



## Management Science

Publication details, including instructions for authors and subscription information:  
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To cite this article:

Ethan Mollick, Ramana Nanda (2016) Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts. Management Science 62(6):1533-1553. <http://dx.doi.org/10.1287/mnsc.2015.2207>

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# Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts

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In fields as diverse as technology entrepreneurship and the arts, crowds of interested stakeholders are increasingly responsible for deciding which innovations to fund, a privilege that was previously reserved for a few experts, such as venture capitalists and grant-making bodies. Little is known about the degree to which the crowd differs from experts in judging which ideas to fund, and, indeed, whether the crowd is even rational in making funding decisions. Drawing on a panel of national experts and comprehensive data from the largest crowdfunding site, we examine funding decisions for proposed theater projects, a category where expert and crowd preferences might be expected to differ greatly. We instead find significant agreement between the funding decisions of crowds and experts. Where crowds and experts disagree, it is far more likely to be a case where the crowd is willing to fund projects that experts may not. Examining the outcomes of these projects, we find no quantitative or qualitative differences between projects funded by the crowd alone and those that were selected by both the crowd and experts. Our findings suggest that crowdfunding can play an important role in complementing expert decisions, particularly in sectors where the crowds are end users, by allowing projects the option to receive multiple evaluations and thereby lowering the incidence of “false negatives.”

**Keywords:** crowdfunding venture funding; theater; judgement; communities

**History:** Received June 23, 2014; accepted March 2, 2015, by Lee Fleming, entrepreneurship and innovation.

Published online in *Articles in Advance* September 11, 2015.

## 1. Introduction

One of the central insights of Schumpeter (1942) was to highlight the distinct roles played by entrepreneurs and investors in bringing new ideas to fruition, since it allowed for the possibility that good ideas might be precluded from the market because they were unable to attract financing from investors. Other scholars have shown that the opinions of funding authorities similarly affect the direction of innovation in other critical fields, including scientific research (Bourdieu 1975, Goldfarb 2008, Nelson 1959) and creative industries (Caves 2000, 2003). In each setting, scholars have noted that constrained financing environments and the control exerted by a small group of experts means that projects that are ultimately funded are not necessarily “objectively best” but are subject to the specific information, agency, and organizational constraints faced by the small number of experts making funding decisions (e.g., Caves 2000, Ferrary and Granovetter 2009, Goldfarb 2008, Kerr et al. 2014, Kortum and Lerner 2000).

Rapid technological advances over the past few years have made it significantly easier for innovators to circumvent experts and instead communicate

directly with a large number of interested stakeholders, leading to the growing reliance on “crowds” to make decisions that once rested solely in the hands of a small number of experts. For example, the crowdfunding platform Kickstarter has raised more than \$1 billion for over 60,000 projects from over six million backers since its founding in 2009, projects that may otherwise have needed to seek funding from venture investors or grant-making bodies. In fact, since 2012, this platform alone raises more money for the arts annually than the total funding provided through the U.S. government-run National Endowment for the Arts. The importance of crowd-based decisions is growing in a wide range of fields, including the funding of technology-based start-ups (Agrawal et al. 2013, Mollick 2014), the development of new products (Afuah and Tucci 2012, Poetz and Schreier 2012, von Hippel 1986), and scientific research (Franzoni and Sauermann 2014).

Despite the growing role of crowds in making decisions once left to experts, little is known about how crowds and experts may differ in their ability to judge projects. Indeed, for crowds, at least, there is even considerable debate over whether their decisions are actually based on rational criteria at all. Two

