**Who should I listen to? The effects of expert and market validation on post-failure persistence and subsequent commercial performance**

**Abstract**

Failure is ubiquitous in entrepreneurial and creative organizational settings. One way that creators determine whether to persist after failure is to consider the feedback they have received about their products from the market and experts. Although these two unique sources of feedback are important for post-failure learning, little work has been done to integrate and compare the discrete value of market versus expert feedback and validation. In this research, we investigate the impact of these two types of feedback on both post-failure persistence and commercial performance. Utilizing failed crowdfunding campaigns in the book publishing category and linking them with post-failure Amazon publishing data, we find that market validation encourages persistence post-failure and that this feedback more likely leads to persistence when expert validation is also present. Yet, only market validation appears to be predictive of post-failure commercial performance. This research adds to the growing body of literature on market validation and rebounding from failure.

Keywords: Failure, Market Validation, Persistence, Entrepreneurship, Performance, Crowdfunding.

1. **Introduction**

A sizable literature examines the role of failure and persistence in organizational contexts (e.g., Jenkins and McKelvie, 2016; McGrath, 1999; McMullen and Kier, 2016; Shepherd, 2003). For entrepreneurs and other creative workers, failure is considered both pervasive and unavoidable (Cope et al., 2004). However, it is also recognized that failure can have potential benefits depending on the insights derived from the experience of failure (Cardon et al., 2011; Cope, 2011; Sitkin, 1992). Extant theorizing points to the substantial information contained within failure experiences (Cardon and McGrath, 1999; Shepherd, 2003; Simmons et al., 2019), and suggests that feedback or the knowledge acquired during failure can indicate to entrepreneurs and creative workers whether persisting post-failure is likely to result in a longer term commercial payoff.

 Feedback or validation received during failure can come from different sources, including experts and/or crowds (see Mollick and Nanda, 2016 for recent work comparing experts and crowds). Expert wisdom entails feedback received from individuals with extensive domain-specific experience (Budescu and Chen, 2015; Mollick and Nanda, 2016). Collective wisdom (i.e., market validation) refers to feedback originating from large populations of users (Keuschnigg and Ganser, 2017; Mannes, 2009). Prior work has demonstrated that both expert and collective wisdom can increase proximal organizational outcomes. For example, expert validation has been shown to increase popular opinion (Eliashberg and Shugan, 1997) and resource acquisition for firms in both traditional funding and crowdfunding settings (Agrawal et al., 2011; Anglin et al., 2019; Butticè et al., 2017; Zhang and Liu, 2012).

 Another key claim in the literature on collective wisdom is that aggregating feedback from groups of individuals can improve forecasting (Clemen, 1989; Soll and Larrick, 2009). This suggests that individuals dealing with failure could utilize feedback from the collective to assess whether persisting post-failure is likely to bring future success. However, prior work on collective wisdom and crowd knowledge has pointed to instances when aggregate feedback did not produce accurate forecasts because of systematic crowd bias (Stevenson et al., 2019a; Younkin and Kuppuswamy, 2018). For organizational actors dealing with failure, it is thus unclear whether collective wisdom is valuable in predicting distal outcomes such as performance. In this research, we ask the following research questions, *do both market validation and expert validation interact to influence post-failure persistence and which form of validation is more predictive of distal firm outcomes, such as subsequent commercial performance?*

To answer this question and develop our theoretical model, we leverage lead user theory (von Hippel, 1986). Lead user theory holds that the involvement and feedback of leading-edge customers, whose product usage is ahead of market trends, provide feedback that can be indicative of commercial success (Morrison et al., 2004; von Hippel, 2005). Using this perspective, we provide clarity by distinguishing between two sources of feedback: market validation and expert validation. Our results indicate that there are distinct differences between different sources of validation, particularly for longer term commercial performance. In contrast to previous studies that have assessed the effects of collective wisdom on proximal success outcomes such as funding (e.g., Mollick and Nanda, 2016), our study aims to evaluate how market and expert sources of validation impact individual action (i.e., persistence) as well as more distal performance outcomes (i.e., subsequent commercial success). Indeed, bringing a new concept to market requires persistence through numerous obstacles and failures (Markman et al., 2005; Shepherd et al., 2009; Wu et al., 2007). Receiving market or expert validation can indicate proximal value for creative workers or entrepreneurs who are dealing with project failure, thus likely encouraging persistence. However, the extent to which these sources of validation are predictive of distal performance is less well understood. In this study, we utilize a sample of failed crowdfunding campaigns in the book publishing category and link these data with post-failure book publishing information to investigate the role of market and expert validation on individuals’ decisions to persist and on future performance.

Our research makes three primary contributions to the literature on entrepreneurship and management. First, we extend prior research by investigating the effects of collective wisdom on more distal outcomes, (i.e., subsequent commercial performance). Recent collective wisdom research has focused on proximal outcomes such as subjective funder judgments (see Mollick and Nanda, 2016; Stevenson et al., 2019a). Although it is important to consider proximal outcomes, previous research has largely eschewed considerations related to longer term commercial performance. Utilizing lead user theory, we demonstrate that market validation is relatively more important than expert validation for commercial success. We theorize that because market validation reflects feedback from leading-edge customers, and thus indicates the commercial potential of a product, that higher levels of market validation will be predictive of more distal performance outcomes. Conversely, we explain that because expert validations are based on industry expertise and seldom based on actual product usage, expert biases can lead to inaccurate product assessments when considering commercial potential. Our results suggest that not all sources of validation are created equally, and that for long-term objective measures of performance, market validation is relatively more important than expert validation.

Second, we contribute to the literature on rebounding from failure (Cope, 2011; McGrath, 1999; Singh et al., 2007; Ucbasaran et al., 2013) by considering the role that market and expert validation received during a failed initiative has on persistence. Prior work has discussed how a desire to learn from failure increases a person’s belief about their potential future performance (e.g., Neck et al., 1999). We build on prior research by showing that higher levels of market validation during failure lead to a greater probability of post-failure persistence. We explain that market validation signals to organizational actors that their creative project is on the right path and that, with increased effort and persistence, future success is possible. Our theory suggests that the increased probability of persisting after failure will largely stem from increased motivation and belief in the commercial potential of a product. Further, we show how expert validation can further legitimize the signal of market validation, resulting in a positive interaction effect on persistence after failure. Thus, our study adds nuance to prior research by providing a theory explaining how discrete sources of validation encourage rebounding after failure.

