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Searching for Success—Entrepreneurs' Responses to Crowdfunding Failure

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Abstract

In this study, we seek to provide new insights into the process of problemistic search by examining entrepreneurs' behavioral responses to failures. Using a comprehensive dataset of over 65,000 crowdfunding projects, we specifically explore how negative performance feedback influences entrepreneurs' search distance. Our results demonstrate that the severity and persistence of failure have a U-shaped and inverted U-shaped relationship with search distance, respectively. Moreover, greater temporal distance between an entrepreneur's failure experience and a subsequent crowdfunding project is not only associated with increases in search distance, but also attenuates the curvilinear main effects.

Keywords

failure, problemistic search, search distance, entrepreneurs, crowdfunding

Failure is an integral part of business life. Especially firms facing high technological and market uncertainty, such as entrepreneurial ventures, frequently experience failure (Cardon et al., 2011; Mantere et al., 2013; Yamakawa et al., 2015).[1] However, in entrepreneurial contexts and elsewhere, failure can be viewed as a double-edged sword. On the one hand, even small failures can prove costly, threaten the survival of a business, and stigmatize founders or managers (Dahlin et al., 2018; Simmons et al., 2014; Ucbasaran et al., 2013). Given their limited resources and experience, uncertainty about the quality of their products or services, and lack of social approval, or what might be referred to as the "liabilities of newness," startups have particularly little room for error (e.g., Baum et al., 2000; Cope, 2011). On the other hand, the literature suggests that entrepreneurs should embrace failure as an opportunity for learning and innovation. Accordingly, failure is a natural and, to some extent, desirable outcome of entrepreneurial activities that

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increases the probability of future success (He et al., 2018; Mantere et al., 2013; McGrath, 1999; Timmons et al., 1999).

Notwithstanding these contrasting perspectives, there is broad agreement that failure is an important predictor of behavior at the individual, team, and organizational level. Drawing on Cyert and March's (1963) behavioral theory of the firm, the management and entrepreneurship literature specifically suggests that failure to meet an aspiration level (i.e., the lowest level of performance deemed acceptable) triggers search and change (e.g., Desai, 2016; Gavetti et al., 2012; Greve, 2003a; Kuusela et al., 2017; Maslach, 2016). For example, studies show that negative performance feedback can lead decision makers to increase an organization's R&D intensity (Chen & Miller, 2007), launch innovations (Joseph & Gaba, 2015), undertake acquisitions (Iyer & Miller, 2008), invest in information systems (Salge et al., 2015), and implement strategy changes (Greve, 1998). The process through which decision makers respond to failures by searching for and implementing alternative solutions that restore performance has been referred to as "problemistic search" (e.g., Cyert & March, 1963; Greve, 2003a; Posen et al., 2018).

While the notion of problemistic search has received support in many empirical studies, our understanding of this process is far from complete. Posen et al. (2018), among others, criticized that problemistic search theory is overly simplistic, conceptualizing search as a mechanistic, quasi-automatic response to failure. In addition, there are conflicting assumptions and mixed evidence on how individuals or organizations respond to performance below their aspiration level (e.g., Audia & Greve, 2006; Kotiloglu et al., 2019). For example, drawing on threat rigidity theory (Staw et al., 1981), several studies in the field have supported the opposite hypothesis that failure leads to rigidity (i.e., decision makers avoid new activities, conserve resources, and keep commitments) rather than to search, risk taking, and change (Greve, 2011; Iyer & Miller, 2008; Joseph & Gaba, 2015; Titus et al., 2020). Interestingly, both problemistic search and threat rigidity are argued to become more likely the greater the *severity of failure* (i.e., degree of discrepancy between the actual performance and aspiration level) and *persistence of failure* (i.e., number of consecutive failures; Desai, 2016; Kuusela et al., 2017; Yu et al., 2019). Thus, it is the threat posed by severe and persistent failures that motivates decision makers to engage in search and, at the same time, prevents them from doing so.

In this study, we seek to address this ambiguity by exploring how and when entrepreneurs alter their responses to negative performance feedback depending on its severity and persistence. Focusing on a specific type of performance feedback, namely the failure to acquire financial resources via crowdfunding, our study is among the first to clarify the influence of these two feedback conditions on entrepreneurs' search distance, defined here as the extent to which entrepreneurs move away from their current activities when searching for solutions to a given problem (e.g., Angus, 2019). Integrating research on threat rigidity and other psychological factors (e.g., self-enhancement motives and attribution) into the conceptualization of problemistic search, we develop and test hypotheses that go beyond simple linear relationships. As the influence of performance feedback is likely to be time-dependent, we also consider the moderating role of time (i.e., temporal distance of the failure event) in these relationships.

To test our hypotheses, we use a sample of over 65,000 crowdfunding campaigns launched on Kickstarter, one of the world's leading crowdfunding platforms on which successes and failures are transparently observable. By focusing on entrepreneurs' responses to failed crowdfunding campaigns, we are able to effectively distinguish problemistic search from related search processes (i.e., institutionalized and slack search).[2] Moreover, this empirical context provides us with a direct measure of aspirations as founders set a funding goal for each crowdfunding project (Mollick, 2014) and allows for the creation of a continuous measure of search distance using text-based analysis of project descriptions (see Angus, 2019). Our findings support some of our predictions, showing positive (but nonlinear) relationships between the severity as well as the persistence of negative performance feedback and search distance, with time acting as a moderator.

Our research offers a number of important contributions. First, we contribute to the literature on problemistic search by enhancing our limited understanding of the drivers of search distance (Iyer et al., 2019; Posen et al., 2018). Mapping the behavioral choices that entrepreneurs confronted with failure make, we provide new insights into when failure leads to local and when to distant search. Second, rather than treating problemistic search and threat rigidity as two alternative responses to negative performance feedback, we integrate these perspectives by examining nonlinear effects with regard to failure severity and persistence. In doing so, we contribute to a more fine-grained understanding of how performance feedback triggers problemistic search and help to reconcile the conflicting findings of past research. Third, we also extend problemistic search theory by introducing time as an important but neglected influence on decision makers' responses to negative performance feedback (Yu et al., 2019). Adding to the growing number of studies on internal and external contingencies of problemistic search such as slack resources, organizational structures, and environmental dynamism (see Kotiloglu et al., 2019 for an overview), we show that a temporal perspective offers a novel explanation of why entrepreneurs' responses to failure may vary. Finally, this study contributes to entrepreneurship research by addressing the call for additional studies on crowd-funded entrepreneurial opportunities (Pollack et al., 2019). In particular, we provide new insights into the search processes of entrepreneurs who repeatedly turn to crowdfunding in an attempt to successfully raise funds (Butticè et al., 2017; Skirnevskiy et al., 2017). By tracing the changes implemented by entrepreneurs in between sequential crowdfunding campaigns, we add a dynamic perspective to this field, showing how prior failure shapes future crowdfunding campaigns.

Theoretical Background and Hypotheses

Problemistic search theory, which is rooted in the behavioral theory of the firm as proposed by Cyert and March (1963), provides the theoretical foundation for our study. Although it should be noted that problemistic search has been predominantly conceptualized as an organizational-level phenomenon (Shimizu, 2007), the theory is also applicable to the analysis of individual behavior (e.g., Greve & Gaba, 2017; Jordan & Audia, 2012).[3] Indeed, describing a process in which organizational decision makers respond to negative performance feedback by searching for solutions that improve future performance (Posen et al., 2018), problemistic search theory is well suited for understanding how, when, and why entrepreneurs respond to failure experiences.

The notion of problemistic search implies that entrepreneurs, or decision makers more broadly, respond differently to positive and negative performance feedback (Cyert & March, 1963; Greve, 2003b). Whether certain outcomes are classified as a success (performance above aspirations) or as a failure (performance below aspirations) depends on the entrepreneur's aspiration level, that is, the smallest outcome he or she deems satisfactory (Cyert & March, 1963; Shinkle, 2012).[4] While success experiences signal that his or her current strategies or actions are effective, and thus should be retained, failures have the opposite effect (Cyert & March, 1963; Greve, 2003b). Negative performance feedback indicates that something is wrong, putting pressure on entrepreneurs to correct problems, challenge their assumptions, and implement change (Khanna et al., 2016; Madsen & Desai, 2010). It is the sense of urgency associated with failure that motivates individuals and organizations to take risks and search for new solutions (Desai, 2016).

Problemistic search has been conceptualized as a relatively simple stimulus-response process that is triggered by negative performance feedback and stops once search has led to identifying a satisficing solution (Cyert & March, 1963; Posen et al., 2018). Given their bounded rationality and risk aversion, decision makers' search efforts are assumed to be myopic or, to put it differently, mostly local in nature (Cyert & March, 1963; Levinthal & March, 1993). Hence, at least initially, search is conducted in the neighborhood of the problem symptom and solutions adopted in the past (Gavetti et al., 2012; Kim & Rhee, 2017). By drawing on knowledge that is closely related to an organization's preexisting knowledge base, local search promises more certain and immediate, but less innovative solutions than distant search (Katila & Ahuja, 2002; Levinthal & March, 1993). Only if local search fails to produce satisficing outcomes, decision makers' search efforts are expected to gradually become more distant (Cyert & March, 1963).

However, alternative theories and conflicting evidence have led scholars to increasingly challenge the view of problemistic search as a uniform process that involves minimal cognitive effort (e.g., Posen et al., 2018). For example, empirical evidence suggests that responses to negative performance feedback can vary substantially depending on contingency factors (e.g., feedback characteristics) and are not as myopic as often believed (Kotiloglu et al., 2019). In particular, based on the threat rigidity hypothesis according to which decision makers are unlikely to engage in risk-taking and commit resources to search activities in threatening situations (Staw et al., 1981), the literature has questioned the assumption that search represents a nearly automatic response to failure (Audia & Greve, 2006; Greve, 2011; Shimizu, 2007). Indeed, when considering psychological influences, including but not limited to threat rigidity (e.g., self-enhancement motives and attribution processes, see Eggers & Song, 2015; Jordan & Audia, 2012), a more nuanced picture of the behavioral consequences of failure emerges.

Below, we draw on these arguments to provide a better understanding of how failure experiences of varying severity and persistence influence the distance of problemistic search.

Explaining Search Distance

Based on the distinction between local and distant search, the literature has described search distance as falling along a continuum ranging from search efforts in the neighborhood of the status quo to those that represent a radical departure thereof (e.g., Billinger et al., 2014; Cyert & March, 1963; Katila & Ahuja, 2002). Invoking a spatial metaphor, this continuum reflects how far decision makers figuratively go in their search for new solutions (Mazzelli et al., 2020; Schilling & Green, 2011). Consistent with this, we define search distance as the degree to which entrepreneurs' move away from their current activities when searching for solutions to the problem at hand. What drives problemistic search distance then? We argue that two characteristics of negative performance feedback, namely its *severity* and *persistence*, play a key role.