popular books separated by 150 years offer starkly different views of the nature of crowd decision making, with Mackay (1852) warning about the “madness of crowds” whereas Surowiecki (2004) more recently extolled the “wisdom of crowds.” Studies to date attempting to understand the differences between crowds and experts have focused on prediction tasks or markets, where aggregated decisions can be more accurate than individual actions (Budescu and Chen 2014, Larrick et al. 2012, Ray 2006, Tetlock 2005), or else on cases where organizations can get positive results by reaching out to crowds under carefully controlled circumstances (Bogers et al. 2010, Terwiesch and Ulrich 2009). Crowdfunding, on the other hand, does not have any such controls, and it differs from these previous phenomena in many ways: there is no market reward mechanism for correct answers, no clear criteria determining what is being “predicted,” no expert oversight of the crowd decision-making process, and no direct coordination between crowd members. In this case, the crowd can be subject to many group decision-making fallacies, as Isenberg (2012) argued about crowdfunding: “Group irrationality is well-documented—crowds are ‘wise’ only in a very limited set of circumstances. As often as not, crowds bring us tulip crazes, subprime meltdowns, the Kitty Genovese scandal, Salem witch trials, and other tragedies.” There is no clear evidence on whether crowds are rational at all and, if they are, what differences might exist between the judgment of crowds and that of experts.

Thus, we are interested in shedding light on two questions about the judgment of crowds compared with that of experts. First, we aim to provide a robust analysis of the degree to which experts would agree with crowdfunding decisions that rely on taste and judgment, rather than prediction, using rich data from the crowdfunding platform Kickstarter. The second related question we seek to understand is whether crowd-based decision making is *mad* (irrational and inconsistent in decision making relative to experts) or *wise* (generally consistent in selecting potentially successful projects).

Several features of our research design aim to address the specific challenges associated with making such a comparison. First, we have complete data on crowdfunding campaigns (that is, the “applications”) for all projects, including those that were unsuccessful, so that we are not sampling on success. Second, we focus our study to theater projects, which have a number of appealing features: evaluating them entails both a subjective artistic component and an understanding of the commercial bottom line, which provides useful variation for our study. Further, it is possible to develop a somewhat objective sense of the long-run success of the projects using data

on ticket sales and critical reviews in the press so that we can also compare the funding decisions with real outcomes. Additionally, theater funding is a one-time event, not subject to the challenges associated with multistage financing that might lead crowds to choose different investments from deep-pocketed professional investors even if they rated projects the same (Nanda and Rhodes-Kropf 2012). Finally, we recruit expert evaluators who have deep expertise judging theater applications for institutions such as the National Endowment for the Arts. The projects were rendered in the same format as the Kickstarter campaigns, had similar financial requirements to traditional grant applicants, and were stripped of any references to the outcome of the campaign. We randomly assign “sets” of projects to these experts to evaluate, where each set consists of three failed and three successful projects. This approach allows us to also include expert fixed effects to examine the robustness of our results.

We have three main findings. First, on average, we find a statistically significant congruence between the realized funding decisions by crowds and the evaluation of those same projects by experts. Projects that were funded by the crowds received consistently higher scores from experts, were more likely to be rated as being the best of the six in the set, and were much more likely to have received funding from the experts. This pattern was equally true for projects that were “overfunded” on Kickstarter—that is, projects that raised more money than was asked for. Given the strong positive correlations we observe in crowd and expert evaluations, even in a category with a subjective nature such as theater, this suggests both broad similarities between how experts and crowds judge projects and that crowds are generally consistent in their choices of which projects to back, allowing us to reject the “madness of crowds” in our setting.

Our second finding is that despite the broad congruence in evaluation, we see a systematic pattern in terms of the disagreement. Of the projects where there is no agreement, the crowd is much more likely to have funded a project that the judge did not like than the reverse. Approximately 75% of the projects where there is a disagreement are ones where the crowd funded a project but the expert would not have funded it. We also see a clear pattern in terms of the characteristics of projects that are liked by the crowds: they offer multiple tiers of rewards and provide more updates. In fact, projects that were ranked highly by the experts but not funded by crowds had systematically fewer reward levels, fewer pictures, and fewer videos. That is, we seem to find that there is an “art” to raising money from crowds, one that may be systematically different from that of raising money from experts. The crowds seem to place emphasis on, or

extract information content from, different attributes of the process than those of experts.

Our third finding relates to the longer-term outcomes of these projects. An attractive feature of the fact that most of the disagreements are related to projects *funded by the crowd*, we are able to compare the long-term outcomes of projects that were liked by both crowds and experts and those liked only by the crowds. Despite the fact that these were not rated as highly by the experts, we find no qualitative or quantitative differences in the long-term outcomes of these projects. They are equally likely to have delivered on budget and result in organizations that continue to operate; moreover, although the metrics for success are subjective, we find strong qualitative evidence that many of these shows had both commercial success and received positive critical acclaim in national outlets such as the *New York Times*.