Third, crowdfunding is used as the empirical setting in this research. We extend the crowdfunding literature by showing that, beyond the financial reward, crowdfunding platforms like Kickstarter provide valuable and actionable feedback from the crowd. That is, crowdfunding can be a useful validation tool even if the project fails to reach the funding goals.[[1]](#footnote-1) Several studies in this area have primarily focused on the antecedents of funding outcomes (see Anglin et al., 2018; Burtch et al., 2015; Plummer et al., 2016). Therefore, this study, which introduces a theoretical model related to non-financial benefits in crowdfunding, enhances and extends the existing body of crowdfunding research. Our study establishes a link between crowdfunding failure and subsequent commercial performance. This is important as no study, to the best of our knowledge, has explored whether the validation originating from a failed crowdfunding campaign translates to a firm’s subsequent commercial performance. By matching crowdfunding projects with commercial data, we demonstrate that, for failed crowdfunding projects, greater validation can convert to higher commercial success in the long run.

1. **Theoretical Foundation**
	1. **Prior Research on the Wisdom of the Crowd and the Wisdom of Experts**

 Research demonstrates that aggregated decisions from large populations can offer higher predictive accuracy compared to individual decisions (Mannes et al., 2012; Ray, 2006; Tetlock, 2005). Two populations that have received increased attention are experts and crowds (Clemen, 1989; Mollick and Nanda, 2016; Soll and Larrick, 2009). Expert wisdom describes feedback received from individuals that have extensive experience in a particular domain (Budescu and Chen, 2015; Mollick and Nanda, 2016). This type of wisdom is considered particularly valuable because the domain-specific feedback provided is based on the knowledge and skills acquired by experts over long periods of time (Ericsson, 2006; Sunstein, 2006). Expert wisdom has been shown to be an accurate indicator of certain outcomes (e.g., Eliashberg and Shugan, 1997; Ginsburgh, 2003; Reinstein and Snyder, 2005), including forecasting market demands (Gompers and Lerner, 2004; Shane and Venkataraman, 2003) and resource acquisition (Baum and Silverman, 2004; Hellmann and Puri, 2002). In entrepreneurial contexts, expert wisdom stems from individuals with domain specific entrepreneurial experiences that become a source of validation and legitimize a venture’s potential (e.g., Baum and Silverman, 2004)

 In contrast, crowd wisdom entails the feedback from groups of stakeholders participating in processes such as collective innovation (Jeppesen and Frederiksen, 2006; O’Mahony, 2003), innovation tournaments (Boudreau et al., 2010; Terwiesch and Ulrich, 2009; Terwiesch and Xu, 2008), and crowdsourcing (Bayus, 2013; Poetz and Schreier, 2012). The aggregated feedback that makes up crowd wisdom has been shown to accurately predict outcomes such as the funding of technology-based start-ups (Agrawal et al., 2014; Mollick, 2014), the development of new products (Afuah and Tucci, 2012; Poetz and Schreier, 2012; von Hippel, 1986), and scientific research (Franzoni and Sauermann, 2014). Crowd wisdom often originates from potential customers within a given market who offer validation based on their product usage (e.g., Gerber and Hui, 2016), sometimes referred to as “lead users” in the literature.

**2.2.** **Lead User Theory**

 Lead user theory holds that creators should highly value behaviors and the feedback from a particular group of users (i.e., lead users) as they represent a critical source of market information (Urban and von Hippel, 1988; von Hippel, 1986). Typically, lead users represent potential customers who use a product before it is commercialized. Since lead users possess usage experience (Mahr and Lievens 2012), using data derived from lead users can increase commercial success and innovation (Morrison et al., 2004; von Hippel, 2005).

Lead user product evaluations tend to be ahead of market trends (Morrison et al., 2004; von Hippel, 2005). Thus, lead users possess product experience and can provide more accurate information about the commercial potential of a given product (Mahr and Lievens, 2012; von Hippel, 2005). That is, because lead users’ feedback is based on actual product usage, it is a good forecasting mechanism for future commercial success. Indeed, such validation is recognized to contribute to multiple outcomes, such as the funding of technology-based startups (Agrawal et al., 2014; Mollick, 2014) and the development of new products (Afuah and Tucci, 2012; Poetz and Schreier, 2012; von Hippel, 1986).

 Lead users in crowdfunding campaigns are represented by individuals (i.e., backers) who validate products through the funding of campaign projects (Stanko and Henard, 2017). These individuals are often able to directly experience a product and thus offer important validation on the potential of a product. Therefore, we suggest that backers in crowdfunding campaigns serve as lead users and offer validation that could be indicative of future commercial performance because backers generally fund products that appeal to them based on their personal use (Cholakova and Clarysse, 2015).

**2.3. Rebounding from Failure and Entrepreneurial Persistence**

Entrepreneurial failure occurs when the performance of an initiative fails to meet certain pre-set goals (Cope, 2011; McGrath, 1999; Ucbasaran et al., 2013) or performance standards (Yamakawa and Cardon, 2015). The uncertain and risky nature of entrepreneurship implies a substantial probability of failure (McGrath, 1999), and there is growing recognition that business failure can have emotional, social, and financial costs (Morris et al., 2012; Shepherd et al., 2009; Shepherd and Cardon, 2009). Given that failure is a painful and sometimes even traumatic experience (Cope, 2005; Singh et al., 2007), failure requires resilient actors who are willing to persist toward eventual success (Shepherd, 2003). Indeed, one of the important factors contributing to the high rate of entrepreneurial failures is a lack of persistence (Bird, 1988; McDaniel, 2002), suggesting that individuals who achieve success in entrepreneurship must persist in their efforts despite repeated failures and setbacks (Ucbasaran et al., 2013).

 Persistence involves the continuation of effortful action despite failures, impediments, or threats (Gimeno et al., 1997). Persistence thus generally suggests not only numerous attempts toward a course of action but also constant efforts in the face of adversity, challenge, or misfortune (Markman et al., 2005; Wu et al., 2007). Specifically, persistence in efforts occurs when an individual chooses to continue with an opportunity regardless of prior setbacks or failures (Cardon and Kirk, 2015). Given that the process of founding and growing a business entails frequent obstacles and failures along the way (Markman et al., 2005; Wu et al., 2007), persistence is a key element in entrepreneurship (Shane et al., 2003). Indeed, entrepreneurs and creative workers who are persistent in pursuit of their goals have a greater chance of success (Timmons and Spinelli, 2008).