Severity refers to the degree of (negative) discrepancy between an entrepreneur's aspiration level and actual performance, also referred to as attainment discrepancy (Lant, 1992). Dating back to Cyert and March (1963), behavioral theorists have argued that more severe performance problems intensify organizational search efforts and increase their scope (Chen & Miller, 2007; Kotiloglu et al., 2019). According to this view, entrepreneurs will perceive greater pressure to solve the problem at hand when performance is far below the aspiration level (Shimizu, 2007). This increases their willingness to commit resources to search activities, take risk, and consider radically new alternatives (Desai, 2015, 2016; Iyer et al., 2019). Along these lines, Kim and Rhee (2017) suggested that since distant search is more costly and risky than local search, decision makers are unlikely to engage in this type of search without having a strong motivation to do so. Other authors have emphasized that compared to small failures, large failures are more visible and receive greater attention (Madsen & Desai, 2010). Such failures send a clear and unambiguous signal that something went wrong, which may also explain why search efforts become more extensive with increasingly negative performance feedback (see Joseph & Gaba, 2015).

The discussion thus far suggests that problemistic search distance increases with the severity of negative performance feedback. Yet, based on the threat rigidity hypothesis (Staw et al., 1981) and supported by empirical evidence (Ref & Shapira, 2017), we expect this relationship to be curvilinear (i.e., taking an inverted U-shape) rather than strictly linear. We specifically argue that search distance first increases with the severity of failure at a decreasing rate to reach a maximum, after which it decreases at an increasing rate. Reflecting a general tendency for individuals and organizations to narrow their scope of attention and preserve their current activities under adverse conditions (Staw et al., 1981), threat rigidity explains why search distance may decrease once a certain degree of attainment discrepancy is reached. For example, research suggests that due to threat rigidity organizations become less entrepreneurially oriented when facing increasingly hostile environmental conditions (Kreiser et al., 2020). Similarly, we expect large crowdfunding failures (i.e., campaigns that failed to meet their funding goal by some margin) to elicit threat-rigidity responses. Entrepreneurs who have failed miserably to acquire funding via crowdfunding are likely to experience this situation as a threat to their project and perhaps entrepreneurial career. In this regard, Greve (2011) noted that the stress and anxiety caused by a large failure lowers decision makers' ability to distinguish and process information, which produces greater reliance on current ways of doing things.

Individuals' tendency to interpret large failures in a self-serving manner also leads us to expect that the relationship between the severity of failure and search distance follows an inverted U-shaped function. Since large failures pose a greater threat to individuals' self-image than small deviations from the aspiration level, these failures increase the likelihood that decision makers (consciously or unconsciously) manipulate interpretations to their own benefit, escalate their commitment to prior actions, and reduce the extent of problemistic search (Jordan & Audia, 2012). This is consistent with research on failure attributions. For example, Baumard and Starbuck (2005) observed that decision makers attribute large failures primarily to exogenous causes (e.g., "exceptional historical conditions") rather than their own abilities and actions, which is a prevalent cognitive strategy of individuals for maintaining a positive sense of self when experiencing failure. Their study shows that the larger the failure, the greater this attribution bias. In turn, the literature suggests that when attributing failures to external factors beyond their control, decision makers are unlikely to take the effort to engage in distant search (e.g., Diwas et al., 2013).

Overall, given the countervailing forces outlined above, we predict:

> ***Hypothesis 1:*** *There is a curvilinear relationship between the severity of negative performance feedback and entrepreneurs' search distance, such that their search distance will be highest at a moderate severity of failure (i.e., inverted U-shaped relationship).*

We predict that the relationship between the persistence of negative performance feedback and entrepreneurs' search distance takes an inverted U-shape as well. First, similar latent mechanism to those discussed above explain why search distance is likely to initially increase with an entrepreneur's number of consecutive failure experiences (the left half of the inverted U-shape). Repeated failure gradually increases the perceived pressure on entrepreneurs to find solutions that provide satisfactory performance, thus creating the motivation to engage in distant search activities (Iyer et al., 2019). Along these lines, Yu et al. (2019, p. 837) stated that "as local solutions fail to deliver results, pressure to make more dramatic changes will accumulate, forcing firms to break away from myopic tendencies and explore more distant solutions." Moreover, compared to singular events, repeated failure provides more consistent and reliable performance feedback. Joseph and Gaba (2015) argued that decision makers place greater emphasis on and are more responsive to such feedback. In particular, when feedback is consistently negative over time, individuals are more willing to recognize their own responsibility for a failure, to learn what went wrong, and to explore alternative solutions (Iyer et al., 2019; Kim et al., 2015).

When a certain number of repeated failures is reached, however, we argue that an entrepreneur's search distance begins to decrease (the right half of the inverted U-shape). In line with research on threat rigidity (e.g., Staw et al., 1981), there is likely to be a tipping point beyond which additional failures cause stress, anxiety, and rigidity rather than further exploration. In a situation, in which numerous attempts to acquire project funding via crowdfunding have failed, entrepreneurs can be expected to shift to survival mode in that they conserve their limited managerial and financial resources, avoid further risks, and try to exploit past solutions. In addition, after repeated failure and problemistic search attempts, entrepreneurs—even more than managers in large organizations who have access to a broader knowledge base—may simply find it increasingly difficult to identify new ways to improve the performance of their next crowdfunding project. Put simply, as they are only aware of a limited number of alternatives determined by their rational bounds (Cyert & March, 1963; Gavetti et al., 2012), problemistic search scope should eventually begin to decrease. Finally, behavioral theorists have argued and shown that persistent negative attainment discrepancy leads to decreasing aspirations over time (Lant, 1992; Mezias et al., 2002). By adapting their aspirations downwards in response to negative performance feedback, entrepreneurs reduce the negative attainment discrepancy, which should ease the perceived pressure to engage in problemistic search. Posen et al. (2018) suggested that the adjustment of aspirations toward current performance, or what they refer to as aspiration degradation, act as a mechanism that can cause problemistic search to stop. As it takes time—or repeated failure—until aspirations have adapted downward by a sufficient amount (see Lant, 1992), this mechanism is less likely to take effect in instances of singular attainment discrepancy. Taken together:

> ***Hypothesis 2:*** *There is a curvilinear relationship between the persistence of negative performance feedback and entrepreneurs' search distance, such that their search distance will be highest at a moderate number of repeated failures (i.e., inverted U-shaped relationship).*

The Moderating Role of Time

Since many organizational phenomena (e.g., decision-making, learning, and innovation) develop, change, and evolve over time, it is increasingly recognized that temporal issues should play an important role in theory building and testing (Ancona et al., 2001; Mitchell & James, 2001). However, with the exception of a few studies (Lehman et al., 2011; Yu et al., 2019), existing conceptual and empirical work on problemistic search has rarely considered time and temporality. We address this gap by investigating whether the proposed curvilinear relationships between the severity and persistence of negative performance feedback and search distance are moderated by time (i.e., the temporal distance between an entrepreneur's failure experience and subsequent project).

In general, problemistic search distance can be expected to increase with greater time lags. Sufficient time allows entrepreneurs to experiment with alternative, more distal solutions to the problem at hand rather than being forced to implement the first solution they find (which is often a familiar one; see Rycroft & Kash, 2002). Time can be viewed as a "slack resource" that provides a safety net for failure, enabling the decision maker to take the risk of exploring opportunities and knowledge in uncharted territories (e.g., Kim & Rhee, 2017). Shorter time frames, in contrast, increase the likelihood of routine choices, and specifically that actors adhere to established routines—even when these routines are no longer effective (e.g., Becker, 2004). Decision makers under time pressure, and high job demands more generally, tend to rely on cognitive shortcuts and engage in limited search to arrive at their choices (Hambrick et al., 2005).

Our focus, however, is on the moderating role of time. Considering the guidelines by Haans et al. (2016) for theorizing moderation of curvilinear relationships, we argue that longer time periods between an entrepreneur's failed and subsequent crowdfunding project attenuate the proposed inverted U-shaped effects of failure severity and persistence on search distance. We specifically expect a *flattening* of both curves, as temporal distance weakens the influence of the mechanisms that initially lead to increases in search distance (the left half of the inverted U-shape) and those that eventually cause search distance to decrease (the right half of the inverted U-shape).

On the one hand, time can be expected to interact with the mechanisms discussed above that explain why search distance first increases with the severity and persistence of negative performance feedback. In particular, we argue that greater temporal distance to the failure event will reduce entrepreneurs' perceived search pressure, and thus their motivation to engage in distant search (Iyer et al., 2019; Yu et al., 2019). Memories of the distant past are generally more abstract than memories of the recent past. With increasing temporal distance to a failure event, concrete details about the event fade away from an individual's memory, rendering performance feedback more ambiguous (e.g., Trope & Liberman, 2003). Ambiguity, in turn, is expected to reduce decision makers' responsiveness to negative performance feedback (Joseph & Gaba, 2015). Furthermore, psychologists suggest that memories of failure events become more positive over time, perhaps because people forget about the details of these negative experiences (Trope & Liberman, 2003).

On the other hand, longer time frames should also reduce the influence of threat rigidity and other factors accounting for decreases in search distance once certain thresholds of failure severity and failure persistence are reached. Research has acknowledged that threat rigidity and time pressure are closely related. Time pressure has not only been conceptualized as a source of threat rigidity in itself (Gladstein & Reilly, 1985), but is also assumed to interact with a threatening event in affecting decision makers' actions (Staw et al., 1981). According to Lehman et al. (2011), time constraints shift decision makers' focus of attention toward survival and risk avoidance when dealing with negative performance feedback. They perceive less control, view risks as less manageable, and feel unable to generate alternative strategies. In contrast, more time to reflect upon the failure experience helps individuals to better understand the complex and often not immediately apparent causes of failures. This should reduce entrepreneurs' tendency to make self-serving attributions that undermine their motivation to engage in explorative search (Eggers & Song, 2015). For example, Shepherd et al. (2011, p. 1233) argued that "time appears to lead to a change in attribution through a change in perspective. When individuals consider past events (at which they were present), they generally perceive the events as if they were external observers instead of participants. This new perspective leads them to attribute failures to more internal sources and, thus, to take more personal responsibility for the outcome."