We should note that this third set of results is more tentative because of the smaller sample size. However, these patterns suggest that the entry that is facilitated by crowdfunding has the potential to lower the incidence of “false negatives” (that is, viable projects that are turned down by funders) by allowing projects the option to receive multiple evaluations and reach out to receptive communities that may not otherwise be represented by experts. Indeed, crowdfunding allows project creators to directly contact potential customers, providing a rich source of data on the potential interest in an artistic endeavor, in addition to any funds raised.

Our results are relevant to the growing interest to management scholars in the role of crowds in addressing traditional organizational functions (Afuah and Tucci 2012, Boudreau et al. 2011, Franzoni and Sauermann 2014, Greenstein and Zhu 2014, Terwiesch and Ulrich 2009). Our findings are also related to the role that crowds may play in reducing financing constraints of new ventures. The falling cost of starting new ventures has allowed the possibility of individuals with small amounts of capital to participate in financing such ventures, and our results shed light on the extent to which backers on these platforms may be able to reduce information asymmetries as opposed to becoming victims to information cascades. We address the generalizability of our findings in §6.

The rest of this paper is organized as follows. Section 2 outlines the theoretical predictions associated with studying differences between crowds and experts. Section 3 outlines our methods and provides details on the implementation of the survey. Section 4 describes the data. Section 5 outlines our main findings. Section 6 provides a discussion of the results. Section 7 concludes.

## 2. Theory

Scholars have long noted the great importance of experts, who have historically held a privileged position in many industries, acting as arbiters of taste, quality, and appropriateness (e.g., Caves 2000, Ginsburgh 2003, Zuckerman 1999). Expert judgments are influential in a number of ways, including acting as predictors of commercial success and influencers of popular opinion (Eliashberg and Shugan 1997), as well as gatekeepers of vital resources (Ginsburgh 2003, Reinstein and Snyder 2005). As an example of these three forms of influence, consider experts who select which entrepreneurial ventures should receive funding: venture capitalists (VCs). VCs select firms to fund based on their predictions of future market demand (Baum and Silverman 2004, Gompers and Lerner 2004, Shane and Venkataraman 2003). Further, venture capital investment serves as an influential signal to other players in the market, suggesting that a start-up is to be taken seriously (Baum and Silverman 2004, Hellmann and Puri 2002). Finally, venture capitalists serve as gatekeepers to vital resources. As Ferrary and Granovetter (2009, p. 346) write, “By selecting start-ups, the VC firms implicitly prevent the other agents in the complex network of innovation from collaborating with start-ups that do not get VC funding. It could be argued that potential valuable innovations have never reached customers because they did not get VC funding.”

In the arts, where profitability is not always the standard goal of creators, experts play an even more critical role as influencers and gatekeepers. Especially in high culture, expert critics are “sometimes more important than creators,” since they determine the governing aesthetics of high culture, as well as which creators receive resources (Gans 2008, p. 75). Studies in the film industry, for example, have shown that expert critics are particularly influential to the success of smaller artistic movies (Reinstein and Snyder 2005). Further, experts are often gatekeepers of funding for the arts, playing critical roles in allocating funding from government, corporate, and foundation sources that make up 24.6% of all revenues for not-for-profit performing arts groups and museums in the United States (Woronkiewicz et al. 2012). Crowdfunding, however, offers an alternative to the traditional expert control over artistic funding and culture.

Crowdfunding provides a method of funding projects that differs in several aspects from expert-run processes such as grant making or venture capital. First, rather than being in the hands of a small group of individuals, it is democratic—over six million people have funded projects on Kickstarter alone. Second, as opposed to the tightly knit expert community (Wenger and Snyder 2000), crowdfunding backers are loosely organized, if at all. Third, compared



with the closed networks of Silicon Valley or the world of theater, in crowdfunding almost all communication between those seeking funding and potential backers occurs in open, online communities. Fourth, crowdfunding in its current form involves no equity or monitoring rights;<sup>1</sup> backers have little to no further influence over organizations they backed and gain no return other than the potential of enjoying the outcome of a project.