 For individuals participating in crowdfunding campaigns, persistence is particularly important, as around 60% of campaigns fail to reach their funding goal (Soublière and Gehman, 2019). Crowdfunding failure provides a clear signal that something went wrong, reveals valuable cause-effect relationships, and prompts an attribution search that can help individuals make sense of the their experience of failure (Cardon et al., 2011; Cope, 2011). Depending on the information available during failure, creative workers could either decide to persist with their ventures or quit.

1. **Hypotheses Development**

**3.1. Market Validation and Persistence Following Failure**

Market validation occurs when a business concept or idea for a new creative product receives feedback and evaluation from a given target market. Specifically, market validation refers to aggregated feedback received from backers that indicates the commercial potential of a product. Because market validation depends on the communal actions of many lead users, entrepreneurs or project creators are likely to assess this source of collective wisdom as more accurate and are thus likely to pay close attention to such validation.

 We expect that higher levels of market validation serve as a signal that a project or venture is on the right path and that, with increased effort and persistence, future success is possible. This increase in persistence will largely stem from individuals’ increased motivation and belief in their venture that results from receiving market validation from lead users. Prior research also supports our expectation, as validation has been shown to increase motivation and effort by increasing one’s awareness that a given goal is valuable (Atkinson, 1957; Feather, 1982; Fishbein and Ajzen, 1974; Lewin et al., 1944; Liberman and Förster, 2008; Vroom, 1964). Further, lead user feedback can promote individual persistence by increasing outcome expectancies and thus the belief that efforts will pay off (Bandura, 1991). This belief, in turn, can drive a person to persist through the many obstacles and challenges encountered on the entrepreneurial journey (Shane et al., 2003).

 In sum, individuals who fail during a project launch or pre-launch must decide whether to persist in their ventures and push forward or quit. We expect that those who receive more market validation will be more willing to persist based on crowd feedback. Because positive feedback in general encourages continued action, we expect higher levels of market validation will promote persistence after failure. That is, market validation will instill the belief that, despite their failure, project creators can persist toward eventual success with their creative projects or entrepreneurial ventures. Formally,

*Hypothesis 1: There is a positive relationship between market validation and persistence.*

**3.2. Expert Validation and Persistence Following Failure**

Market validation is not the only signal that project creators receive during launch or pre-launch activities that can encourage persistence. Project creators also often seek advice and validation from experts. Scholars have long noted the importance of experts and highlighted the trust placed in experts’ opinions on matters involving quality and value (e.g., Caves, 2000; Ginsburgh, 2003; Zuckerman, 1999). Project creators or entrepreneurs are likely to place a high degree of trust in these experts, as research has shown expert validation to be particularly influential (Eliashberg and Shugan, 1997; Reinstein and Snyder, 2005).

 One reason experts can be so highly trusted is that their expertise is achieved by learning from repeated experiences within specific domains (Ericsson, 2006). The resulting acquisition of domain-specific knowledge helps experts become more proficient in evaluating those domains (Ericsson, 2006; Ericsson et al., 2007; Schmidt et al., 1986). Specifically, expertise is distinguished by the ability to utilize information acquired through repeated experiences toward the management of, and influence over, domain specific issues (Chipman et al., 1985; Pfeffer and Sutton, 2000). For example, expert validations have been shown to influence popular opinion (Eliashberg and Shugan, 1997) and the acquisition of vital resources (Ginsburgh, 2003; Reinstein and Snyder, 2005). Expert validations have also been shown to influence which ventures receive funding. That is, the involvement of expert investors (e.g., angel investors, venture capitalists) often signals to other investors that a particular venture is legitimate and worth investing in (Baum and Silverman, 2004; Drover et al., 2017b; Hellmann and Puri, 2002). Such a signal is appraised as extremely trustworthy, as these experts are known to accurately forecast future market demand (Baum and Silverman, 2004; Gompers and Lerner, 2004; Shane and Venkataraman, 2003).

 In the same way that expert validations are deemed legitimate in appraising venture outcomes, we suggest that expert validation will legitimize market validations received by project creators or entrepreneurs and thus strengthen the belief that persistence after an initial project failure will pay off. As an example, when a project creator or entrepreneur receives market validation from lead users during a crowdfunding campaign failure, expert validation could legitimize the positive feedback by lead users in market validation, thus strengthening the relationship between market validation and persistence. We expect that expert validation will legitimize the signal given by market validation that even though an overall project failed, there remains a product worthy of further pursuit. Formally,

*Hypothesis 2: The positive relationship between market validation and persistence is strengthened by expert validation.*

**3.3. Market Validation, Expert Validation, and Subsequent Commercial Success**

We have just argued that expert validation is likely to strengthen the relationship between market validation and persistence following failure. However, if individuals decide to persist after failure and subsequently commercialize their products, the following key question arises: do market and expert validation have similar effects on subsequent commercial success? While our arguments concerning the importance of both market and expert validation for persistence would seem to imply similar effects on commercial success, we expect that market validation will be relatively more important than expert validation for subsequent commercial success.

Entrepreneurs involved in product validation are primarily concerned with idea testing with a group of actual lead users, which is a task geared toward learning about and improving a product or service (Contigiani and Levinthal, 2019). The knowledge gained through this process stems primarily from the feedback offered by potential customers and is the result of processes such as “learning by using” (Mukoyama, 2006; Rosenberg, 1983) and “user innovation” (Gambardella et al., 2017; von Hippel, 1986). Research shows that interacting with customers in this way improves the effectiveness of the product development process (Carbonell et al., 2009; Mahr and Lievens, 2012) and the success of a future product once commercialized (Gruner and Homburg, 2000; Morrison et al., 2004). Thus, the feedback from lead users who “test” a product before it is commercialized offers a reliable signal of the commercial potential of the product.

 The focus on learning about a product’s commercial potential is a key driver for individuals participating in crowdfunding campaigns. Indeed, while many participate in crowdfunding to access funding sources, they also are concerned with receiving feedback from external sources on the commercial potential of their products. Commercialization is the process of bringing new products to market and can be thought of as the transitioning of a product from validation phase to the commercial adoption of a product (i.e., revenue generation). Given that successful commercialization depends on customers deriving value in the use of a given product (Ries, 2011), the validation received during crowdfunding campaigns, which is based on actual product usage, can signal the potential for successful product commercial. However, despite our expectation presented earlier that both market and expert validation will lead to persistence, and while research shows similar effects of market and expert validation on issues such as crowdfunding product quality and funding decisions (Mollick and Nanda, 2016), both types of validation might not accurately signal commercial success.

