B.J. Allen, Deepa Chandrasekaran, & Suman Basuroy

Design Crowdsourcing: The Impact on New Product Performance of Sourcing Design Solutions from the "Crowd"

The authors examine an increasingly popular open innovation practice, "design crowdsourcing," wherein firms seek external inputs in the form of functional design solutions for new product development from the "crowd." They investigate conditions under which managers crowdsource design and determine whether such decisions subsequently boost product sales. The empirical analysis is guided by qualitative insights gathered from executive interviews. The authors use a novel data set from a pioneering crowdsourcing firm and find that three concept design characteristics—perceived usability, reliability, and technical complexity—are associated with the decision to crowdsource design. They use an instrumental variable method accounting for the endogenous nature of crowdsourcing decisions to understand when such a decision affects downstream sales. The authors find that design crowdsourcing is positively related to unit sales and that this effect is moderated by the idea quality of the initial product concept. Using a change-score analysis of consumer ratings, they find that design crowdsourcing enhances perceived reliability and usability. They discuss the strategic implications of involving the crowd, beyond ideation, in helping transform ideas into effective products.

Keywords: product design, crowdsourcing, user design, open innovation, new product development

Online Supplement: http://dx.doi.org/10.1509/jm.15.0481

Increasingly, firms are tapping into a wide range of external sources of knowledge to source innovations (Chesbrough 2003; Laursen and Salter 2006). One popular facet of this new trend is the leveraging of online infrastructure to tap an underexplored and richly heterogeneous pool of knowledge resident in the general population of consumers for innovative ideas (Bayus 2013), a practice termed "crowdsourcing." Extant research on the efficacy of using external sources of knowledge for innovation has centered on the opportunity identification stage (Foss, Lyngsie, and Zahra 2013). For example, research in marketing has examined the practice of involving the crowd during ideation (e.g., Bayus 2013; Poetz and Schreier 2012) and has suggested that such early involvement in new product development (NPD) empowers potential consumers while enabling firms to attract more participants overall and more diverse participants to the idea generation process (Fuchs, Prandelli, and Schreier 2010; Schreier, Fuchs, and Dahl 2012).

Recent evidence has suggested that the role of external knowledge sources may go beyond opportunity identification and extend to opportunity exploitation stages (Foss, Lyngsie, and Zahra 2013). Congruent with this idea, firms are increasingly using crowdsourcing in phases following ideation, specifically, in the solicitation of actionable design solutions (see Table 1), a practice we call "design crowdsourcing." We define design crowdsourcing as the practice of soliciting functional design[1] solutions from the crowd. For example, crowdsourcing platforms, such as Redclay.com, allow firms to submit new product design briefs and seek crowd input for the development and/or refinement of the design. In such situations, the client firm already has a new product idea, but may lack the resources or know-how to bring this idea into fruition, and, therefore, seeks external input from the broader user community to help create a manufacturable design.

B.J. Allen is Assistant Professor of Marketing, Sam M. Walton College of Business, University of Arkansas (email: BAllen@walton.uark.edu). Deepa Chandrasekaran (corresponding author) is Assistant Professor of Marketing, University of Texas at San Antonio (email: deepa.chandrasekaran@utsa.edu). Suman Basuroy is Department Chair and Graham Weston Endowed Professor of Marketing, University of Texas at San Antonio (email: Suman.Basuroy@utsa.edu). The authors thank the Carolan Research Institute and Dr. Joel Saegert for helping fund this research; participants at the Marketing Science Conference and PDMA Research Forum for their helpful comments; and Dr. Ram Ranganathan, Dr. Raji Srinivasan, and Dr. Richard Gretz for detailed comments on earlier versions of the article. The authors are deeply grateful to all interviewees for their invaluable insights. Michael Haenlein served as area editor for this article.

[1]Many of the design crowdsourcing platforms focus on the manufacturing makeup of design; thus, our study focuses on functional design rather than aesthetics. This use is also consistent with extant research studying the early phases of design with a "focus on functional performance in product design, as opposed to the product's aesthetic qualities or appearance" (Dahl, Chattopadhyay, and Gorn 1999, p. 19).

ISSN: 0022-2429 (print)
1547-7185 (electronic)

Journal of Marketing
Vol. 82 (March 2018), 106–123
DOI: 10.1509/jm.15.0481

TABLE 1
Examples of Companies Utilizing Design Crowdsourcing and Design Crowdsourcing Platforms

Organization	Company Description	Use of Design Crowdsourcing
Quirky[a]	Pioneering socially developed product company founded with the vision of making invention accessible.	After selecting a new product idea, Quirky asks its community to help with the design by "[submitting] sketches, images, videos, and prototypes that illustrate industrial design directions for [the product]."
Crowdspring[a]	Platform for bringing companies and designers together	Various companies post creative briefs with the needs and requirements for new industrial and consumer products. Designers submit design concepts for the product and the firm chooses the ones to utilize.
Unilever	Consumer packaged goods company	Unilever operates an open-innovation website, Unilever Foundry, where it collaborates with its community, and many projects involve design crowdsourcing. As stated on its website, "Often we will have specific challenges on which we'd welcome your collaboration: a new formula, a new technique, new packaging or a *fresh design solution to a product we already have in mind*" (Unilever 2016, emphasis added).
Fiat	Global car company	Fiat crowdsourced the design of its Fiat Mio: "Fiat, sought a design for its 2009 concept vehicle, the Fiat Mio. Rather than turning inward to its core team of designers and engineers to come up with the new look, the company... let the world decide how the car would look, feel, and drive" (Markowitz 2011).
eYeka	Third-party website that serves as crowdsourcing platform for brands. Client list includes Procter & Gamble, Nestlé, and Citroen	Firms post ideas for new products along with creative briefs and ask the community to submit design ideas. For example, one firm asked for designs for a new interactive learning and entertainment product for children, and the community submitted design ideas.
Local Motors	Open-innovation car company and community	Local Motors launches a car idea to its community and asks for help in creating and implementing the design. The community, consisting of designers and engineers, collaborates and submits designs for the various car parts.
General Electric (GE) Open Innovation	Branch of GE that generates ideas from consumers via crowdsourcing challenges	GE gives a description of the product it is looking for, along with a few sample sketches, and asks the community to submit design concepts. Submissions include text descriptions of how the product works, along with pictures/sketches. Winners receive cash rewards.
Hyve Crowd	A German third-party crowdsourcing site. Clients include Audi and BMW.	Firms post various requests for product-related ideas, many of which include design requests. For example, companies highlight a specific type of product they are looking for and ask the community to submit concepts and design solutions.
Red Clay	Platform that connects brands with a community of industrial designers.	Small businesses submit product design briefs that are worked on by a community of industrial designers. The project is matched to a small group of designers who submit designs that are then chosen by the firm in a contest format. Thereafter, the firm owns all IP.
Design2Gather	Third-party crowdsourcing platform designed to help firms develop ideas into actionable designs	Companies post product ideas that are then worked on by hundreds of designers to develop a manufacture ready design. Their tagline is "making your idea reality."

[a]Sources of the data for the empirical analysis in the study.

These compelling anecdotal examples raise interesting research questions: Does design crowdsourcing lead to a better new product development process? Does design crowdsourcing lead to improved products and performance? Whether and how crowdsourcing affects critical downstream activities, such as executing ideas in the NPD process, has received little research attention. In fact, studies have highlighted the significant challenges of internalizing external input into the NPD process, including the rejection of outside input by insiders (Katz and Allen 1982), the costs of distant searches (Afuah and Tucci 2012), and the difficulty of communicating tacit information needed for problem solving (Von Hippel 1994). Furthermore, scant research has linked crowdsourcing to product performance (for an exception, see Nishikawa, Schreier, and Ogawa 2013), and current literature has focused primarily on crowdsourcing during ideation.

The goals of this research are to examine (1) whether and how design crowdsourcing affects the NPD process; (2) what design antecedents lie behind the decision to crowdsource; (3) whether design crowdsourcing has a positive impact on product performance—and, if so, to identify some boundary conditions for this effect; and (4) whether design crowdsourcing helps improve the functional design attributes of product ideas. We use the knowledge-based theory (Alavi and Leidner 2001; Chang and Taylor 2016), as well as exploratory insights from interviews (suggested by Kumar et al. [2016] to uncover new phenomena), to propose that (1) the crowd is a repository of design knowledge and design crowdsourcing is a mechanism that enables firms both to tap into the broader community for workable design solutions and to assimilate/exploit these solutions to aid the transformation of new product ideas into products, (2) such identification and the exploitation of external design solutions will improve new product performance, and (3) the efficacy of design crowdsourcing on performance will depend on the quality of the original product ideas.

We test our hypotheses using a novel data set of 86 new products collected from Quirky, a pioneering, community-driven NPD website. The empirical analysis on this data set indicates that the probability of design crowdsourcing was influenced by a need to increase perceived usability and reliability and to decrease technical complexity. Using an instrumental variable procedure (Wooldridge 2010) for dealing with endogenous binary variables, we find that design crowdsourcing has a positive effect on sales, as proposed, with an important boundary condition. The positive impact of design crowdsourcing on sales is contingent on the idea quality of the original product concept—design crowdsourcing is associated with increased sales when the idea quality of the product concept is low. Furthermore, design crowdsourcing enhances perceived reliability and usability from idea to final product.

Our results suggest that design crowdsourcing can help managers move a greater number of ideas through development by using the community's assistance in making (initially) less-promising ideas marketable, thus improving the effectiveness of the NPD process. Rather than discarding such ideas, firms may use external sources of knowledge to develop them and interact with these sources extensively to ensure that the outcome is of high quality. In addition, we highlight specific design functionalities that managers can improve using design crowdsourcing, allowing for a more targeted approach when leveraging crowdsourcing. Finally, our findings suggest opportunities for crowdsourcing platforms to market themselves as solution spaces that provide tangible downstream benefits through enhanced functional attributes. The next sections present the conceptual development as well as managerial insights into design crowdsourcing leading to the hypotheses, data, modeling methodology, results, and discussion.

Conceptual Development

Design Crowdsourcing and Knowledge Management

Grant (1996, p. 112) states that "fundamental to a knowledge-based theory of the firm is the assumption that the critical input in production and the primary source of value is knowledge." A firm's ability both to create new knowledge and to apply knowledge forms the basis of developing a competitive advantage (Alavi and Leidner 2001). One online mechanism that grants firms access to a wide, diverse knowledge pool is crowdsourcing (Schreier, Fuchs, and Dahl 2012). Extant marketing literature has treated the crowd as a resource base for new ideas and treated crowdsourcing as a mechanism that enables the identification of new ideas from this resource base. However, firms may also need to engage external resources, such as the crowd, for opportunity exploitation (Foss, Lyngsie, and Zahra 2013). We propose that the crowd is also a knowledge source for design solutions, which are utilized to solve firm-specific problems in the context of new product development.