The use of crowd judgment in crowdfunding also differs greatly from prior approaches to generating information from large groups. Other attempts to harness the innovative power of large groups—such as crowdsourcing (Poetz and Schreier 2012), innovation tournaments (Boudreau et al. 2010, Terwiesch and Ulrich 2009), and collective and group innovation (Jeppesen and Frederiksen 2006, O'Mahony 2003)—ultimately have an expert authority overseeing the actions of the crowd. And, unlike prediction markets (Chen et al. 2008, Ray 2006, Wolfers and Zitzewitz 2004), crowd-based approaches do not operate similar to markets, in that there are no buyers and sellers trading contracts in an efficient manner. Instead, crowd judgment depends on the aggregate actions of many individuals making small contributions to a larger goal, in the place of experts making large-scale resource allocation choices themselves. Although the success or failure of a particular project may be influenced by the degree of pledges already made (Kuppuswamy and Bayus 2014), backing decisions are individual, not collective. There is no centralized price-setting mechanism, tournament, or selection process that aggregates crowd preferences. Thus, the crowd in crowdfunding consists of a group of mostly uncoordinated amateurs.

Theory provides ambiguous predictions about whether and how crowd evaluations should differ from that of experts. On the one hand, the crowd allows for a wider range of expertise and preferences to be leveraged in group decision making, suggesting that “collective wisdom” might make evaluation more accurate, reducing information frictions and providing greater efficiency in financing decisions. For example, studies on forecasting have supported the idea that experts are no more accurate than informed amateurs (Tetlock 2005), whereas examination of *Wikipedia* has shown that it compares favorably on many dimensions to expert-created content (Clauson et al. 2008, Giles 2005, Rajagopalan et al. 2011). Further, recent research on *Wikipedia* has shown

that although there may be political biases in certain articles (Greenstein and Zhu 2012), as these articles are more heavily edited by the crowd, they ultimately become less biased than similar work produced by the experts at *Encyclopædia Britannica* (Greenstein and Zhu 2014).

The research on crowds that seeks to explain these findings focuses on the value of combining many opinions, as opposed to relying on the views of individual experts (Larrick and Soll 2012). When crowds have diverse sources of information and expertise with a problem area, they can provide more accurate collective forecasting than can even well-informed individuals (Larrick et al. 2012). Indeed, a substantial amount of research has gone into examining the best method of combining the predictions of many individuals as accurately as possible (Budescu and Chen 2014, Larrick and Soll 2012, Makridakis and Winkler 1983). Although these studies have shed considerable light on how to employ the wisdom of the crowd, the emphasis on assessing crowds based on accuracy assumes that there is an objectively defined “correct answer” that both the crowd and experts are attempting to reach. When one is selecting which start-up companies to fund, artistic works to develop, or innovations to pursue, the nature of a correct answer is less clear. In these cases, the key issue is less about selecting a combined prediction and much more about understanding whether there are systematic differences between crowds and experts in the types of projects they seem to prefer or, indeed, if crowds are at all consistent in how they assess projects.

We may expect several factors to drive some systematic differences in the types of projects that are funded by crowds compared with those by experts. First, it is not clear that the crowd, as a whole, has the expertise to evaluate projects in the same way as experts (Simmons et al. 2011). There are no admissions criteria for entering the crowd, making it unclear how the crowd would develop criteria to identify potentially high-quality projects in areas where they do not have expertise. Since crowds are pledging smaller amounts of money per project, they also have less of an incentive to gather information on the project and hence are more likely to be subject to herding driven by information cascades. Such herding can be rational, as outlined by several economics models (Banerjee 1992, Bikhchandani et al. 1992, Devenow and Welch 1996, Scharfstein and Stein 1990), where project backers observe the actions of other project backers and thus view the presence of other backers as a sign of quality. Herding can also be mimetic, as backers simply mimic others, without an underlying rationale (Cipriani and Guarino 2005). Crowds may also suffer from a wide variety of factors identified

<sup>1</sup> The data collected are from a period where crowdfunding where no equity investment is permitted, though the U.S. Congress has authorized equity crowdfunding (Jumpstart Our Business Startups Act (H.R. 3606), passed by the 112th Congress in 2012), it has yet to be fully implemented as of the time of this writing.