 We expect that market validation will represent an accurate forecasting mechanism of future commercial success, because lead users are associated with product evaluation (Afuah and Tucci, 2012; Agrawal et al., 2014; Mollick, 2014; Poetz and Schreier, 2012; von Hippel, 1986) and because market validation is represented by lead users. However, compared to market validation, we do not expect expert validation to be as central for commercial performance. While expert validation can encourage persistence based on the trust individuals place in experts, the same entrenched knowledge that leads to such trust might also make their evaluations less accurate predictors of future commercial success. One notable shortcoming of experts’ domain specific experience is related to “cognitive entrenchment” (Dane, 2010), wherein an expert’s repeated domain specific experience creates stable schemas that limit what experts pay attention to (Cooper and Shallice, 2006; Henderson and Hollingworth, 1999; Walsh, 1995), and thus hinder their ability to accurately judge novel situations. For example, research suggests that as individuals acquire expertise, they tend to become inflexible within their domain (Chi, 2006; Lewandowsky et al., 2007; Lewandowsky and Kirsner, 2000) and often struggle to put aside their current knowledge when predicting future outcomes (Birch and Bloom, 2007; Camerer et al., 1989; Hinds, 1999; Hinds and Pfeffer, 2003; Hoch, 1988; Thaler, 2000). Given that domain experts are less likely to “recognize, interpret, and integrate new information and alter their perspectives” (Furr et al., 2012: 238), domain experts might evaluate products or services based on domain and general knowledge acquired through past experiences, rather than on current, specific product attributes. Such reliance on information about past experiences calls into question the ability of expert validation to accurately signal the future commercial potential of a product. Thus, while trust is often placed in expert judgments (e.g., Caves, 2000; Ginsburgh, 2003; Zuckerman, 1999), experts’ prior experience often leads to the development of heuristics that can limit or even distort their judgements (Cooper and Shallice, 2006; Dane, 2010; Henderson and Hollingworth, 1999; Walsh, 1995).

 Heuristics are thought to help organizational actors simplify the implementation of decisions (Bingham and Eisenhardt, 2014, 2011), yet these same heuristics can also bias the decision-making process (Tversky and Kahneman, 1974), leading to inaccurate situational assessments. These simple cognitive shortcuts and heuristics by experts are widely seen in the crowdfunding context where the campaign staff members simply mark projects as “staff pick”. For individuals seeking validation on their products, relying on such simple and heuristic expert feedback might therefore present some limitations that could lead to inaccurate product evaluations (e.g., Adelson, 1984; Frensch and Sternberg, 1989; Heath and Staudenmayer, 2000; Hecht and Proffitt, 1995; Hinds et al., 2001). Expert validation of crowdfunding products will not accurately reflect customers’ actual needs during commercialization, partly because experts rely on general domain knowledge, rather than on knowledge gained from the direct use of the product they are using. For individuals seeking an accurate signal of their product’s value, this suggests that expert validation within crowdfunding campaigns will not transfer as well to commercial contexts.

 In sum, we expect market validation will be a better predictor of commercial performance relative to expert validation. Accurately validating a product’s future commercial potential during crowdfunding campaigns requires information about customer problems and accurate feedback on how to solve them (von Hippel, 2005). We suggest that market validation reflects such information based on direct exposure to a product, while expert validation is not derived directly from a large pool of potential users. Furthermore, based on their repeated domain specific experiences and resulting schemas, experts are subject to cognitive entrenchment which can hinder the accuracy and comprehensiveness of their judgments in predicting future product performance. While both market and expert validation offer encouraging feedback to entrepreneurs about the *potential* of their product (thus leading to persistence), we expect that market validation received during launch and pre-launch activities is more indicative of actual customer preferences and is therefore likely to be relatively stronger indicator of commercial success compared to expert validation. Formally:

*Hypothesis 3: Market validation will be a stronger predictor of longer-term performance (commercial success) relative to expert validation.*

**4. Methods**

**4.1. Research Context: Crowdfunding and Commercial Platforms**

We chose the context of crowdfunding for our study, based on recent entrepreneurship research that has identified the value of this context for studying early-stage organizations (Anglin et al., 2018; Butticè et al., 2017; Da Cruz, 2018; Davis et al., 2017; Drover et al., 2017a; Josefy et al., 2017; Stevenson et al., 2019b). Crowdfunding is a particularly suitable context to investigate the role of market and expert validation on individuals’ decisions to persist and on future performance, because market and expert validation signals are publicly observable and measurable. We leveraged the Kickstarter.com portal for this research. Kickstarter is a crowdfunding website that helps artists, musicians, filmmakers, designers, and other creators find capital to fund their ventures. Kickstarter is the highest trafficked rewards-based crowdfunding website and has brought together an “enormous global community” of millions of creative workers and resource providers (Kickstarter, 2018). It thus offers an extremely large number of individuals who can provide validation concerning a product’s commercial potential. Kickstarter is an all-or-nothing funding platform; if a project does not reach its funding goal, the project creator does not receive any of the funding (i.e., a failed campaign).

 We chose crowdfunding as our context for multiple reasons. First, crowdfunding provides creative workers early validation on the market demand for their projects (Mollick and Nanda, 2016; Xu, 2018). Based on their exposure and usage of the product, crowdfunding backers can provide valuable information on the potential of a product for market launch. To ensure actual product usage by backers, we chose a specific sample of individuals who were seeking to raise money for a book they were writing and who frequently sent out chapters of their books to their backers as they wrote them. Feedback from the backers was subsequently conveyed through the crowd’s funding decisions. Likewise, Kickstarter staff (crowdfunding experts) could offer feedback by tagging certain Kickstarter projects as “projects we love.” Such feedback is a signal that the tagged project is considered valuable by experts within crowdfunding domains. Thus, we were able to capture both market (lead user) and expert validation.

 Moreover, Kickstarter funding is all-or-nothing based: project creators are allowed to keep the money they raise only if the total amount pledged by backers (the crowd) passes the funding target; if not, the project creator receives none of the funding. Examining unfunded projects therefore allowed us to focus on the effects of validation during failure without any potential confounding effects of financial backing. That is, because Kickstarter’s funding structure is all-or-nothing based, it ensures that all project creators whose campaigns fail do not take any money from investors, eliminating the concern that some failed projects persist and experience commercial success, while others do not because of the variation of funding amount they received.

Finally, our sample enabled us to capture commercial performance by tracking project creators from their failed Kickstarter projects (i.e. books) to their subsequent launch on Amazon. Amazon is one of the largest retailers for books and thus provides creative workers with an ideal forum to commercialize their products. Further, Amazon tracks each product’s performance through objective (sales ranking) and subjective (customer rating) performance, allowing us detailed means by which to measure commercial performance.