Knowledge management theory suggests that the identification/acquisition and assimilation/exploitation of externally generated knowledge improves innovation performance (Cohen and Levinthal 1990). However, in the context of design crowdsourcing, little is understood about how this process manifests itself in practice. Given the lack of research into design crowdsourcing, our research begins with qualitative interviews to investigate this question and then integrates the findings from the interviews with a literature review.

Qualitative Interviews

We conducted exploratory interviews with practitioners from the United States, China, Italy, Israel, and the United Kingdom who had extensive experience with crowdsourcing (see Table 2). Because the purpose of these interviews was to assist in theory development, we ensured that the interviewees were familiar either with the experiences of established firms that engaged in crowdsourcing or with start-ups whose business models involved crowdsourcing. We followed a standard format and approach for each interview.[2] The authors carefully

[2]After a brief description of the research project, each interviewee was asked about issues related to crowdsourcing and how those outside the organization help with providing design solutions. In three of the cases, the interviewee chose to reply to these questions by email, in which case further emails were sent to follow up on responses, if needed. We supplemented these insights with a search for popular press articles to gain a broader understanding of how crowdsourcing aids product development, using the LexisNexis database, as well as by examining firms' internal websites, design crowdsourcing websites, and blog posts.

TABLE 2
Description of Managerial Interviews

No.	Title	Firm Description
1	Vice President, Marketing and Technology	Consulting firm, helps organizations with crowdsourcing & marketing
2	Co-Founder and Chief Operating Officer	Third-party design crowdsourcing platform
3	Senior Brand Manager	Large manufacturing firm known for use of crowdsourcing product design
4	Editor (researches and publishes articles on crowdsourcing)	Website for business news, research, and insights
5	Brand Manager	Large CPG firm that organizes numerous crowdsourcing campaigns
6	Consumer Trends Consultant (consults on crowdsourcing)	Marketing consulting firm that advises organizations on consumer trends
7	Founder and Chief Financial Officer	European crowdsourcing company
8	Content Manager	European crowdsourcing company
9	Founder	Consulting firm that helps firms facilitate open innovation challenges
10	Creative Director	Third-party crowdsourcing firm that works exclusively in design crowdsourcing
11	Co-Founder and Chief Operating Officer	Third-party design crowdsourcing site with emphasis on "design challenges"
12	Senior Technologist (led development of first crowd-sourced laptop)	One of the largest computer manufacturers in the world
13	Former President	One of the largest crowdsourcing firms in the world

read the interview transcripts and notes and documented the main concepts and themes that emerged.

Insights on Design Crowdsourcing and New Product Performance

In this subsection, we explore the link between design crowdsourcing and new product performance by utilizing common themes from the interviews and the literature review.

Design crowdsourcing helps firms move product ideas into development. "How can I execute my innovative ideas?" is a question that represents an increasing concern for chief executive officers and business executives (eYeka 2016). For example, an executive of a design crowdsourcing firm noted this about her clients:

> These people come with new ideas in innovation; they have a great innovation, but they're not really sure how to make that innovation happen. (Cofounder and chief operating officer, design crowdsourcing firm)

Design crowdsourcing helps make development a reality in situations where firms know what product or solution they want but are looking for an executable design. The difference between using the crowd to obtain design solutions and using the crowd for ideation itself seems to be twofold: First, the emphasis of ideation crowdsourcing may be on an unconstrained flow of ideas, whereas design crowdsourcing involves the crowd tackling a focused need and, thus, all submissions and iterations are working toward solving the *same* problem. Second, the solution space in design crowdsourcing may also be smaller (i.e., more manageable). From our investigation of design crowdsourcing websites, the number of design submissions (being in the tens or hundreds and not thousands, as, for instance, in ideation challenges) were more tractable for clients (especially small businesses). Thus, design crowdsourcing moves product ideas closer to development and, thus, to delivering value:

> Different crowds [are viewed] as layers of technology that can powerfully work together. In online sourcing from a crowd ... you're connecting multiple people to get to an end solution. The ideas become more powerful when you bring these different skill sets together ... to get to a solution a little more efficiently. (Cofounder and chief operating officer, third-party design crowdsourcing platform)

Design crowdsourcing helps identify new sources for and types of design solutions. A consistent theme from our interviews was that although in-house specialists may be constrained by their past experience while trying to create new design solutions, crowdsourcing brings in novel and fresh solutions to design problems. For example, when asked why managers would crowdsource product design, one expert noted:

> [Managers are influenced by] a desire to bring a fresh insight to the design process. Crowdsourcing can help with the design

> process by bringing new ways of thinking and unique ideas. An in-house team can be impacted by things like legacy ideas, office politics, and being too close to the product. By bringing in outside help it brings a fresh approach, which aids the creative process. (Editor and author on crowdsourcing)

When asked whether there were differences in the kinds of solutions companies were looking for, an executive commented on the criticality of diversity of perspectives:

> I think it really depends on the company because some of our smaller and medium sized companies don't have any design talent in-house, so they're really looking for that design. Then the companies that do have design talent in-house, they're looking to get more of a new perspective and understanding that when you pull more than two designers into a project, you're going to get a very diverse amount of perspective, which starts to really begin the true design thinking of why we design and go through the full process, which is pulling those different ideas together, iterating on them this idea that there's a community to build on them versus one person's way of thinking. (Cofounder and chief operating officer, design crowdsourcing firm)

This point is consistent with the literature that finds that user involvement in design generates greater numbers of diverse, need-specific, and unconstrained designs (Schreier, Fuchs, and Dahl 2012) compared with in-house design. Furthermore, managers believed that the utilization of the crowd led to a greater congruency between design and user needs. As noted by a leading design expert:

> Just having ideas doesn't work. The question is, really, who are you solving it for? Insights and the human side of design is the most important aspect you can add.... I think using design as a differentiator is what we're seeing in the market. (Former president of a leading crowdsourcing firm/design consultancy group)

Managers are continually looking for ways to respond to consumers' wants and needs in a way that optimizes firm resources (Fennell and Saegert 2004). Firms are thus able to use design crowdsourcing to integrate knowledge to develop a product more congruent with consumer needs, which is more likely to succeed when it enters the marketplace.

Design crowdsourcing increases available resources for NPD. Nearly every manager interviewed mentioned that design crowdsourcing serves as a resource-supplement strategy that simplifies and accelerates the flow of the NPD process:

> A lot of those (client) companies are small. They need to move quick and they need to keep their prices down, so budget becomes a big concern. Innovation becomes a concern. (Cofounder and chief operating officer, design crowdsourcing firm)

> I'm doing all the things that I'm doing as a typical product development cycle, but I'm actually accelerating that by getting the crowd involved.... You know your product, you know your design. You know what you're good at, but you're intentionally leveraging the crowd to get into the market fast. (Vice president, crowdsourcing consulting firm)

Popular press publications also use words like "efficiency," "simplify," and "streamline" when describing why firms crowdsource during NPD. Traditional NPD processes are constrained by resource availability, such that only a small number of the "best" ideas can be implemented. Accessing the crowd increases the knowledge resources available to a firm by both leveraging the skills and expertise of hundreds of people outside the organization and freeing up firm resources, allowing for the development of a greater number of ideas.

Design crowdsourcing may be iterative and collaborative. Design crowdsourcing is not just about obtaining new ideas but also about refining and fine-tuning ideas, and it provides the capability to engage in a high degree of collaboration with the broader community. This represents one of the key differences from traditional ideation crowdsourcing, wherein the firm may select novel ideas, but there is not much collaboration going forward (Bayus 2013). The selected designers, suppliers, and clients often (depending on the crowdsourcing platform) work together collectively, using insights they gain from design submissions to iterate toward a manufacture-ready product. Because members of the "crowd" are neither familiar specialists nor a part of the internal team, there is a need for closer monitoring and internal involvement to move toward a solution. Furthermore, the process of iteration often results in a better translation of tacit suggestions to workable solutions:

> My crowd is going to be an extended team within my company. (Vice president, crowdsourcing consulting firm)

> Today we have an on demand industrial design community.... They start to look at a lot of these different crowds as layers of technology that can powerfully be able to start the work together. In online sourcing from a crowd [you are not just] able to connect [with one person], but you're connecting multiple people to get to an end solution. (Cofounder and chief operating officer, design crowdsourcing platform)

In summary, a firm has the choice of whether to involve the crowd in the design phase or to simply refine the product design in-house. Our exploratory insights suggest that design crowdsourcing enables firms to (1) translate ideas into executable solutions, (2) provide access to new sources that can provide novel and meaningful design solutions, (3) help increase the resources available for NPD, and (4) help create a more iterative and collaborative process in integrating external solutions with in-house guidance. Because a firm's "ability to identify, assimilate, and exploit knowledge from the environment" is related to a firm's innovative performance (Cohen and Levinthal 1990, p. 128), it follows that identifying, assimilating, and exploiting knowledge using design crowdsourcing should increase a new product's performance.

In the specific case of NPD, we expect all four of these factors to contribute to new product success, as prior literature has suggested that (1) the development of an increased number of new products that more accurately reflect customer preferences during the NPD process improves NPD performance (Joshi and Sharma 2004); (2) design newness and creative solutions that are novel and meaningful to consumer needs are key determinants of new product success (Talke et al. 2009); (3) slack creates resources that help better exploit existing competencies, explore new competencies, and develop innovations (Atuahene-Gima 2005); and (4) conscious and meaningful customer interactions in the form of engaging with the design of new products (along with or in addition to ideas) will provide a differentiating advantage to the firm in the marketplace (Ramani and Kumar 2008).

Thus, drawing on the insights derived from our interviews and past theory, we propose:

H_1: Design crowdsourcing has a positive effect on new product performance.

Moderating Effect of Initial Idea Quality

A key premise of the prior hypothesizing on crowdsourcing's positive effect on new product performance is that crowdsourcing the design will help make the product more marketable. What if the initial raw concept (idea) was already marketable? Kornish and Ulrich (2014) establish that better ideas, as assessed by commercial value (purchase intent of the raw concepts), lead to increased sales. Their finding raises two important questions: (1) Is there incremental value added by involving the crowd in suggesting design solutions if the initial product idea itself is good? and (2) Can firms extract value from lower-quality ideas rather than from discarding them?

The managerial insights showed that design crowdsourcing likely leads to an evolutionary process of the new product idea. As one manager said of a product that she managed, "The product just kept developing and iterating." Because design crowdsourcing draws on the knowledge of the crowd to improve functional attributes and involves a process of iteration, it is likely that product ideas with a significant need for improvement will benefit most from the process. We propose that when the idea quality is low, the incremental value of design crowdsourcing will be high. When the initial quality of the raw idea is high, the firm might be better off with in-house design.