by social psychologists and cognitive scientists that degrade the quality of crowd decision making (e.g., Bahrami et al. 2012, Latane et al. 1979, Raafat et al. 2009). For example, groups can be subject to emotional contagion (Barsade 2002) and even to hysterical reaction (Balaratnasingam and Janca 2006), which may cause crowd members to act in nonrational ways. Crowds could also fall into patterns of group thinking, which bias information processing (Janis 1982); may overly rely on the work of others (Earley 1989, Latane et al. 1979); or may deemphasize information that is not shared among group members (Schulz-Hardt et al. 2006).

We do not seek to specify which biases may operate under which conditions in crowdfunding, but rather we argue that there are many potential reasons why crowds would operate in ways that might be less than wise, especially as crowdfunding does not resemble more controlled opinion-aggregation approaches to harnessing crowd wisdom (Budescu and Chen 2014, Simmons et al. 2011). Indeed, early studies have found herding in peer-to-peer lending, a form of crowdfunding, with conflicting evidence over the degree to which herding represents positive information cascades or mere imitation (Chen and Lin 2014, Kuppaswamy and Bayus 2014, Zhang and Liu 2012). Thus, both prior theory and early empirical results suggest that the crowd could be irrational, subject to many potential biases that would result in inconsistent judgments without clear patterns or decision criteria.

Even in the absence of group biases that subvert rational decision making, the crowd and experts may differ based on taste or other preferences. The difference in cultural tastes have long been a subject of interest to scholars (Bourdieu 1984, DiMaggio 1991, Gans 2008, Peterson and Kern 1996), and the funding decision of experts and crowds would reasonably be expected to reflect differences in high culture and popular culture (Gans 2008). Even as cultural tastes change among the elite (Peterson and Kern 1996), there is still a strong belief that many forms of high culture, serious theater prominent among them (Shrum 1991), would not be supported by popular culture. Further, the tastes of the critics serves a role beyond selecting artwork and is part of the process by which elite social classes sustain and replicate themselves (DiMaggio 1991). Additionally, the difference in tastes between the crowd and experts may not even be based on the underlying quality of the work. Given that some significant proportion of crowdfunding is based on the support of friends and family (Agrawal et al. 2010), it could simply be that the crowd is primarily focused on supporting popular individuals, rather than quality products. These differences in tastes are important, as selection contexts that apply

different preferences in funding projects can result in the support of very different forms of art (Wijnberg and Gemser 2000) and alter the sorts of ideas that are ultimately funded and pursued throughout the economy. Therefore, even in the absence of group cognitive biases that make decision making inconsistent, crowds may still have a completely different set of tastes than experts, suggesting that moving from expert to crowd-based judgments could radically alter the type and nature of art being funded.

Ultimately, we are left with two potential views of the crowd. In one case, we have a crowd that is fundamentally wise. It may differ on some selection criteria from experts as a result of taste or the structure in which screening takes place, but it would have a consistent set of decisions that have a rational underlying framework. If the crowd is wise, the key question becomes the taste of the crowd compared with that of experts, and its consequences. A second option is that the crowd is instead more subject to the many potential fallacies of group cognition, is driven by factors unrelated to quality, has radically different tastes than experts, and/or is inconsistent in its judgment. Our study aims to shed light on which of these two polar extremes best typifies the nature of crowdfunding we see today and to explore the differences between expert and crowd judgment.

### 3. Research Design

We chose to work with data from Kickstarter, which is the largest and most prominent crowdfunding platform in the world, having successfully helped raise more than \$1 billion in funding across all applicants in the last five years. Because of the strong network effects that tend to be present in such platforms, working with the largest, most prominent, and successful platform ensures that we are likely to observe a representative set of projects—including the very best—that are seeking funding from crowds. A second attractive feature of our setting is that we have access to all the campaigns run by Kickstarter, including those that did not succeed in meeting their funding goals, which allows us to look at the differences in evaluation, without sampling on success.