**4.2. Data and Sample**

We utilized an initial sample of 1,595 crowdfunding projects between 2011 and 2013. We chose this period for our failed campaign observations so that we could observe subsequent performance over the ensuing four-year period between 2013 and 2017. In the first quarter of 2017, we collected extensive data on each failed crowdfunding campaign by matching the sample with data on book publications from Amazon (including title, author, sales ranking, rating, publication date, price, etc.). We followed prior studies on Amazon when developing our matched crowdfunding and amazon database (Forman et al., 2009; Zhu and Liu, 2018).

Our sampling strategy centered only on one product category for two primary reasons. First, following prior crowdfunding research (Josefy et al., 2017; Mollick and Nanda, 2016; Stevenson et al., 2019a, 2019b), we focused on one category to remove industry biases that have been observed across different categories (McKenny et al., 2018). Second, we determined that the book publishing category was an ideal category for our study as it allowed us to effectively link observed project failures with subsequent commercial activity using data from the largest centralized book seller in the world, Amazon.com. The commercial book publishing market is unique because nearly all commercialized books are available on a central high-volume marketplace (Amazon.com). In contrast, other Kickstarter categories (e.g., Design and Tech) contain several different products with distinct marketplaces, making it difficult to compare subsequent commercial performance.

To create our proprietary dataset, we sought to match each failed Kickstarter project with a subsequent Amazon product launch by tracking their full name, book publication date (to ensure that they launched on Amazon after their Kickstarter campaign), book title, and whether the book was a physical copy, kindle copy, or both. This allowed us to collect data on whether the individual persisted with their publishing project after failure, and if so, how their products performed commercially on Amazon. Cases in which the author did not persist in selling on Amazon were used in the persistence models only but were not applicable in the commercial models. For all other cases, the Amazon database provided two measures of performance: objective performance (i.e., sales ranking), which we used as our primary dependent variable for commercial performance, and subjective performance (i.e., customer book ratings), which we used a secondary robustness check dependent variable for commercial performance.

**4.2.1. Dependent Variables**

 *Persistence***.** We measured persistence after failure with a dummy variable coded as “1” if the project creator persisted in completing their book and subsequently launched it on Amazon.com, and “0” if they did not.

 *Objective**performance*. Objective performance was measured with a variable that was created based on the overall sales ranking of the product (book) on Amazon. Amazon provides sales rankings data for all physical and kindle books on its website, providing a clear and objective performance variable for this research. The Amazon sales ranking variable has been widely used in prior research on management (Forman et al., 2009; Zhu and Liu, 2018). Our Amazon sample comprised physical books and kindle editions. There were three possible outcomes in our Amazon sample after persistence had occurred: (1) the author published a physical book, (2) the author published a kindle book, or (3) the author published both a physical book and a kindle book. All of these outcomes are considered positive signals of persistence, but because sales rankings differ between physical and kindle books, we needed to find a way to standardize our commercial performance variables for comparability. Thus, we computed a composite variable that allowed for relative performance comparisons across all cases.

Our composite measure was created through three steps: first, as Amazon rankings are listed from the highest selling book to the lowest (i.e., lower numbers mean better sales than higher numbers), we reverse coded all the rankings so larger numbers would represent better performance (i.e., inverse of ranking). To do this, we took the raw rank and subtracted 1 plus the lowest rank for all rankings for each variable. The result was that books with stronger sales had higher values than books with low ranks. We performed this step for physical books and kindle books independently. Next, we standardized the physical and kindle scores to enable more accurate comparison. Third, we created a composite score by computing the mean of the two variables (physical and kindle books) to create our primary performance variable (objective performance). In cases where an author published both a physical and kindle book, the author’s score would be the standardized mean of their sales data for both books. However, in cases where an author launched a book in a single format, their score would be the standardized mean for that format only. This allowed for relative performance comparability across cases.

*Subjective performance***.** As a robustness check on our objective performance measure, we decided to also use a subjective measure of performance. We measured subjective performance by the average number of stars (1-5) received for a project on Amazon. Customers who purchase products on Amazon can leave feedback about their experience by leaving star ratings from one to five. The number of stars symbolizes how positive or negative a buyer feels about a certain product and offers a way to filter, rank, and manage the [different choice](https://www.theatlantic.com/health/archive/2019/05/too-many-options/590185/)s presented to potential customers. Thus, the number of stars reflects the average customer rating for a given product and serves as a subjective measure of a product’s performance. In the correlation matrix, we demonstrated that the correlation between the subjective and objective performance measure was 0.35 (p < 0.01), indicating the consistency of these measures.

**4.2.2. Independent Variables**

 *Market validation*. Market validation occurs when the presentation of a business venture is evaluated by a given target market. Specifically, market validation refers to feedback on whether a business idea is of interest to potential customers. Following previous research that used funding allocations as a measure for customer validation (Da Cruz, 2018), we measured market validation as the percentage of funding pledged by backers on Kickstarter. Specifically, market validation was calculated as the percentage of pledges relative to the target amount. All cases in our sample were failed campaigns, and as a result of Kickstarter’s all or nothing policy, no case in our sample received any funding from Kickstarter. Therefore, our measure of validation and future commercial performance was not impacted by the actual dollar value received.

 *Expert validation*. Expertise is achieved by learning from repeated experiences within specific domains (Ericsson, 2006) and through the resulting acquisition of domain-specific knowledge (Ericsson, 2006; Ericsson et al., 2007; Schmidt et al., 1986). As such, Kickstarter staff have significant experience with crowdfunding and knowledge of the onboarding process. Kickstarter staff tag a small proportion of projects as “projects we love” (i.e., the project has been identified by the Kickstarter staff as a project they support). As with other studies illustrating the trust placed in expert opinions on matters involving quality and value (e.g., Caves, 2000; Ginsburgh, 2003; Johnson et al., 2018; Short and Anglin, 2019; Zuckerman, 1999) the chances of a project being successfully funded jumps significantly if it is selected by Kickstarter staff (Mollick, 2014). This is also in line with research showing that expert validations offer a signal for a venture’s investment potential (Baum and Silverman, 2004; Hellmann and Puri, 2002). We coded the variable expert validation as “1” for campaigns in our sample that were tagged by Kickstarter staff as “Projects we love”, and projects that did not receive this tag were coded as “0”.