Summarizing the above discussion, we offer the following hypothesis:

> ***Hypothesis 3:*** *Time moderates the curvilinear relationships between a) the severity of negative performance feedback as well as b) the persistence of negative performance feedback and entrepreneurs' search distance, such that greater temporal distance to the failure experience attenuates these relationships (i.e., the curves are flattened).*

Methodology

Research Context

In this study, we examine entrepreneurs' behavioral responses to failure in the context of crowdfunding. Funds raised through online crowdfunding platforms are increasingly recognized as an important source of financial capital for entrepreneurs (Allison et al., 2015; Courtney et al., 2017). As many entrepreneurs struggle to acquire funding from more traditional sources, crowdfunding is often their only chance to finance their ventures. Estimates suggest that entrepreneurs may already raise more funds via crowdfunding than via venture capitalists (Li et al., 2017; Parhankangas & Renko, 2017).

Similar to other recent studies (e.g., Chan & Parhankangas, 2017; Colombo et al., 2015; Mollick & Nanda, 2016; Wessel et al., 2017), we collected and analyzed data from the crowdfunding platform Kickstarter. As of July 2020, more than $5 billion have been raised to fund more than 185,000 entrepreneurial projects on this platform (Kickstarter, 2020). Kickstarter and other crowdfunding platforms such as Indiegogo provide the technical infrastructure needed to bring together entrepreneurs seeking funding for their ventures and a crowd of individuals, also referred to as backers, supporting these initiatives by making small financial contributions (e.g., Mollick, 2014). Kickstarter is a reward-based crowdfunding platform on which backers provide money for entrepreneurial projects in exchange for non-monetary rewards, including the products to be developed by the capital seekers (Steigenberger & Wilhelm, 2018; Wessel et al., 2017). To allow potential backers to evaluate a crowdfunding project on Kickstarter and make informed funding decisions, entrepreneurs provide detailed information (using text, images, and videos) on the campaign webpages. A typical campaign webpage contains information about the entrepreneurs (e.g., education, experience, and other personal details), project (e.g., technical details about the products to be developed, designated use of the collected capital, and rewards for backers), and current campaign status (e.g., number of backers, funds raised, project updates; Allison et al., 2015; Li et al., 2017).

Kickstarter follows the all-or-nothing funding model, meaning that only campaigns that reach a predefined funding threshold are considered to be successful and receive the collected funds. If the threshold is not reached, a campaign is regarded a failure and all funders will be reimbursed. In light of a success rate of merely 37.4% for projects launched on Kickstarter (Kickstarter, 2020), crowdfunding failure, which we define as failing to meet the funding goal of a crowdfunding project, seems to be the norm rather than the exception and may threaten the survival of new ventures. Based on problemistic search theory, we expect such failures to motivate entrepreneurs to search for solutions that improve the performance of their future crowdfunding projects. The high transparency of performance together with a high failure rate of crowdfunding campaigns imply that crowdfunding represents an ideal context for studying organizational responses to negative performance feedback, while mitigating left-censoring and survival biases that often constrain other studies (Soublière & Gehman, 2020). This is especially true because, even after initial failure, entrepreneurs have been found to repeatedly turn to crowdfunding in the attempt to finance their projects (Butticè et al., 2017; Skirnevskiy et al., 2017). Ryan Grepper's "Coolest Cooler" campaign is a prominent example. After falling short of the $125,000 funding goal in a first campaign in 2013, Grepper launched a second, modified campaign that became the most funded Kickstarter campaign of 2014 by raising over $13 million from over 62,000 backers.[5]

Data

We gathered a time-series dataset with a self-developed web crawler that covers the period from the launch of Kickstarter in April 2009 until October 2019. This initial dataset includes over

450,000 projects that ran during that period. In order to study how entrepreneurs deal with repeated failure in particular, we limited our dataset in the following ways. First, we only included entrepreneurs who launched at least two projects, reducing the number of observations to 134,024. Second, as some creators engaged in excessive creation of projects after the platform removed gatekeeping mechanisms in 2014 (Thies et al., 2018; Wessel et al., 2017), we further limited the number of projects per entrepreneur to a maximum of five, which represents the 99th percentile. Finally, we stopped observing entrepreneurs after they were successful in reaching their funding goal for a campaign or when they quit the platform and made no further attempts. The final panel-dataset consists of 28,843 unique entrepreneurs who created a total of 65,613 campaigns for their projects on Kickstarter. Our panel dataset therefore allows us to track entrepreneurs' crowdfunding activities over time while dealing with different degrees of failure. We are specifically able to observe the changes each creator implemented in his or her campaigns in response to their failure experiences. Variables and modeling techniques used in this study are described in the following.

Measures

Dependent Variable

Our dependent variable *Search Distance* captures the extent to which entrepreneurs' search efforts move away from their current activities. In line with our conceptual definition, we measured this variable by calculating the distance between the textual project description of two consecutive campaigns of the same entrepreneur using cosine similarity. This approach has been proposed by Angus (2019). Examining the performance effects of search distance in app development, he measured search distance by comparing the text descriptions of a developer's first and second app published in the Google Play Store. The degree of similarity between these descriptions reflects the scope of search—the greater the dissimilarity, the more distant the search efforts of organizations, and vice versa. Mathematically, cosine similarity is a measure of similarity between two vectors of an inner product space in terms of the cosine of the angle between these two vectors and is a widely accepted method to measure similarity, or distance, between two text documents (Hoberg & Phillips, 2010).

We followed prior literature (e.g., Angus, 2019; Barlow et al., 2019; Foerderer et al., 2018) by removing stop words (i.e., the most common words in the English language) and stemming words to their root (e.g., innovative, innovation, and innovator all stem to "innov") before creating the word vector for each textual project description to be compared. To develop a measure of distance rather than similarity, we subtracted the cosine similarity result from one and rescaled it to yield a measure of *Search Distance* that ranges from 0 to 100. A value of 0 indicates that the textual project descriptions of the entrepreneur's current and previous campaigns are identical, meaning that the entrepreneur engaged in extremely local search. Extremely distant search is indicated by a value of 100, meaning that the two textual project descriptions do not share any of the same words. Table 1 in the Appendix provides examples of *Search Distance* at the first, second, and third quartile to illustrate the measure's face validity. The examples show that the extent to which the textual description of an entrepreneur's second crowdfunding campaign differs from that of his or her first attempt is, in fact, reflective of changes in the content of the projects (e.g., products to be developed).

Independent Variables

The independent variables in this study are twofold. First, *Severity* of failure indicates by what percentage the aspiration level (i.e., funding goal) was missed in a given crowdfunding campaign. For instance, *Severity* equals 10% if the entrepreneur was able to collect $90,000 of a

$100,000 goal. Second, *Persistence* of failure is a count variable that indicates how many consecutive campaigns of the same entrepreneur failed to reach the aspired funding goal before the given campaign.

Moderating Variable

To analyze the moderating effect of temporality on the relationship between failure and problemistic search, we included the variable *Time*, measured as the number of days between failure and the starting date of the entrepreneur's next crowdfunding campaign.[6]

Control Variables

We incorporated a number of additional project-level time-variant and -invariant control variables in our model to account for alternative explanations. First, we constructed dummy variables that represent in which of the 15 main categories on Kickstarter (e.g., Games, Design, or Technology) the entrepreneur's previous campaign was launched (*Category*). Second, *Category Change* is a dummy variable that is equal to 1, if the entrepreneur switched from one category to another in between two sequential campaigns. We include this variable because switching between categories might encourage entrepreneurs to engage in a more distant search (Eggers & Song, 2015). Third, we included *Failure Rate*, indicating what percentage of campaigns failed within a given month in the category in which the entrepreneur launched his or her previous campaign. If *Failure Rate* is high, entrepreneurs might attribute their failure to market conditions rather than their own performance. Such self-serving attributions might then result in very little behavioral change and an extremely local search for subsequent campaigns (Baumard & Starbuck, 2005; Diwas et al., 2013). Fourth, as our dataset spans several years (2009, 2019), we included dummy variables for the specific *Year* in which the campaign was launched to control for unobservable time-varying effects of changing platform dynamics over the years (e.g., Wessel et al., 2017). Fifth, we included the log-transformed *Funding Goal* in USD specified for the campaign (e.g., Butticè et al., 2017; Steigenberger & Wilhelm, 2018) to control for the aspiration level of entrepreneurs and to mitigate its skewed distribution. Sixth, *Description Length* measures the length of the textual project description. Seventh, as Kickstarter curates the content on the platform so that some campaigns are more prominent than others, we included a dummy variable indicating whether a project was selected as a so-called *Staff Pick,* also called "Projects We Love" from 2016 onward. (e.g., Butticè et al., 2017). Eighth, we added the dummy variable *Video* turning to one when the campaign included a video, as the production of a pitch video requires a certain investment that might influence the search distance for subsequent campaigns. Finally, we also included the log-transformed number of *Comments* written by funders about the previous campaign (e.g., Thies et al., 2016). We include this measure to control for the possible influence funders might exert on the scope of problemistic search by, for instance, suggesting improvements to the project that may then be adopted by entrepreneurs.

Model Specification

To test our hypotheses, we employed a panel ordinary least squares (OLS) model to estimate the effects of *Severity* and *Persistence* of prior crowdfunding failure on the *Search Distance* of the entrepreneur. We used robust standard errors to account for possible heteroscedasticity and checked the variance inflation factor (VIF) for potential multicollinearity problems. All VIF values are well below the recommended threshold values (i.e., <5; Cohen et al., 2003). As our dependent variable *Search Distance* is measured in percentage and bounded between 0 and 100, we also used alternative modeling techniques as describe in the section on robustness checks.

Results

Table 1 summarizes the descriptives and correlations. We used a hierarchical modeling specification starting with a baseline model with all control variables. We then added the *Severity* and *Persistence* of failure variables to the model, as well as their respective squared terms and the proposed interaction variables. Table 2 shows the results of our regression analyses.

Before discussing the results of the hypothesis testing, we first look at some general noteworthy results of the baseline model, and the main effects of the *Severity* and *Persistence* of crowdfunding failure. First, in our baseline model we see a positive and significant effect of *Failure Rate* ($b = 6.22$, $p < 0.001$) on *Search Distance*. Second, a higher number of comments reduce *Search Distance*, which may indicate that positive feedback from other sources alleviates the perceived pressure to engage in distant search. Third, changing the project category appears to be associated with a higher *Search Distance*, underscoring the need for change when adapting to a new environment.

With regard to the main effects of *Severity* ($b = 0.089$, $p < 0.001$) and *Persistence* ($b = 1.582$, $p < 0.001$), we see that both forms of failure do in fact trigger a higher *Search Distance,* supporting our general argument on the responses of entrepreneurs to failure experiences. Still, our main interest lies in the nonlinear effects of *Severity* and *Persistence* of failure on *Search Distance*, as argued in our hypotheses.