This line of thinking is consistent with the broader nature of organizational conflict in the exploration of new and exploitation of current knowledge. Andriopoulos and Lewis (2009) conduct a comparative case study approach of five leading ambidextrous firms in the product design industry. They note that whereas exploitation demands efficiency and convergent thinking to improve product offerings, exploration involves search and experimentation efforts to generate novel recombinations of knowledge, creating tension. Furthermore, there is tension between, on the one hand, the use of standardized best practices for NPD that may breed rigidity, and, on the other hand, engagement in new routines that may bring in fresh thinking and free up resources but may also be less efficient. Organizations often have best practices and routines in place to progress their most promising ideas with their in-house research and development/design teams. Thus, for the best ideas, design crowdsourcing may be less beneficial, because the challenges associated with processing and assimilating new and diverse design solutions may outweigh potential benefits. However, for less marketable ideas, design crowdsourcing may facilitate the process with better interaction to help evolve and develop ideas, leading to better performance. Furthermore, lower-quality concepts can be used as an opportunity to learn which attributes are important to customers, which in turn helps firms develop higher-quality products (e.g., Ries 2011, p. 107). Design crowdsourcing can help uncover such attributes to improve the NPD process. Thus, we propose,

H_2: The positive impact of design crowdsourcing on new product performance is greatest for products with low initial idea quality.

Functional Design Attributes as Antecedents to Design Crowdsourcing

Design crowdsourcing is not a one-size-fits-all strategy to be leveraged ubiquitously. Rather, as one executive noted, "[it needs to be] a very cautious and well-designed, well-thought-out approach." The decision to design crowdsource is strategic and based on product, people, and cost considerations. The next question we consider is how specific design attributes of the product concept may guide the choice of design crowdsourcing. We searched extensively within various literature streams for product design attributes that influence product success and user acceptance (e.g., Poetz and Schreier 2012). We retained five influential design attributes judged by current literature to be relevant and useful in enhancing user response and experience, as well as two core objectives for the utilization of external inputs from users.[3] We then assessed whether the crowd's design knowledge and inputs may help better these attributes. Next, we describe briefly how these functional attributes influence decisions to crowdsource (see Web Appendix Table WA1 for references to these attributes from extant literature and managers).

Technical complexity. We define technical complexity as the perceived degree of complexity due to the technical nature of the design. New products in their initial phases are often complex and need to be simplified. The more complex the design, the costlier it is to build, sell, and service a product (Radjou and Prabhu 2015) and the greater the need for access to a wider range of capabilities, user involvement, and design choices (Gann and Salter 2000; Hobday 2000). Insights from theory and practice (Web Appendix Table WA1) suggest that managers may use design crowdsourcing to simplify the technical complexity of the product. Thus, we expect that the probability of design crowdsourcing will increase with increased levels of perceived technical complexity of the product idea.

Usefulness. Usefulness is defined as the product's ability to meet customer needs (Moldovan, Goldenberg, and Chattopadhyay 2011). User-designed products are perceived as better able to meet the needs of customers than professionally designed products (Poetz and Schreier 2012). Drawing on extant literature and current practice (Web Appendix Table WA1), we expect that the probability of design crowdsourcing will increase with lower levels of perceived usefulness of the product idea.

[3]To the best of our knowledge, this is the first article to test all five design variables simultaneously in the same study. Subsets of these variables are linked together theoretically in extant literature. For example, Bloch (1995) groups durability, technical sophistication, and ease of use as product-related beliefs created or influenced by product form and classifies novelty as affecting how consumers perceive the product relative to other products. Noble and Kumar (2010) divide design elements into three categories: rational value, kinesthetic value, and emotional (differentiating) value. Our five identified dimensions thus emphasize function (reliability and technical complexity providing rational value), user experience (ease-of-use and usefulness providing kinesthetic value), and differentiation (novelty providing emotional value).

Reliability. Perceived reliability relates to how well a product is likely to perform, encompasses aspects such as durability and dependability (e.g., Grewal et al. 1998), and influences perceptions of value and purchase intentions. Managers may look to the crowd for ideas on enhancing reliability. For instance, many design proposals on Crowdspring (a design crowdsourcing website; see Table 1) use the words "durable," and "reliable" in describing what they want in a product design sketch. Even when someone is given a simple product brief, evaluations of durability can be assessed. For example, one industrial designer working on a simple paper sketch, said, "whenever I am sketching, I want to make sure ... it looks durable, that's going to have to come across in the overall design" (Troy 2015). Thus, we expect that the probability of design crowdsourcing will increase with lower levels of perceived reliability of the product idea.

Usability. We define perceived usability as the expected extent of effort (physical or mental) required to use the new product. March (1994, p. 144) notes that "user-centered design ... encompass[es] the cognitive aspects of using and interacting with a product, or how logical and natural a product is to use." Thus, user inputs may be valuable in enhancing usability of the concept, which can be assessed in early stages (see additional insights in Web Appendix Table WA1). For example, in the product briefs submitted to Crowdspring, managers requested a product that "is easy to setup and use," "will be easy to install," and "is unobtrusive and easy to use." Thus, we expect that the probability of design crowdsourcing will increase with lower levels of perceived usability of the product idea.

Novelty. Novelty refers to the degree of newness or originality of the product (e.g., Moldovan, Goldenberg, and Chattopadhyay 2011; Talke et al. 2009). Poetz and Schreier (2012) demonstrate that user-designed products scored higher on novelty than professionally designed products (see practice insights in Web Appendix Table WA1). Thus, we expect that product ideas with lower perceived novelty will have a higher likelihood of being crowdsourced. In summary,

> H_3: The probability of design crowdsourcing increases with perceptions of (a) higher levels of technical complexity, (b) lower levels of usefulness, (c) lower levels of reliability, (d) lower levels of usability, and (e) lower levels of novelty of the original product concept.

Nonlinearity of antecedents. While the associations proposed in H_3 relate to the initial directional nature of the relationships, these relationships need not be strictly monotonic. For example, when creating new products, Rust, Thompson, and Hamilton (2006) recommend offering enough functionality for the product to not be too simplistic, but not so much that consumers perceive the product as being too difficult to use, suggesting a nonlinear effect of usability on product success. Similarly, while managers noted that they are more likely to use crowdsourcing as technical complexity increases, as one of the interviewed managers noted, in some instances crowdsourcing is not possible, "because you cannot expect the general crowd to be intelligent in terms of your mechanical [engineering]." In the absence of a specific theory, we do not propose precise directions but leave it to the empirics to model these nonlinearities. We synthesize these collective insights and theories into Figures 1 (broad conceptual framework) and 2 (specific design crowdsourcing–performance link).

Data

Empirical Context

We collected data on new product concepts from publicly available information from Quirky, a pioneering, community-driven NPD website where members submit new product ideas and participate in development efforts. Staff sorted through idea submissions and selected idea(s) to move forward. Once an idea was selected, Quirky's management decided what help they wanted from the community. *The Wall Street Journal* described the process as such:

> Each week, Quirky's staff whittles down the stream of new ideas into a dozen or so top picks that are scrutinized and voted on.... At that point, engineers and designers, working out [of] a vast red brick warehouse in New York and three other locations, turn sketches into marketable products, tapping the online community for suggestions about design, product names and price points. (Simon 2014)

Quirky's community members were promised a portion of the product sales in exchange for their participation. Quirky's staff chose to ask for help in designing the product and selecting the name, logo, or pricing, or any combination thereof. We captured whether Quirky asked its customers to aid in the design phase. As stated on the website, in the design phase, Quirky asked its community members to "submit sketches, images, videos, and prototypes that illustrate industrial design directions for [the product]. We'll use the top concepts as a starting point for our final design."

FIGURE 1
Conceptual Framework for Testing

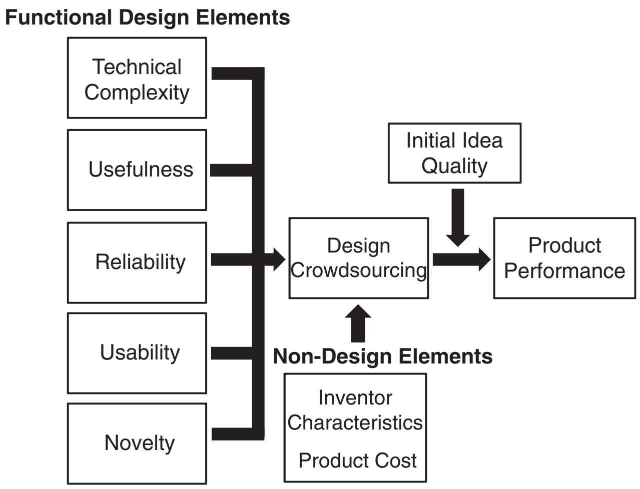
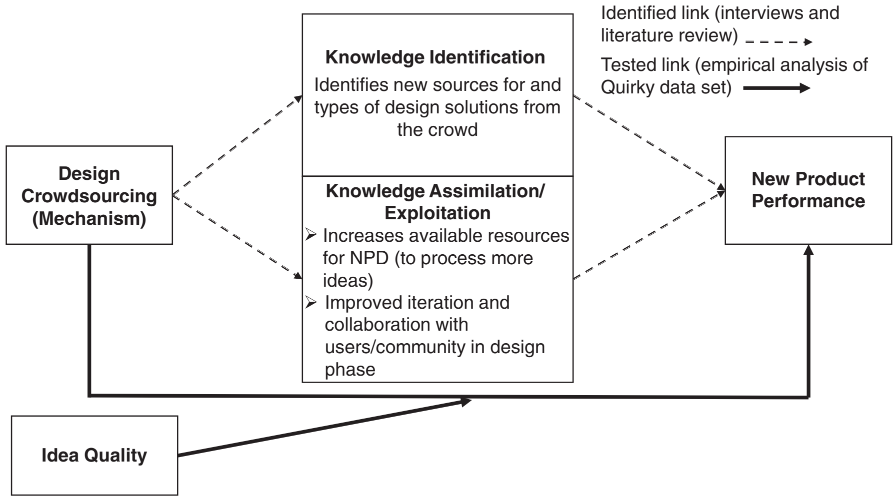


FIGURE 2
How Design Crowdsourcing Affects New Product Performance: A Closer Look at the Link Proposed in Figure 1



The staff made the final decision on design selection. Quirky had no obligation to utilize any ideas from the community, and the staff selected the phases in which to involve the community. Note that this is a similar situation faced by firms that have a product idea and must decide whether to further develop the design in-house or crowdsource the design.