**4.2.3. Control Variables**

We drew on previous research on crowdfunding (e.g., Anglin et al., 2018; Davis et al., 2017; Jiang et al., 2019a, 2019b; Mollick, 2014) to select appropriate control variables for the current study. First, we controlled *gender* with a dummy variable coded “0” for projects led by a male and “1” for projects led by a female as men and women may have crowdfunding experiences (Johnson et al., 2018), and therefore may hold potentially different interpretations of failure and post-failure behaviors. In addition, the structure of crowdfunding campaigns can influence funding outcome (Mollick, 2014) and consequently post-campaign behaviors. To account for such structural differences, we controlled for the effect of the funding goal of a campaign by the dollar amount of funding requested, *funding search time* by the length of time for which the campaign was ran (Davis et al., 2017), and *fundraising effort* bythe total number of words present in the campaign section of the campaign (Anglin et al., 2018). Finally, we controlled for *comment volume* by the total number of comments in the comments section of the Kickstarter project page. We controlled this total volume of comments to isolate the source of feedback (from lead users vs. experts) instead of the volume of feedback that influenced the post-failure behaviors.

**5. Results**

Three separate analyses were conducted for this study. First, a logistic regression was employed to test the impact of market validation, expert validation, and their interaction on persistence. Second, a relative weights analysis was conducted to provide a more accurate assessment of the relative effects of market and expert validation on objective performance. Finally, we used both subjective and objective measures of commercial performance to further validate the robustness of our results. Descriptive statistics and a correlation matrix are reported in Table 1.

<< Insert Table 1 here >>

**5.1. Hypotheses Testing**

The results of the regression models and hypotheses testing for Hypothesis 1 and 2 are displayed in Table 2. Hypothesis 1 stated that there would be a positive relationship between market validation and persistence. As shown in Table 2, Model 1 indicated a significant relationship between market validation and persistence (β = 1.00, p < 0.05), thus supporting Hypothesis 1. Hypothesis 2 suggested that the positive relationship between market validation and persistence would be strengthened by expert validation. Model 2 indicated a significant interaction effect of expert validation on the relationship between market validation and persistence (β = 5.54, p < 0.05), thus supporting Hypothesis 2. Figure 1 plots the interaction effect of expert and market validation and shows that the effect of market validations on persistence was greater for individuals who received expert validation.

<< Insert Table 2 and Figure 1 here >>

Hypothesis 3 stated that although the interaction between market validation and expert validation encourages persistence, market validation would be a stronger predictor of longer-term performance relative to expert validation. Given that Hypothesis 3 suggested that market validation would have a *relatively* higher effect on performance than expert validation, it was important for us to conduct an analysis that could accurately assess the relative contribution of each predictor in explaining performance. This is not possible with traditional regression analysis. A major challenge with regression analysis is that it only accounts for unique variance explained by the predictors in the model. However, predictor variables are typically somewhat correlated with one another, which can strip away potential explained variance of the correlated predictors and make relative comparisons difficult. Fortunately, a relative weights analysis allows for the partitioning of the total variance explained into pseudo-orthogonal portions, with each portion representing the relative contribution of one predictor variable. Thus, relative weight analysis “addresses the problem caused by correlated predictors by using a variable transformation approach to create a set of new predictors that are maximally related to the original predictors but are orthogonal to one another…which means the coefficients no longer suffer from the problems associated with collinearity” (Tonidandel and LeBreton, 2015: 208). The results of the relative weights analysis are presented in Table 3.

<< Insert Table 3 here >>

Following the procedures outlined by Tonidandel et al. (2009), the 95% confidence intervals for the relative weights (Johnson, 2004) and significance tests were based on a bootstrapping approach with 10,000 replications. The results indicated that for objective performance, the relative weight of market validation was significantly higher than expert validation, as the confidence interval for the comparisons did not include zero (CI-L = 0.0085, CI-U = 0.0590). Further, the relative importance of market validation as a percentage of the overall figure R2 (73.82%) was noticeably greater than the relative importance of expert validation (2.09%). Thus, the results from the relative weights analysis provide support for Hypothesis 3.

**5.2. Robustness Analyses**

To validate the robustness of our results, we also ran a regression analysis to test the effects of market and expert validation on both objective and subjective performance measures. Table 4 shows the robust regression results using both objective and subjective measures of performance.In Model 1 there was a significant relationship between market validation and objective performance (β = 1.19, p < 0.05), but not between expert validation and objective performance indicating that market validation had incremental value over and above expert validation in predicting commercial performance. This adds additional robust support for Hypothesis 3.

<< Insert Table 4 here >>

We also ran a second robustness regression model, substituting our primary objective performance measure for a secondary measure of performance (subjective performance). Model 2 indicated a consistent and significant relationship between market validation and subjective performance (β = 2.34, p < 0.05) but not between expert validation and subjective performance. This again supports Hypothesis 3, which held that market validation would be a more important predictor of commercial performance compared to expert validation. Through our relative weights analysis and two robustness regression models, we found support consistent with our expectations for Hypothesis 3.

**6. Discussion**

**6.1. Theoretical Implications**

Extant research points to a substantial amount of information and knowledge that can be gained following the experience of failure (Cardon and McGrath, 1999; Shepherd, 2003) and suggests that the information learned from failure can signal whether persisting after failure is likely to result in future success (e.g., Carver et al., 1979; Locke and Latham, 1990). While creative workers and entrepreneurs often seek such information to help validate the commercial potential of their products (Gerber and Hui, 2016), research has seldom considered how expert wisdom and collective wisdom can inform more distal outcomes such as commercial success. Thus, a better understanding of the role of validation in actual objective performance is needed. We addressed this need by distinguishing between market and expert validation and by illustrating how they both affect persistence and commercial performance after failure. This research therefore adds to the growing body of literature on rebounding from failure and the usefulness of market validation in early-stage venturing and creative work.

**6.1.1. Validation and Post-Failure Persistence**

Much prior literature has focused on failure attributions and learning based on the nature of the failure (e.g., cause, timing, and size of failure), but does not look into the specific sources of information and feedback that reside in the failure experience (Eggers and Song, 2015; Khanna et al., 2016). That is, those studies have not specified how the source of feedback can either facilitate or impede persistence and performance following failure. We extend this literature by separating and testing the effect of two specific types of feedback derived from “collective wisdom” on both persistence and commercial performance. We found that, for individuals dealing with failure, market and expert validation encouraged persistence and that market validation alone was predictive of the longer-term commercial performance.