Our first hypothesis suggested that there is an inverted U-shaped relationship between the *Severity* of negative performance feedback and *Search Distance*. Contrary to our expectations, the results in Table 2 indicate a U-shaped relationship such that *Search Distance* is lowest at moderate levels of *Severity*. However, the significant coefficient of $(Severity)^2$ ($b = 0.002$, $p < 0.001$) is necessary but not sufficient for a U-shaped relationship. To formally confirm this relationship, the slope must be sufficiently steep at both ends of the data range (Haans et al., 2016). We therefore tested the direction of the slope at the low and high end of *Severity* as well as the turning point, which needs to lie within the observed data range (Lind & Mehlum, 2010). The slope at the lower bound (*Severity* = 1) is negative and significant ($b = -0.129$, $p < 0.001$) and the slope at the upper bound (*Severity* = 100) is positive and significant ($b = 0.190$, $p < 0.001$), with a turning point at 40.45% on the severity of failure continuum (0% to 100%). The overall test of presence of a U-shape was significant ($t = 3.77$, $p < 0.001$). To facilitate interpretation, we illustrate these results in Figure 1.

Hypothesis 2 stated that there is an inverted U-shaped relationship between the *Persistence* of failure and *Search Distance*. Consistent with our expectations, the results show an inverted U-shaped relationship such that *Search Distance* is highest at a moderate-to-high level of *Persistence* of failure. To formally test this relationship, we again followed the three step procedure suggested by Lind and Mehlum (2010). First, Model 3 (Table 2) shows significant coefficients for both *Persistence* ($b = 6.629$, $p < 0.001$) and $(Persistence)^2$ ($b = -0.835$, $p < 0.001$). Second, the slope at the lower bound (*Persistence* = 1) is $b = 4.95$ ($p < 0.001$) and $b = -1.72$ ($p < 0.001$) at the upper bound (*Persistence* = 5), with a turning point at 3.97 consecutive failures. Moreover, the overall test of presence of an inverted U-shape is significant ($t = 2.20$, $p < 0.05$). Overall, as also shown in Figure 2, Hypothesis 2 is supported.

Hypothesis 3 proposed that the *Time* between subsequent projects moderates the curvilinear relationships between *Severity* and *Search Distance* as well as between *Persistence* and *Search Distance* so that these relationships are attenuated (i.e., the curvilinear relationship is flattened). First, we see that *Time* has a positive main effect ($b = 3.123$, $p < 0.001$) on *Search Distance* in Model 4 of Table 2. Second, when adding *Severity* × *Time* ($b = -0.051$, $p < 0.001$) and *Persistence* × *Time* ($b = -0.367$, $p < 0.01$) in Model 5, the results indicate that greater temporal distance between campaigns weakens the positive main effects of both failure variables. However, our nonlinear moderation tests are based on the $(Severity)^2 \times Time$ and $(Persistence)^2 \times Time$ coefficients shown in Model 6. We find support for

Table 1. Descriptive Statistics and Correlations.

	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 *Search Distance*	31.45	27.70	0	100	1										
2 *Goal*	8.97	1.72	0.7	18.4	−0.97	1									
3 *Staff Pick*	0.04	0.19	0	1	−0.07	0.09	1								
4 *Video*	0.64	0.48	0	1	−0.15	0.19	0.11	1							
5 *Comments*	0.52	0.98	0	8.68	−0.15	0.21	0.22	0.21	1						
6 *Description Length*	7.61	1.05	0	12.19	−0.44	0.18	0.12	0.22	0.28	1					
7 Category change	0.66	0.47	0	1	0.28	−0.04	−0.04	−0.06	−0.12	−0.09	1				
8 *Failure Rate*	0.64	0.12	0	1	0.05	0.10	−0.00	−0.11	−0.00	−0.01	0.06	1			
9 *Severity*	89.68	19.28	0	100	0.16	0.15	−0.19	−0.15	−0.47	−0.18	0.11	0.11	1		
10 *Persistence*	1.69	0.77	1	5	0.09	−0.12	−0.05	−0.04	−0.05	−0.05	0.04	0.01	0.04	1	
11 *Time*	4.55	1.60	0	8.13	0.17	0.01	0.05	0.12	0.08	0.11	0.12	−0.06	−0.08	0.01	1

Note. Correlations with the absolute value greater than 0.01 are statistically significant at the $p < .05$ level ($N = 35{,}499$); As our models include lagged variables such as the performance of the preceding campaign the number of observations is reduced from 65,613 to 35,499; Log-transformed variables: *Goal, Comments, Description Length, Time.*

Table 2. Panel OLS Regression on *Search Distance*.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Controls												
Category	Included		Included		Included		Included		Included		Included	
Year	Included		Included		Included		Included		Included		Included	
Goal	−0.312***	(0.073)	−0.486***	(0.078)	−0.549***	(0.079)	−0.438***	(0.076)	−0.451***	(0.076)	−0.568***	(0.077)
Staff Pick	−0.933	(0.491)	−0.135	(0.492)	0.128	(0.494)	−0.498	(0.474)	−0.677	(0.473)	−0.347	(0.473)
Video	−2.313***	(0.260)	−2.066***	(0.260)	−1.942***	(0.261)	−2.797***	(0.254)	−2.807***	(0.254)	−2.622***	(0.254)
Comments	−0.424***	(0.123)	0.353*	(0.137)	0.465***	(0.139)	0.210	(0.133)	0.192	(0.133)	0.371**	(0.134)
Description Length	−9.144***	(0.128)	−9.039***	(0.128)	−8.986***	(0.129)	−9.392***	(0.126)	−9.398***	(0.126)	−9.322***	(0.126)
Category Change	12.127***	(0.240)	11.913***	(0.240)	11.852***	(0.240)	10.417***	(0.239)	10.336***	(0.239)	10.207***	(0.239)
Failure Rate	6.220***	(1.294)	4.926***	(1.296)	4.507***	(1.298)	6.223***	(1.266)	6.046***	(1.263)	5.439***	(1.263)
Main effects												
Severity			0.089***	(0.007)	−0.129***	(0.034)	0.103***	(0.007)	0.342***	(0.023)	−0.728***	(0.136)
Persistence			1.582***	(0.192)	6.629***	(1.172)	1.016***	(0.190)	2.716***	(0.629)	13.842***	(3.741)
Nonlinear effects												
$(Severity)^2$					0.002***	(0.000)					0.008***	(0.001)
$(Persistence)^2$					−0.835***	(0.191)					−1.826**	(0.609)
Moderator												
Time							3.123***	(0.074)	8.681***	(0.497)	5.852***	(1.400)
Linear Moderation												
Severity × *Time*									−0.051***	(0.004)	0.107***	(0.027)
Persistence × *Time*									−0.367**	(0.124)	−1.909*	(0.750)
Nonlinear moderation												
$(Severity)^2$ × *Time*											−0.001***	(0.000)
$(Persistence)^2$ × *Time*											0.246*	(0.123)
Constant	1137.200***		1132.214***		1145.689***		405.888***		306.092**		313.070**	
R^2	0.268		0.273		0.274		0.311		0.314		0.317	

Note. N = 35,499; Standard errors are in parentheses; Log-transformed variables: *Goal, Comments, Description Length, Time*; Lagged variables: *Category, Year, Goal, Staff Pick, Comments, Description Length, Failure Rate, Severity, Persistence*; *p < .05, **p < .01, ***p < .001.

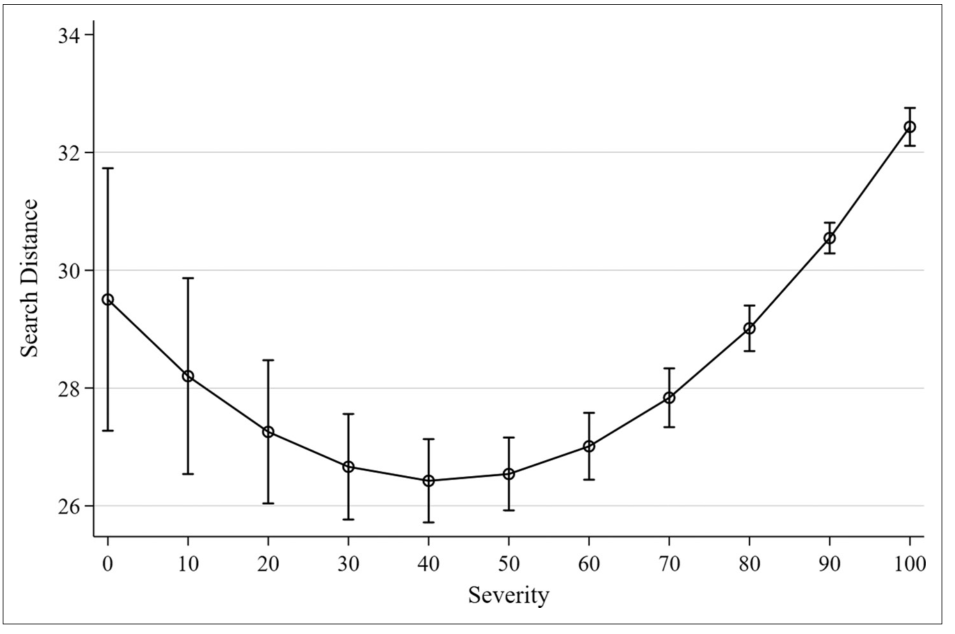

Figure 1. Relationship between the *Severity* of failure and *Search Distance*.

