
- Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems of p values. *Psychonomic Bulletin & Review*, 14(5), 779–804.
- Wagenmakers, E.-J., Lee, M., Lodewyckx, T., & Iverson, G. J. (2008). Bayesian versus frequentist inference. In H. Hoijtink, I. Klugkist, & P. A. Boelen (Eds.), *Bayesian evaluation of informative hypotheses* (pp. 181–207). Springer.
- Wagenmakers, E.-J., Lodewyckx, T., Kuriyal, H., & Grasman, R. (2010). Bayesian hypothesis testing for psychologists: A tutorial on the Savage–Dickey method. *Cognitive Psychology*, 60(3), 158–189.
- Wasserman, L. (2000). Bayesian model selection and model averaging. *Journal of Mathematical Psychology*, 44(1), 92–107.
- Watanabe, S., & Oppen, M. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of Machine Learning Research*, 11(12), 3571–3594.
- Williams, S., Zainuba, M., & Jackson, R. (2003). Affective influences on risk perceptions and risk intention. *Journal of Managerial Psychology*, 18(2), 126–137.
- Yip, J. A., & Côté, S. (2013). The emotionally intelligent decision maker: Emotion-understanding ability reduces the effect of incidental anxiety on risk taking. *Psychological Science*, 24(1), 48–55.
- Younkin, P., & Kuppaswamy, V. (2018). The colorblind crowd? Founder race and performance in crowdfunding. *Management Science*, 64(7), 3269–3287.
- Yu, S., Johnson, S., Lai, C., Cricelli, A., & Fleming, L. (2017). Crowdfunding and regional entrepreneurial investment: An application of the CrowdBerkeley database. *Research Policy*, 46(10), 1723–1737.
- Zawojka, E., Bartczak, A., & Czajkowski, M. (2019). Disentangling the effects of policy and payment consequentiality and risk attitudes on stated preferences. *Journal of Environmental Economics and Management*, 93, 63–84.
- Ziegler, T., Shneor, R., & Zhang, B. Z. (2020). The global status of the crowdfunding industry. In *Advances in crowdfunding* (pp. 43–61). Palgrave Macmillan.



- Zucker, L. G. (1986). Production of trust: Institutional sources of economic structure, 1840-1920. *Research in Organizational Behavior*, 8, 53-111.
- Zyphur, M. J., & Oswald, F. L. (2015). Bayesian estimation and inference: A user's guide. *Journal of Management*, 41(2), 390-420.

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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