Description of Empirical Setting and Data

Our data set includes the 86 different products sold on the Quirky website during our data collection period in October 2014. Quirky was very transparent with details about the NPD process, design contributions, and sales, which makes this original data set unique and valuable for addressing our research questions. We gathered three key pieces of information from the website: First, we retrieved the raw new product idea as submitted by the original community member, including the text describing the product and, if available, pictures or sketches submitted by the original inventor. (Web Appendix Figure WA1 provides an example of the Quirky design process.) Second, we collected information on whether Quirky subsequently asked the community to help with the product design (yes/no). The third key variable we collected from the website was monthly unit sales for each product, which Quirky published on its website.

Measures: Key Dependent, Independent, and Control Variables

New product performance. To assess new product performance, we used data on total sales of new products (including sales from both its website and retailing partners [e.g., Amazon, Costco]). Because not all products are released at the same time, we used total units sold in the first year, starting with the first complete month that Quirky reported. Of the products in our data set, we observed sales for a full 12-month period for 66 products (77%). For the remaining 20 products, we used a simple three-month moving average approach to estimate the sales for the missing months.[4]

Decision to design crowdsource. We collected information on whether Quirky asked the community to help in the functional design of each of its selected ideas (yes/no). This event was clearly defined by Quirky as the "design phase." In response to such requests for help, community members submitted product drawings or sketches from which the Quirky staff selected the best one. Community members had a high degree of autonomy when it came to submitting designs. The submission could be similar or different from the original idea; all that was required was that it kept to the general essence of the product's purpose. Of the products in our data set, 22 (26%) did not go through a design phase with community help.

Functional attributes of design. We utilized consumer ratings of the functional design attributes because managerial crowdsourcing decisions will be based on consumer perceptions. As one manager noted, "This leads to your ... question [about when one incorporates the end user]. I believe it is key to empathize with the end user(s) throughout the entire design process." We recruited 119 undergraduate business students at a large U.S. university to assess raw product ideas. We took a similar block design approach as in prior research and divided the 86 products into 14 different blocks, with 6–7 products in each block (Kornish

[4]We used unit sales within the first year for a few reasons: First, most products have observed sales for one year, so it limits extrapolating beyond what is known. Second, it focuses our analysis on performance soon after initial launch; this timing seems reasonable because Talke et al. (2009) show that product design affects sales most at the beginning of a product's life cycle. Our results are robust to other possible methods of completing yearly sales, such as proportional annualization (Chandrasekaran et al. 2013) or measuring sales at three or six months (see Table WA4 in the Web Appendix).

TABLE 3
Product Concept Constructs and Reliabilities

Construct	Construct Questions[a]	Reliability[b]
Technical complexity	1. The design of this product seems highly complex. 2. This product appears very technical.	.869
Usefulness (adapted from Moldovan, Goldenberg, and Chattopadhyay 2011)	1. This product would be beneficial. 2. This product fulfills a need.	.803
Product reliability (adapted from Grewal et al. 1998)	1. The product appears be reliable. 2. The product appears to be of good quality. 3. The product appears be dependable.	.922
Usability (adapted from Davis 1989; see also Venkatesh et al. 2003)	1. I would find it easy to get this product to do what I want it to do. 2. My interaction with this product would be clear and understandable. 3. It would be easy to become skillful in using this product.	.887
Novelty (adapted from Dahl, Chattopadhyay, and Gorn 1999)	1. This product is unique. 2. This product is original. 3. This product is one of a kind.	.930
Initial idea quality (measured via purchase intent; adapted from Schreier, Fuchs, and Dahl 2012)	1. I would seriously consider purchasing this product right now. 2. I would actively search for this product. 3. To me, purchasing this product in the future is highly probable.	.966

[a]On a Likert scale measured by 1 = “strongly disagree,” and 7 = “strongly agree.”
[b]Cronbach’s alpha or correlations if two-item scale.
Notes: To filter out respondents who were not paying attention, we included a test question worded, “If you are paying attention, click on ‘somewhat agree’ in the evaluation of each product.” Any respondent who missed multiple test questions across the products they evaluated were removed from the analysis. This left us with 97 of the 119 respondents.

and Ulrich 2014), to simplify the survey and minimize respondent fatigue. Each raw design for each final product sold on Quirky’s website was randomly assigned to one of the 14 blocks.[5]

Each respondent viewed the product concept (picture and description) and was asked to evaluate each design on items relating to technical complexity, usefulness, reliability, usability, and novelty. Each product was evaluated seven times, on average, by independent raters. Responses to each question were averaged across the respondents who evaluated that product. The scale questions and their reliabilities appear in Table 3. To check the validity of the model, we successfully tested the construct scales using a confirmatory factor analysis. The root mean square error of approximation is .085, comparative fit index is .964, Tucker–Lewis index is .949, and average variance extracted is .800, all of which show good measurement validity. While larger samples are usually desirable when performing confirmatory factor analyses, these fit statistics provide confidence that our constructs meet validity assumptions. All questions were on a 1–7 Likert scale, anchored by “strongly disagree” and “strongly agree.” We had one filtering question to filter out those respondents who were not paying attention (discussed in Table 3). All construct scales were averaged across their scale questions to create composite construct scores.

Idea quality. Along with the design constructs, after viewing the product concept, respondents answered three questions (scale items in Table 3) capturing the purchase intent construct (adapted from Schreier, Fuchs, and Dahl 2012). Similar to prior research, we use purchase intent as the measure of idea quality (e.g., Kornish and Ulrich 2014).

Control variables. We collected data for product category, price, and characteristics of the idea’s inventor. Our products fall into five categories, as defined by Quirky: electronics (37 products), home (17 products), kitchen (23 products), and travel and health (9 products combined). Given the small number of products in the travel and health categories, we reclassified these products into one of the other three categories.

Modeling Methodology and Results

We tested our hypotheses using two different models that are integrated in a two-step process. First, we modeled the factors that influence whether firms will crowdsource product designs using a binary response (probit) model. In this case, we modeled the dichotomous outcome (crowdsource design: yes/no) against the various ratings of design attributes of the submitted product concepts (e.g., usability, novelty) and other variables. Second,

[5]We note that some of the final products originated from the same raw design and design phase, but because we wanted to have a unique estimate for each final product, we allowed each final product’s raw design to be rated separately. We ensured that each of these designs were inserted into different blocks. We ran robustness checks to demonstrate that this does not influence the results, which we describe subsequently.

we examined the impact of crowdsourcing product designs on market outcomes (unit sales) using an instrumental variable regression controlling for the endogenous nature of the crowdsourcing decision (Wooldridge 2010), since the firm self-selects which products will be crowdsourced (i.e., the event is not purely exogenous). The two-step process allows us to observe the variables that influence the decision to crowdsource design and enables us to utilize the probit model to address the endogenous nature of the crowdsourcing variable in the model predicting sales.

Wooldridge (2010) outlines the following procedure for dealing with endogenous binary variables that utilizes the following process, where Y represents the dependent variable of interest (in our case, unit sales), G represents the binary endogenous variable (design crowdsourcing), Z represents the instruments, and X represents the vector of control variables: (1) estimate a binary choice model of dichotomous variable G on Z and a set of controls X, (2) obtain the fitted probabilities of $\hat{G}$ estimated in step 1, and (3) estimate a two-stage least squares (2SLS) instrumental regression model, regressing Y on G and X, using $\hat{G}$ as an instrument for G. This procedure has a few notable advantages. First, it takes the binary property of the endogenous variable into account. Other procedures, such as the standard 2SLS, may produce biased estimates in finite samples. Second, note that this is different than directly inserting the fitted probabilities of the probit in place of the endogenous variable. Using the estimated probabilities in place of the dichotomous variable in a standard ordinary least squares requires very strict assumptions on the error terms and the functional form to be a valid option (Adams, Almeida, and Ferreira 2009). Third, the 2SLS procedure is robust to misspecification in the probit model and provides consistent estimates with asymptotically valid errors when using standard corrections for heteroskedasticity in the instrumental variable estimation (Adams, Almeida, and Ferreira 2009; Wooldridge 2010, p. 939, procedure 21.1). We present these two models sequentially next.

Model Specification

Model for predicting product performance. The model used to test the relationship between crowdsourcing the design and performance, as measured by unit sales, can be represented by the following functional form:

$$\begin{aligned}(1)\quad \text{Ln(UnitSales)}_i = {} & \alpha + \beta_1\text{CrowdsourceDesign}_i \\ & + \beta_2\text{IdeaQuality}_i \\ & + \beta_3\text{CrowdsourceDesign}_i \\ & \times \text{IdeaQuality}_i + \beta_4\text{HolidayLaunch}_i \\ & + \beta_5\text{Ln(Price)}_i + \delta_1\text{PCharacteristics}_i \\ & + \delta_2\text{PCategory}_i + \varepsilon_i,\end{aligned}$$

where Ln(UnitSales)_i is the natural log of all units sold for product i in the first year. $\text{CrowdsourceDesign}_i$ is a dummy variable that takes on a value of 1 if the product design was crowdsourced and 0 otherwise. Idea Quality_i is the initial idea quality of the product and is measured via purchase intent for the raw concept as discussed previously (Table 3). We created an interaction term between $\text{CrowdsourceDesign}_i$ and Idea Quality_i to test for the moderating effect of idea quality on design crowdsourcing. We hypothesized this interaction to be negative, indicating that design crowdsourcing is less impactful for high-quality product ideas. HolidayLaunch_i is a dummy variable that controls for whether the product was first introduced (its first few months on the market) during the holiday season (November or December) to control for the positive proliferation effect that may come from launching the product during a high-volume period. Ln(Price)_i is the natural log of the selling price of the product at the time of data collection. $\text{PCharacteristics}_i$ represents the five design-related constructs that we predict will influence design crowdsourcing, along with their squared terms. We inserted these as control variables because it is possible that these constructs will also affect the unit sales of the product. In addition, because we predicted that they will influence the decision of whether to crowdsource the design, we included them as controls to assure that the crowdsourcing variable is capturing variance unique to crowdsourcing's effect. PCategory_i represents a vector of product category dummies.

Instrumenting for price. In addition, price is often considered an endogenous variable, given the simultaneous relationship between price and demand. Cost is used as an instrument for price because it is a determinant of price but remains orthogonal to the error term (e.g., Rossi 2014). Rossi (2014, p. 666) states that "the idea here is that costs do not affect demand and therefore serve to push around price (via some sort of mark-up equation) but are uncorrelated with the unobserved demand shock." The cost of raw materials does not influence demand because consumers are not aware of the cost of the items. We used the cost of raw materials as an instrument for price. Following Kornish and Ulrich (2014), for the Quirky data, we used the pictures and descriptions of the final products being sold on the website to estimate the cost of the materials used to manufacture the product. We recruited three mechanical engineering doctoral students from the same university, with an average age of 28.5 years and all with industry work experience. These students estimated the cost of the raw materials used to produce the final product in a separate task. The three doctoral students first researched the current market costs of raw materials (e.g., metal, plastic, cotton) and then used the product pictures and descriptions of the final product to estimate the cost of the raw materials (in dollars) used to manufacture the product. We averaged their cost estimates to develop an instrument for price and utilized the instrument in the 2SLS procedure. The correlation between the natural log of price and the natural log of the raw material cost is .792.