H3a, as $(Severity)^2 \times Time$ is negative and significant ($b = -0.001$, $p < 0.001$). Hence, temporal distance attenuates the curvilinear effect, meaning that the U-shape is flattened and shifted upward as illustrated in Figure 3. We also find supportive evidence for H3b, as the $(Persistence)^2 \times Time$

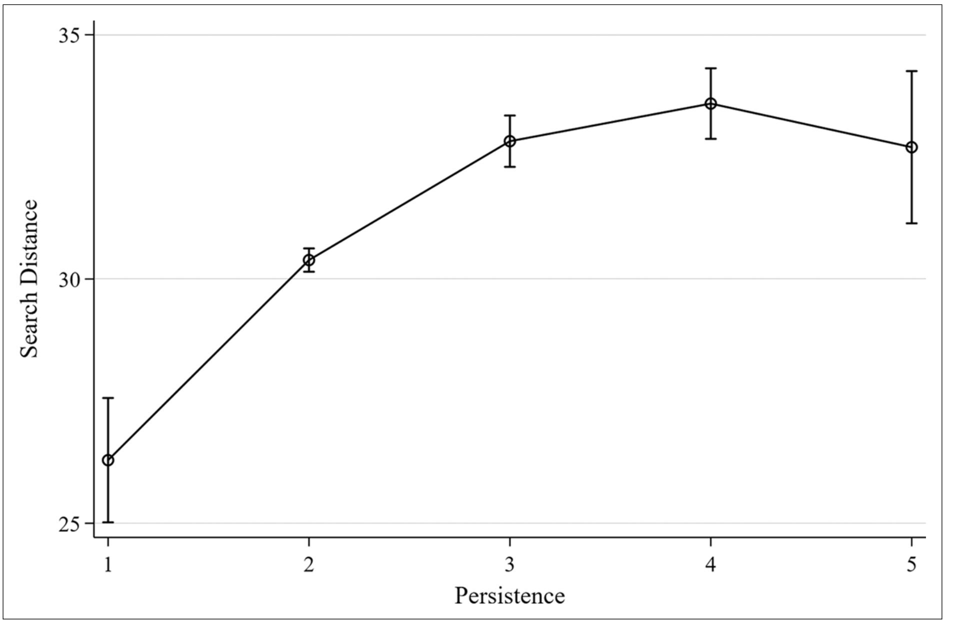

Figure 2. Relationship between the *Persistence* of failure and *Search Distance*.

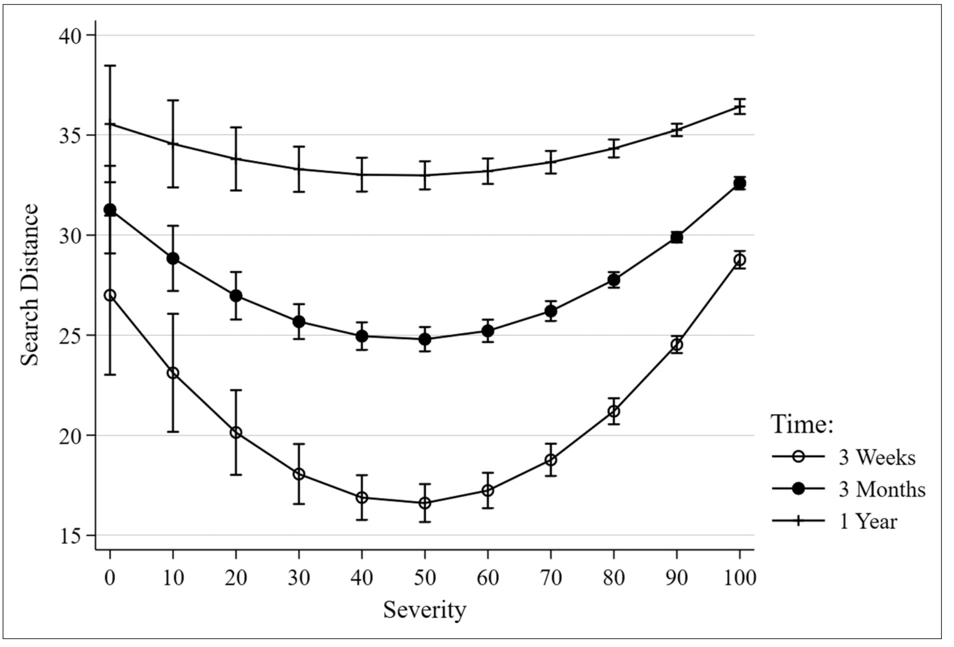

Figure 3. Moderating effect of *Time* on the relationship between the *Severity* of failure and *Search Distance*.

interaction is positive and significant ($b = 0.246$, $p < 0.05$). As hypothesized, Figure 4 shows a flattening of the inverted U-shaped curve (Haans et al., 2016). Taken together, consistent with our expectations, there is a strong moderating role of *Time* with regard to the effects of *Severity* and *Persistence* of failure on entrepreneurs' *Search Distance*.

Robustness Checks

To check the robustness of our results, we conducted further analyses (Table 2 of the Appendix). First, we loosened our initial restrictions on the dataset and included entrepreneurs that started more than five projects on Kickstarter, because we assumed that failing more than five times a row would result in frustration and lack of seriousness in entrepreneurs' crowdfunding attempts (Model 1). Coefficients remain largely consistent, with *Persistence* being generally less impactful. This could be expected, as the inclusion of high number of failed projects dilutes the effect. Second, it could be argued that a considerable number of entrepreneurs simply rerun their campaign after they failed. We therefore excluded all campaigns that were launched less than 1 month after the completion of the initial campaign (Model 2). Once we remove these campaigns, the effect of *Persistence* and the moderating effect of *Time* become insignificant. A possible explanation is the loss of variance in the variables *Persistence* and *Time* due to the reduced sample size. Third, up until mid 2014, Kickstarter staff manually screened all campaigns for quality before they could be launched on the platform (Thies et al., 2018; Wessel et al., 2017). Once the gatekeeping mechanism was removed, entrepreneurs could simply launch their campaigns without prior approval. We used a subsample of our data from mid-2014 onward for a robustness check to remove potential bias introduced through the manual screening. We found no noteworthy differences in the coefficients (Model 3). Fourth, extremely high or low values for the funding goal may impact our analysis. Following prior literature (e.g., Mollick, 2014), and to focus

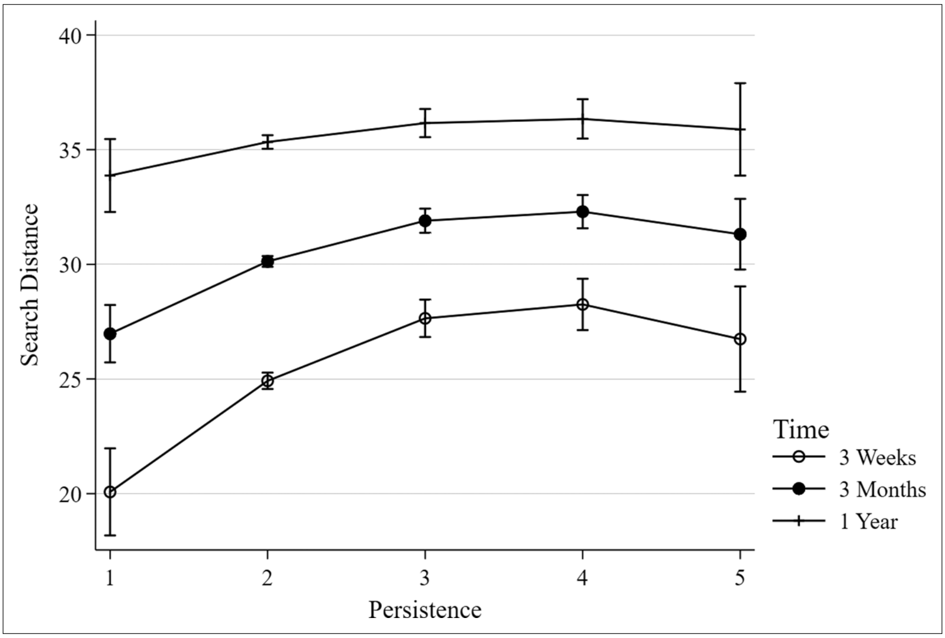

Figure 4. Moderating effect of *Time* on the relationship between the *Persistence* of failure and *Search Distance*.

on serious entrepreneurial initiatives, we ran an additional model for which we excluded all campaigns with a funding goal below $5000 (Model 4). In this model, the results for *Severity* are consistent with the main model based on the entire dataset, while the coefficients for *Persistence* become insignificant ($p > 0.05$). This may be due to the stark reduction in observations by almost 60%. We also reran the model using 99% winsorization of the funding goal at both ends. This procedure excludes campaigns with a funding goal below $50 and above $500,000. The results of this model (Model 5) are highly consistent with those of the main model based on the entire dataset. Fifth, recognizing potential differences between campaigns launched in different Kickstarter categories, we reran our analyses (Model 6) using only campaigns launched in the categories Design, Technology, and Games that are mainly focused on consumer goods and require substantially more effort as compared to artistic categories (e.g., Mollick, 2014). The results are consistent with those of the main model based on the entire dataset, both in direction and magnitude, for the main and nonlinear effects of *Severity* and *Persistence*. However, the interaction effect *Persistence* × *Time* becomes insignificant.

Moreover, we checked whether our findings are robust to alternative modeling techniques. First, we reran all of our models using the generalized estimation equation method (GEE) in order to check for possible autocorrelation of the standard errors (Model 7). Second, we created an alternative dependent variable *Search Distance* via mean splitting, which reflects local (0) and non-local search (1). We then ran a panel probit regression with the same specifications confirming our initial modeling approach (Model 8). Third, as our dependent variable is measured in percentage and ranges from 0 to 100, an OLS estimator can be inconsistent due to a potential censoring problem. We therefore used a tobit estimator in Model 9 to check for the robustness of our estimates as suggested by Wooldridge (2010). All alternative modeling techniques in models 7 through 9 lead to largely consistent results, where only the nonlinear moderation coefficients of *Persistence* lose significance in the GEE (Model 7) and probit estimation (Model 8). The nonsignificant moderation effect of *Persistence* and *Time* in the probit model may simply indicate that the more fine-grained continuous search distance measure used in our main analysis better captures the construct than the dichotomous operationalization.

Finally, it is possible that the relationships between *Severity* and *Search Distance* as well as *Persistence* and *Search Distance* may suffer from endogeneity. In particular, two main issues could potentially introduce endogeneity in our regression models, namely, reverse causality and omitted variables. First, regarding reverse causality, we have lagged independent variables in our panel regression models, helping us to alleviate concerns about the direction of causality. Second, we ran two additional tests to uncover potential issues of omitted variable bias. A first concern is that competitive conditions within Kickstarter's platform (e.g., strong growth of the entire market or high market concentration) may influence both our independent variables as well as our dependent variable *Search Distance*. That is, if entrepreneurs compare their performance to that of a reference group (entrepreneurs in the same category or entrepreneurs with similar campaigns across the platform), the subsequent performance aspirations and search behavior may be affected, for instance, in that entrepreneurs are more risk-seeking in their actions (e.g., Baum & Dahlin, 2007; Ferrier et al., 2002). To account for this concern, we controlled for the total market volume, accumulating the total funding of all projects of a given month, in our main model. Moreover, we controlled for market concentration (i.e., the concentration of funding among projects within each project category) by using the Herfindahl-Hirschman Index (HHI; Hirschman, 1964). Adding these control variables did not affect the proposed relationships between the independent variables and *Search Distance* (Model 10). Second, as entrepreneurs may shift attention away from performance-based aspirations to survival goals when faced with severe threats (e.g., bankruptcy), aspiration degradation may be the true cause of changes in problemistic search (e.g., Audia & Greve, 2006; Chen & Miller, 2007). As such, we also added the relative change of the funding goal of the entrepreneur in order to control for possible effects of aspiration degradation (Model 10). The results of Model 10 are consistent with our main findings.