In terms of persistence, we established that market validation signals provide guidance to individuals on whether their project or venture is on the right path and that, with increased effort and persistence, and whether future success is possible. The increase in persistence stems from the increased motivation and belief in the commercial potential of a product that results from receiving validation. In addition, we also found that expert validation could legitimatize market validation’s signal that future effort will pay off, thus increasing the chance of persistence after failure. Our research suggests that experts’ domain specific knowledge is trusted by individuals and helps legitimize the signal sent by market validation during failure. Just as expert validations associated with new ventures are deemed more legitimate, this research sheds light on how expert validations associated with market validation help legitimatize the idea that increased effort through persistence may lead to future success. In sum, the present research deepens our understanding of rebounding from failure and learning via validation by illustrating the important distinction between market and expert sources of validation for performance.

**6.1.2. Collective Wisdom and Performance Outcomes**

This study contributes to the topic of collective wisdom that is gaining traction in entrepreneurship theories (i.e., lean startup) by illustrating how collective wisdom affects persistence behaviors and distal measures of performance. We developed hypotheses that predict the relative importance of market versus expert validation on performance outcomes by leveraging lead user theory. Lead user theory holds that the involvement of leading-edge customers, whose product usage is ahead of market trends, provide feedback that can be indicative of commercial success (Morrison et al., 2004; von Hippel, 2005). While prior studies have investigated how collective wisdom impacts funder judgments (Stevenson et al., 2019a), how the role of feedback effects creator identity (Grimes, 2018), and how collective wisdom affects subjective measures of performance (Mollick and Nanda, 2016), little is known about how the validation derived from collective wisdom influences longer-term commercial performance. This is surprising given the importance of understanding the antecedents of performance in the literature on entrepreneurship and strategic management (e.g., Baron et al., 2016; Chandler and Hanks, 1993; Hmieleski and Sheppard, 2019; Krueger et al., 2000; Zahra, 1993).

The present study addresses this gap by focusing on two sources of validation gathered from a crowd-based platform. We also tracked failed project creators and assessed whether they launched subsequent commercial products and analyzed the performance of such commercialized products. This is useful in the sense that recent technological and financial development allow for more crowd-based information exchange for creative workers and entrepreneurs (e.g., crowdfunding), suggesting that crowdfunding platforms provide “collective wisdom” that can inform a product’s commercial potential. Indeed, the quality and accuracy of such feedback was recently validated by Mollick and Nanda (2016) who found significant agreement between the funding decisions of crowds and experts. We extend this important work and provide novel insights into the effects of collective wisdom on longer-term measures of commercial performance.

Our results demonstrated that market validation, as indicated by lead users’ exposure to pre-commercialized products, is an important signal of future commercial performance through the accurate feedback derived from the potential customers’ product usage. Further, we also found that market validation is relatively more important than expert validation for commercial performance. This may seem counter intuitive given that experts are believed to be trusted sources of domain specific knowledge and should thus offer accurate feedback concerning the future potential of a product. However, the same domain knowledge that leads to such trust also renders experts’ evaluations less accurate and comprehensive predictors of commercial success.

As a primary motive for entrepreneurs and creative workers who launch projects on crowdfunding portals is to receive validation concerning their products’ potential, understanding how such validation affects actual commercial performance is important. In this study, we showed that collective wisdom provides important feedback concerning the commercial potential of a product, yet we also found that the source of wisdom matters. That is, market validation is a relatively better indicator of future commercial performance compared to expert validation.

**6.1.3. Not Just Financial Capital: Crowdfunding as a Source of Valuable Information**

Finally, this study extends the crowdfunding literature in two important ways. First, we showed that, beyond the financial reward, crowdfunding portals like Kickstarter can provide valuable feedback from a crowd. Crowdfunding can be a useful validation tool, even in the cases where individuals fail to reach their funding goals. This is an important finding because prior crowdfunding studies tend to focus solely on the antecedents of funding outcome (i.e., how to secure funding), while ignoring its potential validation benefits (i.e., persisting after failure and commercial performance). Second, we established a direct link between crowdfunding performance (% of funding raised) and objective commercial performance (product sales). This is important as no study, to the best of our knowledge, has explored whether the validation received from a crowdfunding campaign translates to a firm’s subsequent objective commercial performance. By matching crowdfunding projects with Amazon sales data, we demonstrated that, for failed projects on crowdfunding, greater validation could convert to higher commercial performance even if the project does was not successful on Kickstarter.

**6.2. Managerial Implications**

This study has important managerial implications for early-stage entrepreneurs and creative workers. First, our study for the first time shows that although individuals may fail during crowdfunding, the validation received during their campaigns can encourage persistence and future efforts that bring about long-term success. Thus, failed crowdfunding participation may increase entrepreneurial intentions and subsequent entrepreneurial actions. Individuals who fail can utilize this validation as a source of inspiration to persist on with their ventures and potentially experience future success. Second, the validation received during early failure experiences can facilitate learning and future improvements when transitioning to the commercial stage. Importantly, however, our results indicate that these benefits depend on the source of validation. For those contemplating persisting after failure, both expert and market validation may seem to be a viable indicator of commercial potential, yet our findings indicated that market validation is a better predictor of true future commercial performance. This means that it is imperative for entrepreneurs and creative workers to distinguish between these two different types of validation and utilize them appropriately to improve.

**6.3. Limitations and Future Research Directions**

Like all studies, this research has several limitations. First, this study focused only on one specific failure event: crowdfunding failure. There are several other distinct types of organizational failure, such as technological failure and management failure (Eggers and Song, 2015; Khanna et al., 2016) that future research should investigate. Specifically, it would be fruitful to examine the distinctive nature and consequences of different types of failure. For example, our findings suggest that validation from crowds during R&D failure could potentially provide important benefits for persistence and future product performance. Given that early failures in R&D provide better learning opportunities for firms than failures that come later in the R&D process (Khanna et al., 2016), might expert validation lead to more “intelligent failures” (Sitkin, 1992) during early stage failures when developing patents is crucial, while expert validation might be more helpful in later stage failures, when customer feedback is more important.

Second, while we did consider the interaction effect between expert validation and market validation on persistence, we believe there are other moderators worthy of consideration, including personality and environment characteristics. One such moderator could be regulatory focus (Gamache et al., 2015), whereby a prevention-focus or promotion-focus might help or stymie their seeking and processing of feedback. For example, promotion focused individuals are opportunity seeking and therefore often dismiss negative information, whereas prevention focused individuals are concerned with preventing potential failures, and thus actively seek out information to help prepare them for such failures (McMullen and Kier, 2016). Thus, an interesting question is whether promotion focused individuals are more likely to take advantage of market and expert feedback during failure because they actively seek out such validation (of success). Conversely, would prevention focused individuals “fail to notice” such information because it does not help prevent future failures?