Model for predicting design crowdsourcing. Following the methodology outlined previously, we specify the model predicting whether an item will be crowdsourced using a discrete choice specification. We derive a probit model for the design crowdsourcing decision of the new product concept i:

$$(2)\qquad \Pr(\text{CrowdsourceDesign}_i|X) = \Phi(X'\beta + \varepsilon_i),$$

where Φ is the standard normal cdf, and

$$(3) \quad X'\beta = \alpha + \beta_1\text{Technical}_i + \beta_2\text{Technical}_i^2 + \beta_3\text{Useful}_i + \beta_4\text{Useful}_i^2 + \beta_5\text{Reliability}_i + \beta_6\text{Reliability}_i^2 + \beta_7\text{Usability}_i + \beta_8\text{Usability}_i^2 + \beta_9\text{Novelty}_i + \beta_{10}\text{Novelty}_i^2 + \delta_1\text{Controls}_i + \delta_2\text{Instruments}_i,$$

where Technical_i, Useful_i, Reliability_i, Usability_i, and Novelty_i correspond to their respective construct ratings. These constructs were measured by the construct scores developed from the surveys described previously. In addition to each linear term, we also included a quadratic term for each of these constructs. Controls_i represents a vector of control variables. As noted by Wooldridge (2010), the probit model should contain all exogenous control variables that are inserted in Equation 1. Instruments_i represents a vector of variables used as instruments (explained in detail subsequently).

Instruments and Exclusion Restrictions

So that the probit (Equation 2) results can be utilized in the 2SLS procedure for Equation 1, the probit model must contain additional instruments (as noted by Instruments_i in Equation 2) that are not simultaneously listed in Equation 1. These variables should influence design crowdsourcing decisions but should remain unrelated to unit sales. Next, we describe the instruments (inventor characteristics and cost variables) and justify their use as instruments (Rossi 2014).

Social network: number of community members the inventor is following. The managers in our interviews highlighted that a primary motivation behind crowdsourcing is to secure the engagement of many people. When managers crowdsource, they must forecast the likelihood that there will be enough potential problem-solvers (Afuah and Tucci 2012) to ensure diverse and better solutions. Thus, we seek a variable that will signal to the firm that a large number of people are likely to participate in providing solutions. We propose that the inventor's social network size is a good proxy for the likelihood that a large number of people will be aware of the product and, thus, will participate in the crowdsourcing process. Indeed, social connections of the inventor are something firms take into account (Lohr 2015). Social networks can lead to a better crowdsourcing process, due to improved reciprocity, collaboration, feedback, and integration of ideas (Piller, Vossen, and Ihl 2012). Therefore, we have a strong rationale that the social network of the inventor will matter in the decision to crowdsource design.

We look for a variable that approximates the inventor's social network and meets exclusion restrictions. The Quirky community profile allowed us to capture the number of people the inventor is "following." The act of following forms a tie in the networks literature (e.g., McGee, Caverlee, and Cheng 2013), where the strength of the tie is indicated by markers such as reciprocity in following. The literature predicts that there is greater mobility of information and social cohesion through weak ties than through strong ties (Granovetter 1973), where weak ties represent links with distant acquaintances, such as, in this context, following someone on an online network. Thus, irrespective of whether the follower is followed back, the act of following is a tie and all such ties form the social network. Furthermore, businesses monitor brand-related conversations on social media platforms to gain access to valuable information, influential people, and relevant conversations (Kumar and Mirchandani 2012). Similarly, by choosing to follow other people/inventors, the inventor keeps abreast of any key developments (e.g., inventions, opinions, trends). The act of following is an act of engagement/listening (e.g., Crawford 2009) and not an entirely costless act, as the inventor may choose to follow people on a crowdsourcing platform like Quirky depending on his or her available time and cognitive resources. Thus, an inventor who is following a large number of people belongs to a larger network with the attendant reciprocal advantages, and his or her ideas are more likely to benefit from a better crowdsourcing process. We show subsequently that this measure is also statistically informative. Thus, the number of people the inventor follows is an informative and relevant instrument that meets exclusion restriction requirements because it is unlikely to directly affect sales, as this measure is not salient to the average buyer on Quirky's website.[6] In addition, the measure contains exogenous information driving design crowdsourcing. The number of people the inventor follows is the decision of the inventor and not a *result* of external forces.

Product cost. We used the cost (the same instrument used for price) of the item as a second instrument. Nearly every manager we interviewed highlighted crowdsourcing as a way to reduce manufacturing and production costs. Thus, because the cost of goods sold includes the cost of raw materials and the production cost of the individual item, if the cost of raw materials is high, managers are more likely to look for ways to reduce production costs; this will enable the firm to keep the total cost as low as possible. As noted previously, we used the doctoral students to estimate the cost of the materials used to manufacture the product. This measure of cost is a valid instrument, as it is unlikely that cost directly affects consumer demand (Rossi 2014), but it does affect the crowdsourcing decision. We further included a quadratic term for cost, because not all increases in costs will be associated with the same increases in crowdsourcing. For example, the change in probability of crowdsourcing between items that cost \$10 versus \$20 might be quite different than between items that cost \$200 versus \$210.

Finally, we also included interaction terms between the instruments—namely, cost and the number of community members that the inventor is following. The desire to lower costs will trump other external cues (such as the inventor's network) to determine whether the firm should crowdsource. Thus, the hypothesized direction for the number of people the inventor is following will hold at low levels of cost, but the effect should be nonlinear per our managerial insights, which we capture with the interaction with cost. The probit model indicates that all of the instruments are significant (see Table 4), and the pseudo R^2 increases from .286 to .476 with the inclusion of these instruments. We next discuss results for Equation 2 and then Equation 1.

[6]To find information about who an inventor follows, a consumer would have to consciously click through the website to find the inventor's profile. Furthermore, much of Quirky's sales occurs in other retailer settings, for example, in Walmart, where such retail customers will know nothing about individual inventors.

Characteristics That Influence Design Crowdsourcing

The summary statistics and correlation matrix are included in Table WA2 of the Web Appendix.[7] Table 4 displays the results for Equation 2. Heteroskedasticity-robust standard errors are used in computing the Wald tests. The results show that while the estimated coefficients for Useful and Novelty are not significantly different from zero, the linear and quadratic terms for all the other constructs are statistically significant. Specifically, Usability_i has a negative linear term ($\beta = -62.245$, $p = .001$) and a positive quadratic term ($\beta = 5.418$, $p = .001$); this suggests that, initially, the probability of crowdsourcing design decreases with an increase in usability. After the perceived usability reaches a certain level, the probability of crowdsourcing design increases. This suggests that firms are more likely to crowdsource designs that appear overly difficult or too easy to use. The lowest probability occurs at about its mean, where the squared term dominates the linear term, around 5.74 on the 7-point Likert scale ($\approx 62.245/[2 \times 5.418]$). The effect of perceived reliability of the raw concept on the choice to crowdsource design follows a somewhat similar pattern. The negative linear term ($\beta = -32.391$, $p = .004$) suggests that as the perceived reliability of the concept increases, the probability of crowdsourcing design decreases. Thus, at low levels of perceived reliability, the firm is more likely to seek the help of the community in developing the design. The positive quadratic term ($\beta = 3.158$, $p = .005$) suggests that after a certain level of reliability—which occurs at roughly 5.13 ($\approx 32.391/[2 \times 3.158]$), increases in perceived reliability are not associated with a decrease in design crowdsourcing.

Technical complexity (Technical_i) of the product follows a pattern opposite those of usability and reliability. The positive linear coefficient ($\beta = 4.322$, $p = .006$) demonstrates that the more technical a product idea is, the more likely the firm is to crowdsource design. However, with higher levels of technical complexity, marginal increases in technical complexity are associated with a decreasing probability of crowdsourcing, as indicated by its negative quadratic term ($\beta = -.685$, $p = .001$). The inverted U-shape of technicality shows that the highest probability of crowdsourcing is 3.155 ($\approx 4.322/[2 \times .685]$) on the 7-point scale, with the lowest probability occurring at the ends. This supports the notion presented by some of the managerial insights that firms are less likely to crowdsource designs that are too technical, because the community will lack the needed expertise, and supports extant research that suggests that crowdsourcing is less likely when a firm doubts the crowd's ability/expertise to evaluate solutions (Afuah and Tucci 2012).

Overall, these results suggest a strong relationship between the probability of crowdsourcing a design and the design attributes of the raw product concept. The constructs we hypothesized, with the exception of usefulness and novelty, were related to the decision to design crowdsource, in support of H_{3a}, H_{3c}, and H_{3d}. We discuss further validation of the importance of these design characteristics on design crowdsourcing decisions next.

Validating the Importance of Design Characteristics on Design Crowdsourcing Decisions

We next demonstrate that these design constructs influence similar decisions in a different data context. The following analysis is not meant to replicate the exact same decision but to provide convergent evidence that design constructs drive design crowdsourcing decisions.

Our second data set comes from Crowdspring, an online crowdsourcing platform where firms post design challenges. Crowdspring allows clients in need of design help to post their requirements and get responses from the crowd (see Web Appendix Figure WA2). On average, a brief receives over 90 entries, and the client typically picks a winning design from these entries. We obtained data on 27 completed design projects from Crowdspring. We retained consumer-oriented products and deleted fashion-related products (e.g., clothes, jewelry) because these projects deal with aesthetics more than functional design, leaving a total of 20 projects. We collected the winning design(s) and selected ten other "nonwinning" designs at random for each of the design briefs. The submitted product designs (the winning designs plus the ten chosen at random) were evaluated using the same construct scales (Table 3) by respondents from Amazon's Mechanical Turk (MTurk). Each respondent (there was an average of eight respondents per product) saw a picture of the design submission and a write-up describing the product. Their answers were averaged to form the constructs' scores; all construct reliabilities (Cronbach's alpha) or correlations (for two-item measures) were greater than .80.