Post-Hoc Analysis

We also performed additional analyses to extend our findings, focusing on the performance consequences of problemistic search distance. Although of great interest to scholars and practitioners alike, especially in entrepreneurial contexts, this issue is not well understood (Angus, 2019). To explore the relationship between *Search Distance* and subsequent campaign *Performance*, we used our original dataset including all entrepreneurs (i.e., not only those whose first crowdfunding project failed) that created at least two campaigns on Kickstarter. We conducted a panel OLS regression to estimate the effects of *Search Distance* on the subsequent *Performance*, measured as the amount of money a campaign received as a percentage of the amount requested (Steigenberger & Wilhelm, 2018; Zhang & Liu, 2012). Table 3 depicts the regression results of our post-hoc analysis. *Search Distance* has a significant negative effect on *Performance* ($b = -0.001$, $p < 0.001$). Prior work suggested a possible tradeoff between local and non-local search, as non-local search might prove profitable but context-specific knowledge might be forfeited (Angus, 2019). We therefore also tested a nonlinear relationship in Model 3, where an inverted U-shape becomes apparent as $(\textit{Search Distance})^2$ is negative and significant ($b = -0.001$, $p < 0.001$). As in the main analysis, we confirmed the inverted U-shape relationship with the turning point at 27.06 using the proposed three step approach suggested by Lind and Mehlum (2010). The relationship is illustrated in Figure 5, showing that a moderate amount of *Search Distance* yields the highest increase in *Performance*. Overall, we can infer that *Search Distance* is associated with changes in the performance of crowdfunding campaigns, which underscores the importance of our main findings.

Table 3. Panel OLS Regression on *Performance.*

	Model 1		Model 2		Model 3	
Controls						
Category	Included		Included		Included	
Year	Included		Included		Included	
Goal	−0.242***	(0.003)	−0.242***	(0.003)	−0.241***	(0.003)
Staff Pick	0.246***	(0.014)	0.245***	(0.014)	0.242***	(0.014)
Video	0.011	(0.011)	0.006	(0.011)	0.006	(0.011)
Comments	0.424***	(0.005)	0.423***	(0.005)	0.422***	(0.005)
Project Rewards	0.009***	(0.001)	0.009***	(0.001)	0.009***	(0.001)
Project Updates	0.011***	(0.001)	0.011***	(0.001)	0.010***	(0.001)
Project Number	0.018***	(0.005)	0.018***	(0.005)	0.018***	(0.005)
Main effects						
Search Distance			−0.001***	(0.000)	0.002***	(0.001)
Nonlinear effects						
(*Search Distance*)^2					−0.001***	(0.000)
Constant	2.311***	(0.041)	2.358***	(0.041)	2.307***	(0.041)
R^2	0.452		0.453		0.453	

Note. N = 78,450; Standard errors are in parentheses; Log-transformed variables: *Goal, Comments*; *p < .05, **p < .01, ***p < .001.

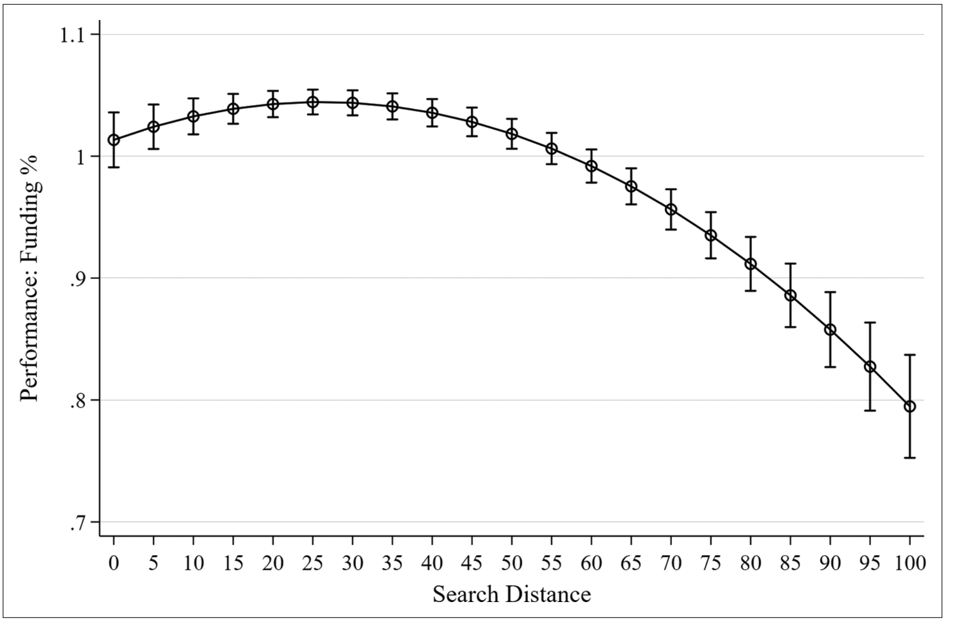

Figure 5. Relationship between *Search Distance* and subsequent *Performance.*

Discussion

The aim of this study was to shed new light on problemistic search processes. Examining this phenomenon in the context of entrepreneurial crowdfunding, we focused on how key characteristics of negative performance feedback influence the distance of entrepreneurs' search for solutions that improve the performance of their next crowdfunding project. We found search distance to increase as a function of the severity and persistence of failure. However, as hypothesized, both feedback conditions had a curvilinear rather than simply linear effect on search distance. While the persistence of failure showed the expected inverted U-shaped effect, surprisingly, the relationship between the severity of failure and search distance followed a U-shaped function. Additionally, we observed that time plays an important role in predicting problemistic search distance. Greater temporal distance between the failure experience and a crowdfunder's next campaign was not only associated with an increase in search distance, but also attenuated the curvilinear effects of the severity and persistence of failure on search distance. Below, we discuss the implications of these findings that extend and challenge existing research on problemistic search in entrepreneurial contexts and elsewhere.

Theoretical and Practical Implications

First, this study contributes to research and theory on problemistic search. Our unique sample containing failed crowdfunding projects enabled us to effectively distinguish problemistic search from other types of search processes. Using these data, we addressed one of the main blind spots in the theory that Posen et al. (2018) identified in their recent literature review, namely, the conditions under which local or distant search in response to negative performance feedback are invoked. Our research provides strong evidence that the severity and persistence of failure are key factors influencing entrepreneurs' search distance after failed crowdfunding campaigns. With the notable exception of two studies on firms' innovation (Yu et al., 2019) and acquisition (Iyer et al., 2019) behavior, especially the persistence of failure has been largely neglected in the literature. The observed differences between the severity and persistence of failure regarding the shape of their relationship with search distance (i.e., U-shaped vs. inverted U-shaped) imply that rather than influencing search behavior through the same mechanisms, these feedback characteristics have a unique impact that needs to be taken into account.[7]

Perhaps most importantly, by hypothesizing and testing nonlinear relationships, our research helps to reconcile the conflicting findings on how severe and repeated failures influence problemistic search (e.g., Audia & Greve, 2006; Kotiloglu et al., 2019). When integrating threat rigidity and other psychological factors (e.g., self-enhancement motives and attributions) into the conceptualization of problemistic search, the rather mechanistic, linear relationship between a performance shortfall and subsequent search proposed by the theory in fact appears to be too simplistic (Posen et al., 2018). This is especially true since performance feedback is characterized by ambiguity and subject to interpretation (Joseph & Gaba, 2015). Our results support this view, showing that entrepreneurs respond differently to negative performance feedback depending on where their failure experiences reside on the severity and persistence continuums. Overall, this study underscores the analytical value of exploring nonlinear effects on problemistic search in order to account for the countervailing forces that shape these processes and complexities involved.

We also extend prior research on problemistic search by showing how time affects these processes and, in doing so, answer the recurring calls for integrating temporal factors into organization and management theories (Ancona et al., 2001; George & Jones, 2000; Mitchell & James, 2001). Although time is argued to be highly relevant to search and decision making more broadly, temporal issues have been largely overlooked in the problemistic search literature (Lehman et al., 2011; Yu et al., 2019). Introducing temporal distance as a new moderator of the relationship between negative performance feedback and entrepreneurs' search distance, we provide strong evidence that entrepreneurs' responses to failures are time-dependent. Our observation that greater time lags between failure experiences and entrepreneurs' next crowdfunding projects are associated with a "flattening of the curves" suggests that, over time, it becomes less relevant what type of failure (e.g., small or large) has occurred when it comes to search distance. This might be the case, because temporal distance makes it increasingly difficult for individuals to remember events in detail and therefore to distinguish between different types of failure experiences (Trope & Liberman, 2003).

Second, we contribute to research on crowdfunding—a "hot topic" in the entrepreneurship literature (Pollack et al., 2019). This growing body of work has paid surprisingly little attention to the consequences of crowdfunding failure. By showing what happens after failed crowdfunding campaigns, we respond to Pollack et al. (2019) call to improve our limited understanding of the "before, during, and after crowdfunding." The longitudinal perspective of our study adds a new dimension to this debate, namely that history matters when it comes to predicting entrepreneurs' current crowdfunding activities and success. In this regard, our study represents a shift in perspective from crowdfunders as signal senders to signal receivers. Given information asymmetries between entrepreneurs and potential backers, research has emphasized that success in crowdfunding critically relies on the disclosure of information that signal the underlying quality of the project and its developers (Courtney et al., 2017; Parhankangas & Renko, 2017). While these studies show how different signals sent by entrepreneurs contribute to varying crowdfunding success, our study suggests that the signals (i.e., performance feedback) they receive in return might be equally important.

Finally, this study provides practical guidance for responding to negative performance feedback. Interpreting negative performance feedback, drawing the right conclusions, and adopting a suitable search strategy to solve the problem is far from easy, especially for entrepreneurial organizations that often lack prior experience of the same type (see Kim & Miner, 2009). Against this backdrop, two specific implications can be derived from our findings. First, by shedding light on the conditions under which entrepreneurs are more or less responsive to negative performance feedback, our research helps decision makers to reflect upon and improve their own response behavior. For example, the observation that entrepreneurs tend to be least responsive to failures of moderate severity serves as a reminder to focus more attention on such failures. Second, the observed inverted U-shaped relationship between search distance and crowdfunding project performance suggests that decision makers should not fall into the trap of over-searching to correct failures. Rather than pursuing a suboptimal nonlocal search strategy, we echo the recommendation of Angus (2019) that entrepreneurs are well advised to follow a moderate search strategy. This approach may entail carefully analyzing the causes of project failure, evaluating what has worked and what has not been effective, and selectively adapting current strategies and actions.