Another limitation is that we only examine commercial performance as the outcome. In crowdfunding contexts, another critical outcome to investigate is subsequent fundraising (Stevenson et al.,2019b). For example, does crowdfunding failure indicate a lack of future funding potential from angel investors and venture capitalists. The answer to this question could advance the crowdfunding literature by examining how signals during crowdfunding failure possibly influence the extent to which investors are willing to fund previously unsuccessful ventures. Finally, this study bares the generalizability limitation in that we only examined failure within the book category in one crowdfunding site, namely Kickstarter. Future research could expand to other product categories and other crowd-based platforms such as Indiegogo. In doing so, future research could also consider other market validation mechanisms with more fine-grained measures such as product review and customer interviews, instead of solely relying on the funding percentage.

**7. Conclusion**

We contribute to the growing body of literature on market validation and rebounding from failure by explaining how two types of wisdom, market and expert validation, affect both persistence and commercial performance following failure. Utilizing failed crowdfunding campaigns in the book publishing category and linking them with post-failure Amazon book publishing data, we found that market validation could encourage persistence following failure by signaling the future potential of a creative product, and that this signal is deemed more legitimate by individuals who also receive expert validation. Further, we found that market validation was relatively more important for predicting commercial success compared to expert validation, suggesting that while both sources of validation encourage persistence, they are not equally important for signals of future performance.

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**Figure 1 Interaction Plot for Persistence Model**



|  |
| --- |
| **Table 1 Correlations and Descriptive Statistics** |
|  |  |  |  |  |  |  |  |  |  |  |  |
|    Variable | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1 | Persistence | 0.30 | 0.46 |  1.00 |   |   |   |   |   |   |   |   |
| 2 | Objective Performance | -0.07 | 0.96 | n.a. |  1.00 |   |   |   |   |   |   |   |
| 3 | Market Validation | 0.09 | 0.14 | 0.06\* |  0.18\*\* |  1.00 |   |   |   |   |   |   |
| 4 | Expert Validation | 0.02 | 0.14 | -0.02 | -0.00 |  0.19\*\* |  1.00 |   |   |   |   |   |
| 5 | Gender | 0.67 | 0.47 | -0.01 |  0.00 |  0.00 |  0.03 |  1.00 |   |   |   |   |
| 6 | Funding Goal | 8327.11 | 11827.32 | -0.04 |  0.06 | -0.11\*\* |  0.02 |  0.07\*\* |  1.00 |   |   |   |
| 7 | Funding Search Time | 41.63 | 17.34 |  0.03 | -0.03 |  0.00 |  0.04 |  0.03 |  0.02 |  1.00 |   |   |
| 8 | Fundraising Effort | 456.15 | 482.24 |  0.00 | -0.02 | -0.01 | -0.00 | -0.01 |  0.02 | -0.04 |  1.00 |   |
| 9 | Comment Volume | 0.56 | 1.60 |  0.01 |  0.09 |  0.37\*\* |  0.18\*\* | -0.00 |  0.09\*\* |  0.05 | -0.00 |  1.00 |

 Note: Gender: 0 = Male, 1 = Female. \*\*: p < 0.01. There is no correlation shown between objective performance and persistence because objective performance is only available when persistence = 1, otherwise objective performance is missing when persistence = 0. N = 481 objective performance and N = 1,595 for all other variables.

|  |  |
| --- | --- |
| **Table 2 Logistic Regression Models**  |  |
|  | Dependent variable: Persistence |  |
|  | Model 1 |  | Model 2 |  |
|  | β | s.e. |  | β | s.e. |  |
| Gender | -0.04 | 0.12 |  | -0.03 | 0.12 |  |
| Funding Goal | 0.00 | 0.00 |  |  0.00 | 0.00 |  |
| Funding Search Time |  0.00 | 0.00 |  |  0.00 | 0.00 |  |
| Comment Volume | 0.00 | 0.04 |  | 0.00 | 0.04 |  |
| Fundraising Effort |  0.00 | 0.00 |  |  0.00 | 0.00 |  |
| Expert Validation | -0.59 | 0.45 |  |  -2.37\* | 1.06 |  |
| Market Validation (H1) |  0.99\* | 0.42 |  | 0.79 | 0.43 |  |
| Expert Validation x Market Validation (H2) |  |  |  |  5.54\* | 2.80 |  |
| -2 Log Likelihood | 1942.42 |  |  | 1936.58 |  |  |
| N = 1,595 \* = p < 0.05.  |  |

**Table 3 Relative Weights Analysis**

|  |  |
| --- | --- |
|  | Dependent variable: Objective performance |
| Predictor | Raw Weights | CI-Lower Bound | CI-Upper Bound | Raw Weight% as % of R2 |
| Gender | 3.20 | -0.0243 | 0.0039 |  0.08% |
| Funding Goal | 4.60 | -0.0122 | 0.0180 |  11.35% |
| Funding Search Time | 8.04 | -0.0218 | 0.0066 |  2.00% |
| Comment Volume | 3.96 | -0.0136 | 0.0153 |  9.81% |
| Fundraising Effort | 3.47 | -0.0220 | 0.0042 |  0.86% |
| Expert Validation (H3) | 8.45 | -0.0220 | 0.0065 |  2.09% |
| Market Validation (H3) | 2.98 | 0.0051 | 0.0576 |  73.82% |
| R2  | 0.04 |  |  |  |
| N = 481 |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |

|  |  |
| --- | --- |
| **Table 4 Robustness Checks** |  |
|  | Dependent variable: Objective performance  | Dependent variable: Subjective performance |  |
|  | Model 1 |  | Model 2 |  |
|  | β | s.e. |  | β | s.e. |  |
| Gender | 0.01 | 0.09 |   |  0.09 | 0.19 |  |
| Funding Goal |  0.00 | 0.00 |  |  0.00 | 0.00 |  |
| Funding Search Time | 0.00 | 0.00 |  |  0.01 | 0.00 |  |
| Comment Volume |  0.01 | 0.03 |  |  0.04 | 0.06 |  |
| Fundraising Effort |  0.00 | 0.00 |  |  0.00 | 0.00 |  |
| Expert Validation | -0.96 | 0.72 |  | -2.13 | 1.50 |  |
| Market Validation |  1.19\* | 0.34 |  |  2.34\* | 0.71 |  |
| Expert Validation x Market Validation |  0.83 | 1.32 |  | 0.66 | 2.73 |  |
| R2 | .04 |  |  | .04 |  |  |
| Note: \* = p < 0.05. N = 481 |  |

1. As is the case in our study; we selected only failed campaigns for our sample. [↑](#footnote-ref-1)