Using this new data set, we tested whether the same design characteristics that affected the earlier design crowdsourcing decision also influence which design managers select as the winning design from all submissions (and presumably choose to implement). We utilized a binary regression method similar to the previous analysis because the outcome variable is dichotomous (whether the design was chosen or not), with one modification: we controlled for the fact that each design is not independent but is clustered within a specific project and that the winner is determined from the specific cluster. We did this using a conditional logistic regression model, which is fitted to such situations where the data are based on matched cases (groups), via the "clogit" command in STATA 13. This controls for the conditional nature of the outcome variable where the likelihood estimation is calculated relative to the group. We included all five design characteristics from Equation 2 (for the results, see Table WA3 of the Web Appendix).

[7]There may be a possible concern about the quadratic terms having a multicollinearity problem as a result of their linear terms. As Allison (2012) notes, high correlation between variables and their product is expected and "is not something to be concerned about, because the p-value for [the product] is not affected by the multicollinearity,... so the multicollinearity has no adverse consequences." Furthermore, the variance inflation factor analysis of the base models for Equation 2 (without interactions and nonlinear terms) confirms that multicollinearity is not an issue due to high correlations between constructs, because all of the variance inflation factor values were substantially less than ten.

TABLE 4
Probit Model: Predicting Design Crowdsource

	Coefficient Est.	SE	*p*-Value
Functional Design Elements			
Technical	4.322	1.568	.006
Technical^2	−.685	.206	.001
Useful	−3.698	12.283	.763
Useful^2	.421	1.155	.715
Reliability	−32.391	11.311	.004
Reliability^2	3.158	1.133	.005
Usability	−62.245	19.018	.001
Usability^2	5.418	1.663	.001
Novelty	4.509	4.886	.356
Novelty^2	−.543	.541	.316
Instruments (Nondesign Elements)			
Social Network: Following	.003	.001	.004
Ln(ItemCost)	1.808	.957	.059
Ln(ItemCost)^2	−.530	.239	.027
Following × Ln(ItemCost)	−.009	.003	.001
Following × Ln(ItemCost)^2	.006	.002	.000
Additional Controls from Equation 1			
Idea quality	1.534	.507	.002
Holiday launch	1.204	.495	.015
Category dummies included	Yes		
Observations (N)	86		
Log pseudolikelihood	−25.638		
Pseudo R^2	.476		

Notes: For brevity, product category dummies along with the constant are estimated but not displayed. Robust standard errors are presented. The z-values for the instruments are as follows: Following (z = 2.91), Ln(ItemCost) (z = 1.89), Ln(ItemCost)^2 (z = −2.22), Following × Ln(ItemCost) (z = −3.39), Following × Ln(ItemCost)^2 (z = 3.62).

Two of the significant constructs from our prior analysis on Quirky data are also significant in this data set ($p < .10$)—usability and reliability—with both linear and quadratic terms significant. The probability of a design being chosen (as a winner) increases as Usability increases ($\beta = 10.612$, $p = .079$); its quadratic term, Usability^2 ($\beta = -1.004$, $p = .069$), indicates a tapering effect, suggesting that it increases at a decreasing rate. Reliability positively increases the probability of a design being chosen, ($\beta = 18.877$, $p = .091$), with Reliability^2 indicating a tapering effect ($\beta = -1.882$, $p = .081$). Technical complexity was not statistically different from zero for either the linear or quadratic terms ($p > .10$). It could be that there may be a higher degree of variation in this construct when measuring across different products (such as with Quirky), but not across different designs for the same product, as in Crowdspring, where managers may have been more explicit about technicality. The significant results for two design constructs, usability and reliability, and their quadratic terms, across data contexts provide convergent evidence for their influence on crowdsourcing decisions.

Design Crowdsourcing and New Product Performance

We next present the results on the impact of design crowdsourcing on postlaunch new product performance using data from Quirky.

Table WA2 of the Web Appendix presents the summary statistics and correlation matrix. Equation 1 is estimated with 2SLS using the instrumental procedure, as previously noted, where the predicted result from the probit model (Equation 2) is used as an instrument. Table 5 shows the results of Equation 1 utilizing two nested models. First, we present the results of the main-effects-only model (excluding the multiplicative term β_3) and then present the results of the full model with interaction effects. Both models use heteroskedasticity-robust standard errors. Table 5 also shows the first-stage F-statistics and the partial R-squares of the instruments as estimated in the first-stage regressions of the 2SLS procedure. The diagnostics for the crowdsourcing dummy, the crowdsourcing × idea quality interaction, and price instruments show that, collectively, our instruments are not weak (Stock and Watson 2003).

The results in Table 5 demonstrate an interesting relationship between design crowdsourcing and unit sales. Model 1 (main effects only) shows that the design crowdsourcing dummy does not significantly affect sales ($\beta = .566$, $p = .527$). This indicates that the effect of design crowdsourcing, on average, is not statistically different from zero. However, Model 2, the full model that includes interaction, presents a more nuanced picture. The estimate for CrowdsourceDesign ($\beta = 12.824$, $p = .002$) and the interaction between CrowdsourceDesign and IdeaQuality ($\beta = -3.188$, $p = .001$) are both statistically significant. We remind the reader that the beta coefficients in Model 1 (the main-effects-only model) represent the estimation of the main effect, or the average effect across the dependent variable based on the conditional mean function E(y|x) (Baum 2013). The coefficient for CrowdsourceDesign in Model 2 (the full model with interaction) represents the estimation of the simple effect or the estimated impact of CrowdsourceDesign when IdeaQuality is at zero (for a

TABLE 5
The Effect of Crowdsourcing the Design on Unit Sales

A: Results for Equation 1

	Model 1: Main-Effects-Only Model			Model 2: Full Model		
	Coefficient Est.	**SE**	***p*-Value**	**Coefficient Est.**	**SE**	***p*-Value**
CrowdsourceDesign	.566	.895	.527	12.824	4.116	.002
IdeaQuality	–.149	.431	.729	1.512	.656	.021
CrowdsourceDesign × IdeaQuality				–3.188	.945	.001
Controls						
Ln (Price)	–.965	.373	.010	–1.627	.482	.001
Technical	–1.517	1.115	.173	–2.641	1.438	.066
Technical^2	.198	.148	.180	.337	.192	.079
Useful	–1.749	4.503	.698	–.627	5.080	.902
Useful^2	.138	.454	.761	.091	.495	.854
Reliability	–3.144	1.627	.053	.047	2.806	.987
Reliability^2	.407	.173	.019	.192	.264	.467
Usability	2.320	3.829	.545	4.826	4.622	.296
Usability^2	–.251	.372	.499	–.530	.456	.245
Novelty	–3.846	3.265	.239	–5.703	3.437	.097
Novelty^2	.458	.357	.200	.702	.376	.062
HolidayLaunch	.047	.354	.893	–.118	.440	.788
Category dummies included	Yes			Yes		
Observations (N)	86			86		
R-squared[a]	.295			.208		

B: Instrument Diagnostics for Equation 1

	Model 1: Main-Effects-Only Model		Model 2: Full Model	
	First-Stage F-Stat.	**Partial R^2**	**First-Stage F-Stat**	**Partial R^2**
CrowdsourceDesign	29.618	.377	19.905	.379
CrowdsourceDesign × IdeaQuality			28.056	.427
Ln(Price)	37.569	.519	28.952	.520

[a]R-squared is shown for directional purposes only. R-squared for 2SLS models is not interpreted the same as ordinary least squares (percentage of variance explained). See Wooldridge (1999).
Notes: Robust standard errors presented. A constant and category dummies are estimated but not displayed for brevity.

discussion of simple effects in interactive models, see Echambadi and Hess 2007). The significance of CrowdsourceDesign in the model with interactions and lack of significance in the model without interactions suggest that crowdsourcing the design helps sales, but only when the concept has low IdeaQuality. The sign of the interaction term helps make sense of this distinction. The negative interaction term suggests that the positive effect of design crowdsourcing on sales dissipates as the idea quality of the product concept increases.

To increase the managerial relevance of our findings, we aim to show that crowdsourcing the design helps, on average, all products with low levels of IdeaQuality (not only those at zero). We measure the marginal effect at different low levels of IdeaQuality. The marginal effect of CrowdsourceDesign is positive and significant at various levels of IdeaQuality. In fact, the positive effects do not become insignificant ($p > .10$) until around IdeaQuality's mean. Thus, we find support for H_1 when the product idea shows room for improvement, and we find support for H_2. Table WA4 in the Web Appendix shows robustness of this analysis to alternative measures of sales. We also show that the results are robust, accounting for the fact that some products originated from the same raw design by using clustered standard errors (Tables WA5 and WA6 in the Web Appendix).

What Product Functionalities Does Design Crowdsourcing Influence?

A logical follow-up question to the preceding analysis is whether design crowdsourcing improves the functional design attributes from idea to final product. To test this notion, we collected additional data to assess the design of the final product as presented on the Quirky website. We replicate the main-effects-only model (Model 1 from Table 5), replacing unit sales (the previous dependent variable) with the change scores of the three design characteristics found to be significant in the probit model (reliability, technical complexity, and usability) as the new dependent variables. We assess the change scores, using consumer ratings, by measuring the improvement from the initial product idea to the final product for each of the measured design characteristics. We utilized the same design, same filtering questions, and the same construct questions used for the initial product ideas to assess the design characteristics of the final product, using students from the same population, but excluding any respondents who participated in evaluating the raw concepts. After aggregating the questions into the final constructs, we calculated a change score for each of the design constructs by subtracting the initial rating from the final rating.

For example, ΔReliability$_i$, the dependent variable, would be calculated as Reliablity$_{i,final}$ – Reliability$_{i,initial}$, where Reliability$_{i,final}$ relates to the score for perceived reliability of the final product and Reliability$_{i,initial}$ relates to the score for perceived reliability of the initial idea. This model used the same instrumental variables procedure as before and controls for the initial level of the product characteristic ratings.

Three different models were run, using ΔReliability$_i$, ΔTechnical$_i$, and ΔUsability$_i$ as the dependent variables, respectively, and design crowdsourcing dummy as the key independent variable. The results (Web Appendix Table WA7) show that the design crowdsourcing dummy positively influences ΔReliability$_i$ (β = .548, p = .079) and ΔUsability$_i$ (β = .772, p = .000), but not ΔTechnical$_i$ (β = –.211, p = .542). These results suggest that design crowdsourcing enhances perceived reliability and usability from product idea to final product.[8]

Data Robustness Checks

Use of student sample. Another potential concern with our data could be that we used undergraduate business students to assess design ratings and idea quality. The primary objective of crowdsourcing is to design products that are aligned with what people want. Thus, it is clear that consumer preferences around product design attributes drive the crowdsourcing decision. Our use of student surveys is representative of these considerations of obtaining consumer preferences to aid managerial decision making. Students are often used as proxies for general consumers (e.g., Aaker and Keller 1990; Larson and Billeter 2013). Furthermore, students are a specific target segment for Quirky, as evident from some of the product descriptions, such as "dorm occupants needn't schlep their shower shoes; just hook a cord around them and they're along for the ride." Therefore, students are representative of a strong consumer base for Quirky. However, to show that the student ratings are similar to the ratings from other general segments, we collected product ratings for a subsample of the same products from two different groups of respondents: one group recruited from MTurk and another group of business professionals (master of business administration [MBA] graduates, using a panel provided by Qualtrics).[9] We randomly selected 42 products (3 products from each of the 14 blocks) and had each group rate the products on the same construct questions shown in Table 3. We compared these ratings with the earlier ratings for the same 42 products taken from our original (undergraduate business) sample. We first performed a comparison of between-sample similarities using correlations between the samples, and then a comparison of within-sample similarities using the Jennrich test (Jennrich 1970).