Limitations and Future Research

As with all empirical studies, this study is subject to limitations that should be taken into account when interpreting our results. These limitations, however, provide opportunities for future research. First, using data on entrepreneurs' responses to crowdfunding failure may limit the generalizability of our findings. For example, it is quite possible that problemistic search processes in entrepreneurial crowdfunding are more explorative than those in other contexts (e.g., large manufacturing firms; Greve, 2003a) in which this phenomenon has been typically examined. Compared to decision makers in organizations who collectively make sense of and decide how to respond to negative performance feedback, entrepreneurs tend to have greater discretion, to be less strongly affected by path dependencies, structural rigidities, as well as political processes, and to have a more positive attitude toward failure and risk taking (see Cope, 2011; Vissa, 2011). Thus, our results may overstate the influence of failure experiences on search distance. That being said, since we have hypothesized and tested nonlinear rather than linear relationships, this is less of a concern. Quite the contrary, settings where search tend to be more distant allow for a more conservative test of the assumption that threat rigidity and other factors eventually lead to decreasing search distance. Future studies investigating the relationships proposed in this article at an organizational level and/or in other settings (e.g., new product development) offer the opportunity to expand the generalizability of our findings.

Second, our sample contains entrepreneurs' (repeated) failed efforts to acquire financial resources. While this focus on failed crowdfunding campaigns is clearly a strength of this study in that it allows us to effectively distinguish problemistic search from the related processes of institutionalized and slack search, we argue that it is necessary to enhance our limited understanding of the idiosyncrasies and similarities of different search processes (Posen et al., 2018). Most importantly, as the behavioral theory suggests that decision makers respond differently to performance above and below the aspiration level (e.g., Greve, 2003a; Iyer & Miller, 2008), studies are needed to examine whether similar (nonlinear) relationships to those observed in this study can be found when there is positive attainment discrepancy.

Third, there are potential measurement issues that need to be considered. To measure problemistic search distance, we calculated the cosine similarity between the text descriptions of a crowdfunder's subsequent campaigns (e.g., first and second campaign). While similar measures have been used in previous studies (Angus, 2019), we recognize that this approach is not without limitations. In particular, it is difficult to say whether differences in the text description of two projects reflect actual changes in the project content (e.g., product modifications, a new business model) or simply linguistic changes. While the project examples depicted Table 1 in the Appendix suggest that even a medium search distance is associated with significant product changes, these cases are, of course, not generalizable. However, we argue that even when a crowdfunder has only revised the project page by providing a better, more detailed description of the product to be developed or by using different language (e.g., expressing emotions and enthusiasm), problemistic search may have occurred. Such changes can be seen as the attempt to better advertise the project, and thus represent a crowdfunder's solution to the performance problem. Our robustness checks provide further confidence in our measure. For example, our observation that category change (i.e., the subsequent project is launched in a different crowdfunding category) and search distance are significantly correlated suggests that distant search is indeed often associated with changes in the project content. Nevertheless, additional research is clearly needed to validate our findings using alternative measures of search distance (e.g., patent data; see Katila & Ahuja, 2002).

Fourth, although cognition plays an important role in our theorizing, unfortunately, our archival data did not allow us to examine how cognitive processes shape entrepreneurs' responses to crowdfunding failure. Thus, in-depth studies delving into the micro-level processes of problemistic search and explain how entrepreneurs experience, make sense of, and react to negative performance feedback are needed to complement our research. This is in line with recommendations by Posen et al. (2018) for advancing problemistic search theory. They argued that the prevalent conceptualization of problemistic search as a routinized, quasi-automatic response process has hindered theoretical progress. Bringing cognition into the foreground might be fruitful for providing a better understanding of various issues that have received limited research attention, including how decision makers form and change aspirations.

Finally, we cannot entirely eliminate the possibility of omitted variable bias. Though our robustness checks give no indication that omitted variables are biasing our empirical results, there are characteristics of entrepreneurs that are beyond what our data allows us to control for in this study. For example, since our sample focuses on crowdfunding campaigns launched on Kickstarter, we cannot rule out that project creators have not been active on other crowdfunding platforms as well. Although somewhat unlikely, because crowdfunders tend to focus their activities on one crowdfunding platform (Butticè et al., 2017), such activities might bias our results by influencing entrepreneurs (failure) experience and search behavior. Methodologically, future studies could use experimental designs or an instrumental variable approach to be able to make strong causal claims about the relationship between crowdfunding failure and subsequent problemistic search.

Conclusion

How do entrepreneurs respond to failure? This question, which we addressed in the context of crowdfunding, is of great interest to scholars and practitioners alike. Our results show that: (i) the severity and persistence of failure are key determinants of entrepreneurs' search behavior or, more precisely, search distance, (ii) problemistic search processes are time dependent, and (iii) a moderate degree of search distance in response to failure is most beneficial for improving the performance of future crowdfunding projects. Some of our findings are consistent with the predictions of problemistic search theory, whereas others, such as the observation that the relationship between the severity of failure and search distance follows a U-shaped function, may be surprising. Together, they suggest that problemistic search processes are shaped by countervailing forces and are clearly more complex than often believed. Thus, we hope that future studies will continue to explore nonlinear effects on problemistic search.

Appendix

Table 1. Search Distance Examples.

	Description of Project$_{i-1}$	Description of Project$_{i}$
Low *Search Distance* (0.08)	This project is to raise the funds to enable me to complete the release of an augmented reality tour and story telling app based in major cities around the world starting with London. The app will be available on Android and iOS platforms and will incorporate great storytelling with technology, the first stage of release will focus on tours around the city of London ranging from your popular tours to more bespoke and personalised tours like graffiti of urban London, all of these are to help explore the London we all know and also the London we don't know be it from pub crawls, haunting's and ripper tours where you will have a narrator throughout your journey and scene recreations at key points which will enable you to see a particular place at a certain time or event, for example a murder victim of Jack the Ripper or the riots in Brixton with the aid of augmented reality. Following on and progressing from the tours we will be creating highly interactive and engaging fictional stories and mysteries which will have you seeing the cities like never before. All donations are welcomed and highly appreciated	This project is to raise the funds to enable me to complete the release of an augmented reality tour and story telling app based in major cities around the world starting with London. The app will be available on Android and iOS platforms and will incorporate great storytelling with technology, the first stage of release will focus on tours around the city of London ranging from your popular tours to more bespoke and personalised tours like graffiti of urban London, all of these are to help explore the London we all know and also the London we don't know be it from pub crawls, haunting's and ripper tours where you will have a narrator throughout your journey and scene recreations at key points which will enable you to see a particular place at a certain time or event, for example a murder victim of Jack the Ripper or the riots in Brixton with the aid of augmented reality. Following on and progressing from the tours we will be creating highly interactive and engaging fictional stories and mysteries which will have you seeing the cities like never before. Be a part of the revolution. All donations are welcomed and highly appreciated

(Continued)

Table 1. Continued

	Description of Project$_{i-1}$	Description of Project$_i$
Medium *Search Distance* (0.47)	For those of us who have used flax seed heat pillows, getting time with our warm pillow is the best part of our day. I decided to improve on something that's already so close to perfect. I've made the [Project name removed to preserve anonymity] larger than the competition and over-stuffed which gives the pillows extra weight and more couture that your body so deeply enjoys. Unfortunately, I don't have the right sewing machine, quality fabrics, or matching thread that they need to look neat and professional. Sewing them by hand takes hours now, verses minutes once I have the right sewing machine. That's where you come in. [Name] is the name of the holistic health company I started in 2006 with a close friend. We mainly focused our line on body products but since becoming a licensed massage therapist, I've been focusing on holistic health and very much enjoying heat therapy and aromatherapy and its benefits. Migraine and fibromyalgia sufferers, especially, greatly benefit from the mixture of aromatherapy and holistic heat therapy with flax seed pillows. I am a sufferer of migraines and fibromyalgia pain as well as my family members and some of my closest friends. With my large pillows and unique shapes, I'm able to address specific areas and hold the body in particular ways that help ease and adjust problem areas. The first unique-shaped pillow I designed hugs your chest and sternum in a giant "*T*" shape	For those of us who have used flax seed heat pillows, getting time with our warm pillow is the best part of our day. I decided to improve on something that's already so close to perfect. I've made the [Project name removed to preserve anonymity] for little ones like my two young boys. They hold the stuffie and they feel better. Unfortunately, I don't have the right sewing machine, quality fabrics, or matching thread that they need to look neat and professional. Sewing them by hand takes hours now, verses minutes once I have the right sewing machine. Also, between this endeavor and my [Project name], I need to make a professional website and I'd like to get these to local businesses to sell for me or have my own store front. That's where you come in. [Name] is the name of the holistic health company I started in 2006 with a close friend. We mainly focused our line on body products but since becoming a licensed massage therapist, I've been focusing on holistic health and very much enjoying heat therapy and aromatherapy and its benefits. With my large pillows and unique shapes, whether you just have a sleepy one or a little one with fever or pain, the Creatures will comfort them right to sleep
High *Search Distance* (0.93)	Hello people of Kickstarter, my name is [Name removed to preserve anonymity], a high school senior who has always had a passion for programming, and I especially enjoy making apps. This app here is [Project name], an app that allows users to request someone to pick them up by sending either a text message from your phone or via the app if both users have it. The great thing about this app is that the people you are asking to give you a ride have the ability to say yes or no, if they can pick you up. A great feature that we have implemented is that the receiving user is automatically gives your location, directions, distance and how long it will take, so that that person can make an informed decision on if they can drive you. Another feature that goes along with our location services is, if the user accepts to pick you up, you get updates every 15 s of where the user is in relation to you on a map view. With the funding that we are requesting, we want to bring this to iOS devices, currently it is only on android. Also with the funding we would like to integrate support for taxis, so if none of your friends or family are available to pick you up, with one click of a button you will be connected to the nearest taxi company, who is guarantee to answer. I hope you join us in our adventure by supporting our campaign. If you are unable to support us, or you already have and want to do more, feel free to share this Kickstarter page on any form of social media. Thank you!	We wanted to create a device that integrated with your already existing daily routine, and also helped you prepare for the day. We concluded that the mirror was the best way to do this. We are constantly checking mirrors to see how we look, why not get essential information about the upcoming day right in front of you. While we are having our product open to developers to create widgets of their own, we are also dedicated to bringing more and more widgets internally based on what customers want. We strived to find a balance between providing enough information to be useful, and give you information about the day, without overwhelming you. We understand that this is not a device a place that users will consume a lot of content, therefore, all of our widgets give you information at a glance. The mirror is all controlled via an app, available for iOS and Android. The app allows you to pick up to six widgets to display on the mirror, and where you want to place them. We also allow you to leave spaces blank if you want a more simplistic mirror look. We have working versions of the mirror, which is shown in the video, and we just need funding to start our manufacturing run

Table 2. Results of Robustness Checks (1/2).