The high and significant correlation between the MTurk ratings and the undergraduate ratings across the 42 products for technical complexity (.714, p < .001), usefulness (.528, p = .003), reliability (.305, p = .049), usability (.609, p < .001), and novelty (.449, p = .003) demonstrates that the construct scores are consistent across these different respondent groups. Next, we used the Jennrich test of equality of correlation matrices, which formally tests whether the correlational structure for the five constructs differs between the groups (Jennrich 1970). In other words, it tests whether the correlation matrix for the student sample is similar to the correlation matrix in the MTurk sample (e.g., Compas et al. 1989; Gande and Parsley 2005), without requiring the assumption of equal means or standard deviations (Gande and Parsley 2005). The test shows no significant difference (p = .87). In other words, we fail to reject the null hypothesis that the correlational structures are equal, indicating that the relationships among constructs are similar across samples. Similarly, if we include the design crowdsourcing dummy and the idea quality rating in the correlation matrices, the test again shows no significant difference (p = .61).

Next, we recruited 135 business professionals using a Qualtrics panel to rate the same 42 products. All constructs between the two samples (students and MBA professionals) were significantly correlated (p < .01), except for Reliability, demonstrating that the ratings on the construct scores are generally consistent across these two respondent groups. The Jennrich test showed no significant difference (p = .59) between matrix structures. Similarly, if we include the design crowdsourcing dummy and rating on idea quality, the test again shows no significant difference (p = .72). We elaborate on the Jennrich test and other robustness checks regarding our sample in the section on additional robustness checks in the Web Appendix.

Nonlinearities. One possible question is whether the use of *all* of the quadratic terms is warranted in the model predicting the probability of design crowdsourcing. We have noted that extant theory suggests that at least two of the constructs should be nonlinear (technical complexity and usability). Therefore, we replicate Equation 2 but include only two quadratic terms for technical complexity and usability (see Web Appendix Table WA8). The same constructs that are significant in the previous analysis (Table 4) are significant (Technical, Technical^2, Reliability, Usability, and Usability^2) and in the same direction. In addition, the same constructs that were previously not significant (Useful and Novelty) are still not significant.

[8]We rationalize post hoc that technical complexity may be more significant in the antecedents model than in the change-score analysis because technical complexity may be more internal and, thus, significant when firm capabilities matter in the decision of whether to crowdsource. The change-score results demonstrate that crowdsourcing improves those attributes of design that are perhaps more user-centric.

[9]For the MTurk sample, we recruited 165 respondents to rate 42 products (average age = 39.8 years old, 39% male, median household income: \$50,000–\$99,999). Respondents in the Qualtrics sample had all graduated from an MBA program (average age = 48 years old, 64% male, medium household income: \$50,000–\$99,999, average work experience in business: 18 years). The same scales were used for the five design constructs and the average rating across the respondents (at least five respondents per product) was obtained. All Cronbach's alpha/correlations are above .80 for the MTurk sample and above .70 for the Qualtrics sample.

Discussion

The use of design crowdsourcing to seek external inputs during design is emerging as a significant practice. Our article is one of the first to build and test a theoretically grounded model of factors that influence the design crowdsourcing decision and the effect of design crowdsourcing on performance, providing implications for both academics and managers.

Contributions to Theory

Knowledge management theory. Our exploratory insights contribute to the knowledge management literature by revealing *how* design crowdsourcing, as a mechanism, can help improve the NPD process and performance. Design crowdsourcing aids in knowledge identification by aggregating diverse sources of user-based design knowledge and extracting novel, workable, and meaningful design solutions. The literature on ideation crowdsourcing reveals similar insights on the use of the crowd as a resource base for ideas during the opportunity identification stage. We complement this research by illustrating how crowdsourcing can strategically tap into the crowd during the critically important design stage. Design crowdsourcing bolsters opportunity exploitation by supplementing NPD resources and creating a more collaborative process of integrating external solutions with in-house guidance, thereby contributing to product development and performance.

Crowdsourcing theory. We add to the extant crowdsourcing literature by illuminating the antecedents of design crowdsourcing and by examining design crowdsourcing's effect on new product performance. Exploratory interviews and results reveal that the inherently iterative, user-driven, and evolutionary process of design crowdsourcing can lead to a more focused search for innovative solutions while simultaneously enhancing product effectiveness. Our analysis reveals that product ideas with significant need for improvement may likely benefit the most from this iterative process that allows for crowd-driven refinement and enhancement of such ideas.

Product design theory. We contribute to the literature on product design by finding that design elements—usability, reliability, and technical complexity—matter in influencing crowdsourcing decisions. Surprisingly, usefulness and novelty do not emerge as significant drivers from our data. One post hoc explanation is that novelty and usefulness matter during idea selection, where the emphasis may be on differentiation, while the other dimensions are of consequence during design selection, where the emphasis may be on objective functionality and user experience. Based on the design literature (Noble and Kumar 2010), it seems that managers may be seeking utility from design crowdsourcing to enhance function (rational value), and user experience (kinesthetic value), rather than differentiation (emotional value). Furthermore, this research establishes that the crowd can serve as a knowledge resource for design solutions, and design crowdsourcing can improve user perceptions of design from ideas to products.

Managerial Implications

Our results provide three important managerial implications. First, whereas managers may fear losing control of the design process by opening it up, our interviews indicate that they can maintain better control over the design process, while creating slack for their research and development/design team, through the process of engagement/iteration with users/designers by selecting appropriate design crowdsourcing platforms. Furthermore, managers are faced with pressure to generate greater numbers of innovative products while being constrained by internal resource limitations. Therefore, they often prioritize only their best product ideas and concepts, discarding many others. Our results suggest that design crowdsourcing can help managers move a greater number of ideas through development by using the community's help in making (initially) less-promising ideas marketable. Thus, we address the question we posed previously: there *is* incremental value to be extracted from even initially less-promising ideas. Rather than discard such ideas, firms may use external sources of knowledge to develop them, and interact with these external sources extensively to ensure that the outcome is of high quality. Newer crowdsourcing firms, such as Crowdspring, are now setting up systems for the idea generator (client firm) to provide feedback to the community as the community aids in the design process. This feedback process may be rated and monitored by the crowdsourcing platform. It is this interactive and iterative process of design and development that eventually moves ideas into production, and herein lies the true value of design crowdsourcing.

Second, our analysis suggests design crowdsourcing increases the perceived reliability and usability from ideation to final product. Managers of client firms aiming to improve specific functional attributes of design may turn to crowdsourcing as a supplementary design resource.

Third, we provide insights to the crowdsourcing platforms, as well as the client firms, on better managing the process of crowdsourcing. First, design crowdsourcing firms are increasingly facing pressure from members of design communities, who perceive a threat posed by the availability of thousands of low-cost designs provided by the crowd. (Grefe 2016). Our research suggests that design crowdsourcing can help improve specific design functionalities through a process of iteration and feedback. Design crowdsourcing firms can (re) position themselves as intermediaries that help solve genuine product needs. Second, this research emphasizes the iterative process of design. However, given the start-up nature of many of the crowdsourcing platforms, there may be difficulties in empathizing with the end user(s) throughout the entire design process. As an executive remarked when we presented our summary results, "[Empathizing] sometimes falls by the wayside due to outside constraints such as budget, timing, exhaustion, or purely wanting to keep things simple." Our results may provide insights to such platforms on the optimal timing of user engagement at different phases of NPD. Third, our qualitative interviews suggest that managing the design crowdsourcing process may not be trivial, similar to insights from ideation research that suggested that firms may be overwhelmed with ideas from the crowd, and, thus, this research suggests that the decision to crowdsource should not be taken lightly. This is one reason for the growing popularity of third-party platforms, as these platforms assist in managing much of the process and provide important guidance to managers.

Limitations and Promising Avenues for Future Research

We note a few limitations of this research and discuss research opportunities. First, our key results are based on the product performance (sales) of a single firm. Although our results have significant implications, they do not directly speak to the viability (or profitability) of the overall business models.[10] Future research will benefit from a large-scale study involving nonplatform firms. Second, our sample for the product concepts originated from students. While we validate our constructs using another crowdsourcing platform and ratings from other sources, future studies can make substantial contributions by using broader consumer and managerial surveys. Third, we do not consider firm capabilities, which may influence the decision to seek an external solution (Afuah and Tucci 2012). While this limitation is mitigated because all our products come from the same firm, caution should be used when extrapolating these results to other companies. Fourth, all of the product ideas in this data set originated from the community, and crowdsourcing design may have different results depending on whether the product idea had originated internally or from the community. Fifth, there are likely differences in efficacy or the degree of collaboration depending on whether design solutions were consumer generated or designer generated. Although the current context cannot address these issues, these are promising questions for future research. Future research could examine effective mechanisms to incentivize collaboration in crowdsourcing platforms and determine best practices for managing design crowdsourcing. It is our hope that our findings motivate further research on crowdsourcing decisions in various phases within the NPD process.

[10]Quirky has since filed for bankruptcy and changed its website structure. We thank our anonymous reviewers for highlighting this point.

REFERENCES

Aaker, David, and Kevin Lane Keller (1990), "Consumer Evaluations of Brand Extensions," *Journal of Marketing*, 54 (1), 27–41.

Adams, Renée, Heitor Almeida, and Daniel Ferreira (2009), "Understanding the Relationship Between Founder–CEOs and Firm Performance," *Journal of Empirical Finance*, 16 (1), 136–50.

Afuah, Allan, and Christopher L. Tucci (2012), "Crowdsourcing as a Solution to Distant Search," *Academy of Management Review*, 37 (3), 355–75.

Alavi, Maryam, and Dorothy E. Leidner (2001), "Review: Knowledge Management and Management Systems: Conceptual Foundations and Research Issues," *Management Information Systems Quarterly*, 25 (1), 107–36.

Allison, Paul (2012), "When Can You Safely Ignore Multicollinearity?" (accessed September 8, 2017), https://statisticalhorizons.com/multicollinearity.

Andriopoulos, Constantine, and Marianne W. Lewis (2009), "Exploitation-Exploration Tensions and Organizational Ambidexterity: Managing Paradoxes of Innovation," *Organization Science*, 20 (4), 696–717.

Atuahene-Gima, Kwaku (2005), "Resolving the Capability: Rigidity Paradox in New Product Innovation," *Journal of Marketing*, 69 (4), 61–83.

Baum, Christopher F. (2013), "Quantile Regression," (accessed January 18, 2016), http://fmwww.bc.edu/EC-C/S2013/823/EC823.S2013.nn04.slides.pdf.

Bayus, Barry L. (2013), "Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community," *Management Science*, 59 (1), 226–44.

Bloch, Peter H. (1995), "Seeking the Ideal Form: Product Design and Consumer Response," *Journal of Marketing*, 59 (3), 16–29.

Chandrasekaran, Deepa, Joep W.C. Arts, Gerard J. Tellis, and Ruud T. Frambach (2013), "Pricing in the International Takeoff of New Products," *International Journal of Research in Marketing*, 30 (3), 249–64.

Chang, Woojung, and Steven A. Taylor (2016), "The Effectiveness of Customer Participation in New Product Development: A Meta-Analysis," *Journal of Marketing*, 80 (1), 47–64.

Chesbrough, Henry W. (2003), *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Boston: Harvard Business School Press.

Cohen, Wesley M., and Daniel A. Levinthal (1990), "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35 (1), 128–52.

Compas, Bruce E., David C. Howell, Vicky Phares, Rebecca A. Williams, and Normand Ledoux (1989), "Parent and Child Stress and Symptoms: An Integrative Analysis," *Developmental Psychology*, 25 (4), 550–59.

Crawford, Kate (2009), "Following You: Disciplines of Listening in Social Media," *Continuum*, 23 (4), 525–35.

Dahl, Darren W., Amitava Chattopadhyay, and Gerald J. Gorn (1999), "The Use of Visual Mental Imagery in New Product Design," *Journal of Marketing Research*, 36 (1), 18–28.

Davis, Fred D. (1989), "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *Management Information Systems Quarterly*, 13 (3), 319–40.

Echambadi, Raj, and James D. Hess (2007), "Mean-Centering Does Not Alleviate Collinearity Problems in Moderated Multiple Regression Models," *Marketing Science*, 26 (3), 438–45.

eYeka (2016), "Online Co-Creation to Accelerate Marketing and Innovation," (accessed March 10, 2016), available at https://en.eyeka.com/resources/whitepapers#online-cocreation.

Fennell, Geraldine, and Joel Saegert (2004), "Identifying Prospects and Reaching Targets: Neglected Distinction Within Marketing," in *Proceedings of the 2003 SCP Summer Conference*. San Francisco: Society for Consumer Psychology, 193–202.

Foss, Nicolai J., Jacob Lyngsie, and Shaker A. Zahra (2013), "The Role of External Knowledge Sources and Organizational Design in the Process of Opportunity Exploitation," *Strategic Management Journal*, 34 (12), 1453–71.

Fuchs, Christoph, Emanuela Prandelli, and Martin Schreier (2010), "The Psychological Effects of Empowerment Strategies on Consumers' Product Demand," *Journal of Marketing*, 74 (1), 65–79.

Gande, Amar, and David C. Parsley (2005), "News Spillovers in the Sovereign Debt Market," *Journal of Financial Economics*, 75 (3), 691–734.
Gann, David M., and Ammon J. Salter (2000), "Innovation in Project-Based, Service-Enhanced Firms: The Construction of Complex Products and Systems," *Research Policy*, 29 (7), 955–72.
Granovetter, Mark S. (1973), "The Strength of Weak Ties," *American Journal of Sociology*, 78 (6), 1360–80.
Grant, Robert T. (1996), "Toward a Knowledge-Based Theory of the Firm," *Strategic Management Journal*, 17 (Winter), 109–22.
Grefe, Richard (2016), "What's the Harm in Crowdsourcing?" *AIGA* (June 24), http://www.aiga.org/whats-the-harm-in-crowdsourcing.
Grewal, Dhruv, R. Krishnan, Julie Baker, and Norm Borin (1998), "The Effect of Store Name, Brand Name and Price Discounts on Consumers' Evaluations and Purchase Intentions," *Journal of Retailing*, 74 (3), 331–52.
Hobday, Mike (2000), "The Project-Based Organization: An Ideal Form for Managing Complex Products and Systems?" *Research Policy*, 29 (7), 871–93.
Jennrich, Robert I. (1970), "An Asymptotic χ^2 Test for the Equality of Two Correlation Matrices," *Journal of the American Statistical Association*, 65 (330), 904–12.
Joshi, Ashwin W., and Sanjay Sharma (2004), "Customer Knowledge Development: Antecedents and Impact on New Product Performance," *Journal of Marketing*, 68 (4), 47–59.
Katz, Ralph, and Thomas J. Allen (1982), "Investigating the Not Invented Here (NIH) Syndrome: A Look at the Performance, Tenure, and Communication Patterns of 50 R&D Project Groups," *R&D Management*, 12 (1), 7–20.
Kornish, Laura J., and Karl T. Ulrich (2014), "The Importance of the Raw Idea in Innovation: Testing the Sow's Ear Hypothesis," *Journal of Marketing Research*, 51 (1), 14–26.
Kumar, V., Ashutosh Dixit, Rajshekar (Raj) G. Javalgi, and Mayukh Dass (2016), "Research Framework, Strategies, and Applications of Intelligent Agent Technologies (IATs) in Marketing," *Journal of the Academy of Marketing Science*, 44 (1), 24–45.
Kumar, V., and Rohan Mirchandani (2012), "Increasing the ROI of Social Media Marketing," *MIT Sloan Management Review*, 54 (1), 55–61.
Larson, Jeffrey S., and Darron M. Billeter (2013), "Consumer Behavior in 'Equilibrium': How Experiencing Physical Balance Increases Compromise Choice," *Journal of Marketing Research*, 50 (4), 535–47.
Laursen, Keld, and Ammon Salter (2006), "Open for Innovation: The Role of Openness in Explaining Innovation Performance Among U.K. Manufacturing Firms," *Strategic Management Journal*, 27 (2), 131–50.
Lohr, Steve (2015), "The Invention Mob, Brought to You by Quirky," *The New York Times* (February 14), http://www.nytimes.com/2015/02/15/technology/quirky-tests-the-crowd-based-creative-process.html.
March, Artemis (1994), "Usability: The New Dimension of Product Design," *Harvard Business Review*, 72 (5), 144–49.
Markowitz, Eric (2011), "The Case for Letting Your Customers Design Your Products," *Inc*. (September 20), http://www.inc.com/guides/201109/how-to-crowdsource-your-resarch-and-development.html.
McGee, Jeffrey, James Caverlee, and Zhiyuan Cheng (2013), "Location Prediction in Social Media Based on Tie Strength," in *Proceedings of the 22nd ACM International Conference on Information & Knowledge Management*. New York: Association for Computing Machinery, 459–68.
Moldovan, Sarit, Jacob Goldenberg, and Amitava Chattopadhyay (2011), "The Different Roles of Product Originality and Usefulness in Generating Word-of-Mouth," *International Journal of Research in Marketing*, 28 (20), 109–19.
Nishikawa, Hidehiko, Martin Schreier, and Susumu Ogawa (2013), "User-Generated Versus Designer-Generated Products: A Performance Assessment at Muji," *International Journal of Research in Marketing*, 30 (2), 160–67.
Noble, Charles H., and Minu Kumar (2010), "Exploring the Appeal of Product Design: A Grounded, Value-Based Model of Key Design Elements and Relationships," *Journal of Product Innovation Management*, 27 (5), 640–57.
Piller, Frank, Alexander Vossen, and Christoph Ihl (2012), "From Social Media to Social Product Development: The Impact of Social Media on Co-Creation of Innovation," *Die Unternehmung*, 66 (1), 7–27.
Poetz, Marion K., and Martin Schreier (2012), "The Value of Crowdsourcing: Can Users Really Compete with Professionals in Generating New Products Ideas?" *Journal of Product Innovation Management*, 29 (2), 245–56.
Radjou, Navi, and Jaideep Prabhu (2015). *Frugal Innovation: How to Do More with Less*. New York: The Economist.
Ramani, Girish and V. Kumar (2008), "Interaction Orientation and Firm Performance," *Journal of Marketing*, 72 (1), 27–45.
Ries, Eric (2011), *The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*. New York: Crown Books.
Rossi, Peter E. (2014), "Invited Paper—Even the Rich Can Make Themselves Poor: A Critical Examination of IV Methods in Marketing Applications," *Marketing Science*, 33 (5), 655–72.
Rust, Roland T., Debora Viana Thompson, and Rebecca W. Hamilton (2006), "Defeating Feature Fatigue," *Harvard Business Review*, 84 (2), 98–107.
Schreier, Martin, Christoph Fuchs, and Darren W. Dahl (2012), "The Innovation Effect of User Design: Exploring Consumers' Innovation Perceptions of Firms Selling Products Designed by Users," *Journal of Marketing*, 76 (5), 18–32.
Simon, Ruth (2014), "One Week, 3,000 Product Ideas," *The Wall Street Journal* (July 3), http://www.wsj.com/articles/one-week-3-000-product-ideas-1404332942?mod=djem_jiewr_swwps_071014.
Stock, James H., and Mark W. Watson (2003), *Introduction to Econometrics*. New York: Addison-Wesley.
Talke, Katrin, Soren Salomo, Jaap E. Wieringa, and Antje Lutz (2009), "What About Design Newness? Investigating the Relevance of a Neglected Dimension of Product Innovativeness," *Journal of Product Innovation Management*, 26 (6), 601–15.
Troy, Julia (2015), "How to Sketch Like an Industrial Designer," Skillshare (accessed February 17, 2016), https://www.skillshare.com/classes/design/How-to-Sketch-Like-an-Industrial-Designer/625650159].
Unilever (2016), "Open Innovation," (accessed February 10, 2016), https://www.unilever.com/about/innovation/open-innovation/challenges-and-wants/.
Venkatesh, Viswanath, Michael G. Morris, Gordon B. Davis, and Fred D. Davis (2003), "User Acceptance of Information Technology: Toward a Unified View," *Management Information Systems Quarterly*, 27 (3), 425–78.
Von Hippel, Eric (1994), "'Sticky Information' and the Locus of Problem Solving: Implications for Innovation," *Management Science*, 40 (4), 429–39.
Wooldridge, Jeffrey M. (1999), *Introductory Econometrics: A Modern Approach*. Mason, OH: South-Western.
Wooldridge, Jeffrey M. (2010), *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.