Results of Robustness Checks (1/2).										
	Model 1		Model 2		Model 3		Model 4		Model 5	
	All projects (incl. project number >5)		Without quick relaunches		Post policy change—2014		Goal above $5000		99% quantile goal	
Controls										
Category	Included		Included		Included		Included		Included	
Year	Included		Included		Included		Included		Included	
Goal	−0.555***	(0.077)	−0.622***	(0.089)	−0.499***	(0.091)	−1.553***	(0.124)	−0.562***	(0.080)
Staff Pick	−0.348	(0.472)	−0.796	(0.505)	−0.256	(0.602)	−1.315*	(0.650)	−0.349	(0.476)
Video	−2.629***	(0.252)	−2.018***	(0.286)	−2.609***	(0.311)	−3.377***	(0.426)	−2.647***	(0.257)
Comments	0.351**	(0.133)	0.237	(0.145)	0.291	(0.162)	0.277	(0.191)	0.379**	(0.136)
Description Length	−9.310***	(0.136)	−9.224***	(0.137)	−9.658***	(0.145)	−9.509***	(0.191)	−9.309***	(0.129)
Category Change	10.210***	(0.239)	8.787***	(0.260)	10.129***	(0.297)	10.270***	(0.382)	10.117***	(0.242)
Failure Rate	5.522***	(1.251)	2.990*	(1.397)	4.413**	(1.659)	4.120*	(2.087)	5.186***	(1.279)
Main effects										
Severity	−0.730***	(0.135)	−0.372*	(0.186)	−0.846***	(0.162)	−0.704**	(0.231)	−0.720***	(0.137)
Persistence	4.569***	(1.211)	9.266	(7.139)	14.467**	(4.748)	9.814	(6.056)	15.376***	(3.936)
Nonlinear effects										
(Severity)^2	0.008***	(0.001)	0.004**	(0.001)	0.008***	(0.001)	0.007***	(0.002)	0.007***	(0.001)
(Persistence)^2	−0.317**	(0.115)	−0.694	(1.166)	−2.006**	(0.771)	−1.321	(0.973)	−2.042**	(0.644)
Moderator										
Time	4.078***	(1.009)	7.832***	(2.182)	5.070**	(1.673)	3.339	(2.262)	6.387***	(1.438)
Severity × *Time*	0.107***	(0.027)	0.031	(0.035)	0.134***	(0.031)	0.108*	(0.044)	0.105***	(0.027)
Persistence × *Time*	−0.662**	(0.247)	−1.088	(1.316)	−2.200*	(0.932)	−0.833	(1.175)	−2.230**	(0.784)
Nonlinear moderation										
(Severity)^2 × *Time*	−0.001***	(0.000)	−0.000	(0.000)	−0.001***	(0.000)	−0.001***	(0.000)	−0.001***	(0.000)
(Persistence)^2 × *Time*	0.050*	(0.025)	0.054	(0.216)	0.318*	(0.152)	0.105	(0.190)	0.297*	(0.129)
Constant	316.680**	(112.731)	−49.025	(126.157)	531.435**	(181.724)	560.758**	(184.147)	328.820**	(114.299)
R^2	0.316		0.329		0.321		0.336		0.315	
Observations	36,073		26,185		24,584		14,543		34,572	

Results of Robustness Checks (2/2)										
	Model 6		Model 7		Model 8		Model 9		Model 10	
	Core categories		GEE estimation		Probit estimation (0/1)		Tobit estimation		Endogeneity controls	
Controls										
Category	Included		Included		Included		Included		Included	
Year	Included		Included		Included		Included		Included	
Market Volume									1.359***	(0.212)
HHI									2.326*	(1.123)
Goal Adjustment									0.000	(0.000)
Goal	−0.574***	(0.147)	−0.587***	(0.072)	−0.058***	(0.007)	−0.551***	(0.074)	−0.571***	(0.077)
Staff Pick	0.409	(1.036)	−0.375	(0.561)	−0.056	(0.056)	−0.304	(0.581)	−0.313	(0.473)
Video	−2.140***	(0.475)	−2.639***	(0.240)	−0.211***	(0.023)	−2.558***	(0.249)	−2.661***	(0.254)
Comments	0.420	(0.297)	0.360*	(0.142)	−0.026	(0.014)	0.461**	(0.147)	0.381**	(0.134)
Description Length	−9.494***	(0.231)	−9.238***	(0.110)	−0.681***	(0.016)	−9.589***	(0.116)	−9.347***	(0.126)
Category Change	3.037**	(0.940)	10.170***	(0.223)	0.830***	(0.024)	10.364***	(0.231)	10.177***	(0.239)
Failure Rate	6.019**	(2.009)	5.424***	(1.218)	0.307**	(0.114)	5.610***	(1.261)	4.216***	(1.274)
Main effects										
Severity	−1.067***	(0.251)	−0.725***	(0.134)	−0.065***	(0.013)	−0.717***	(0.139)	−0.687***	(0.135)
Persistence	5.707**	(1.791)	12.817***	(3.488)	0.389	(0.354)	13.782***	(3.711)	13.982***	(3.736)

(Continued)

Table 2. Continued

Results of Robustness Checks (2/2)										
	Model 6		Model 7		Model 8		Model 9		Model 10	
	Core categories		GEE estimation		Probit estimation (0/1)		Tobit estimation		Endogeneity controls	
Nonlinear effects										
(Severity)^2	0.010***	(0.002)	0.008***	(0.001)	0.001***	(0.000)	0.007***	(0.001)	0.007***	(0.001)
(Persistence)^2	−0.404*	(0.187)	−1.702**	(0.567)	−0.031	(0.058)	−1.819**	(0.603)	−1.853**	(0.609)
Moderator										
Time	3.230	(1.912)	5.666***	(1.408)	0.204	(0.141)	6.086***	(1.479)	5.831***	(1.396)
Severity × *Time*	0.157**	(0.051)	0.106***	(0.028)	0.010***	(0.003)	0.105***	(0.029)	0.098***	(0.027)
Persistence × *Time*	−0.548	(0.384)	−1.761*	(0.729)	−0.011	(0.074)	−1.920*	(0.774)	−1.936**	(0.749)
Nonlinear moderation										
(Severity)^2 × *Time*	−0.002***	(0.000)	−0.001***	(0.000)	−0.000***	(0.000)	−0.001***	(0.000)	−0.001***	(0.000)
(Persistence)^2 × *Time*	0.031	(0.041)	0.232	(0.119)	−0.001	(0.012)	0.253*	(0.126)	0.258*	(0.123)
Constant	374.503	(210.255)	303.464**	(111.326)	62.434***	(10.299)	282.749*	(114.595)	1131.182***	(165.397)
R^2	0.272								0.318	
Observations	10,502		35,499		35,499		35,499		35,499	

Notes. Standard errors are in parentheses; Log-transformed variables: *Goal*, *Comments*, *Description Length*; *Time*; Lagged variables: *Category*, *Year*, *Goal*, *Staff Pick*, *Comments*, *Description Length*, *Failure Rate*, *Severity*, *Persistence*; Core categories: Design, Technology and Games; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

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Notes

1. In contrast to errors, which refer to incorrectly executed tasks or routines, failures are generally understood as undesirable performance outcomes relative to some standards that actors aspire to meet or exceed (Dahlin et al., 2018). While failures may result from errors, Frese and Keith (2015) emphasized that not every error leads to failure. Instead, they suggested that a multitude of factors, including errors, intent, risk, and chance—often in combination—are potential causes of failures.
2. Institutionalized search refers to routine search activities that organizations conduct even in the absence of particular triggers, whereas slack search is driven by the availability of resources that decision makers seek to employ more effectively (Greve, 2003a; Salge, 2011).
3. In this study, we draw on the individual-level processes posited by problemistic search theory (see Greve, 2003b). Referring to decision makers as those who interpret performance feedback and make decisions on behalf of their organization, behavioral theorists have in fact acknowledged the role of

managerial cognition in shaping organizational responses to performance feedback (March & Simon, 1958; see also Posen et al., 2018). In this regard, we argue that entrepreneurs are in many ways comparable to the powerful organizational decision makers (e.g., top managers) on which the literature has focused. Similar to organizational failures, entrepreneurs' crowdfunding project failures not only represent an individual concern, but also involve an organizational dimension in that entrepreneurs face expectations of their target audience and potentially other stakeholder groups (see Parhankangas & Renko, 2017). While differences between individual and organizational goal-setting, decision making, as well as search and risk-taking behavior (e.g., due to conflicting interests and political processes in organizations) should be recognized, we expect the basic process of problemistic search to similarly unfold across levels of analysis (Greve, 2003b; Jordan & Audia, 2012). This is consistent with Greve and Gaba (2017), who concluded that given evidence showing similar effects of negative performance feedback at the organizational and individual level (e.g., with regard to change and risk-taking behavior), the theory is generally scalable over levels of analysis.

4. Managers are assumed to rely on two different types of aspirations when making sense of their organization's current performance, historical (i.e., the organization's past performance) and social (i.e., the performance of comparable organizations) aspirations, both of which providing them with guidance of how well the organization should perform (Greve, 2003a; Kim et al., 2015; Salge, 2011).
5. https://www.kickstarter.com/projects/ryangrepper/coolest-cooler-21st-century-cooler-thats-actually
6. In our Kickstarter sample, the average length between failure and an entrepreneur's next crowdfunding project was 250 days (median 100 days). Over 25% of the new projects are launched within the first month after failure, many of them within a couple of days.
7. Our finding that the relationship between severity of failure and search distance follows a U-shaped rather than an inverted U-shaped function, as we hypothesized, requires explanation. In crowdfunding, moderate failures (which are relatively "rare events" as most campaigns fail by large margins; Mollick, 2014) suggest that an entrepreneur has missed the funding goal by some margin but has nevertheless been able to attract funders who made a non-negligible financial contribution. In other words, the feedback from the crowd about the project is somewhat mixed, which may impede performance assessment and decision-making. Research indicates that decision makers become risk averse and are more likely to rely on established decision rules that guide their behavior when they receive inconsistent performance signals, both of which provides a potential explanation for entrepreneurs' relatively low search distance in response to moderate failures (see Blagoeva et al., 2019; Kim et al., 2015).

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