Since a key goal of our paper is to examine the extent to which experts would agree with the funding decisions of crowds, we focused our analysis on a field where there is an established set of externally validated experts that could be used to examine the judgment of crowds. We also wanted to focus on an area where projects have both a subjective artistic component and a measure of a commercial bottom line, since the former is a setting where tastes may be expected to differ and the latter is a feature that is particularly relevant for new ventures outside of the

**Figure 1** (Color online) Example of a Project

**Notes.** This example project was funded by the crowd, not by judges. It was a commercial success, with 48 shows at a 300-seat theater that were two-thirds to completely full, with tickets priced at \$24–\$44. It also received positive local reviews, including the Best Local Musical and four other awards by *BroadwayWorld*, as well as generally positive reviews from local papers such as the *San Francisco Examiner*. "This is their first original production and is definitely worth it. I had such a good time that I will likely be going back" (Thomas 2012).

arts. Given these two criteria, we decided to focus on theater, where the existing literature suggests a long-standing tension between experts and mass audiences in artistic endeavors (Gans 2008, Kim and Jensen 2011, Wijnberg and Gemser 2000) while at the same time embodying many features of projects that have a commercial bottom line. As previously mentioned, theater is especially relevant in crowdfunding, because, as of 2012, Kickstarter campaigns became a larger funder of the arts than the expert-run National Endowment of the Arts.

Figure 1 provides an annotated example of a Kickstarter theater project from our sample. As can be seen in the figure, project creators generate a pitch to convince backers to support their project, using a

combination of video, text, and images to communicate their vision for the completed project. As is common in reward-based crowdfunding, backers may receive some sort of reward for a project, such as a ticket or a mention in a program, but they do not gain any financial stake in the project or profit from the project in any way. Pitches, project goals, and aspirations of project creators can vary widely between projects, and the projects in our sample included revivals of Broadway plays, adaptations of books to the stage, original musicals, works aimed at children, and new dramatic productions.

Theater also has the attractive property that it is possible to measure "real outcomes" in a manner that is independent of the funding decision,



by learning about the commercial performance or critical reviews of projects following the Kickstarter campaign. Although some of these data are noisy, they help shed some light on whether the real outcomes also correlate with funding decisions. They are also especially useful in addressing whether projects attempt to deliver their promised outcomes.

We restrict our attention to Kickstarter projects that were aiming to raise at least \$10,000 in funding. The funding goal of at least \$10,000 focuses on the subset of applicants whose ambitions and goals are more closely aligned with those applying for funding from traditional sources such as the National Endowment for the Arts (NEA), as well as several other grant-making organizations for theater. To put this in perspective, the NEA made 1,083 grants in the first round of funding for FY 2014, with an average grant size of approximately \$24,000. The average funding goal for projects in our sample is \$20,500, with the largest goal for successful projects being \$75,000.

For experts, we draw on the experience of 30 judges who have deep and extensive knowledge of theater, as evidenced by their background in evaluating theater applications for national grant-making bodies such as the National Endowment for the Arts.<sup>2</sup> We asked each of these judges to evaluate six projects, three of which were successes and three of which were failures. We were able to strip out any data on the outcome of the project but still render the projects, including videos, for the judges in a manner that was equivalent to the display on Kickstarter (including fonts, graphics, typographic errors, etc.) This not only allows us to have a representative set of applications for funding (rather than just evaluating the successful cases) but also allows us to display the applications similar to the way that the crowds viewed them, and hence evaluated them.

Evaluations were conducted using an online survey instrument derived from extensive interviews and testing with individuals who had been involved in judging for the NEA. We identified five key criteria and asked three questions about each, using a Likert scale from 1 to 5, with 5 being “strongly agree.” The five criteria we evaluated were novelty (e.g., “This project is original”), feasibility (e.g., “This project can be implemented with the resources in the proposal”), quality (e.g., “The proposal for the project is of high quality”), reach (e.g., “This project would reach a diverse audience” and “This project would

be commercially viable/profitable”), and social relevance (e.g., “Assuming it was completed as planned, this project would advance a cultural, political, or artistic dialogue”). The appendix contains the full list of questions as well as details on the survey instrument. Additionally, we showed judges the goal of the Kickstarter project in question, and we asked “How much do you think this project should be funded for, in dollars? Answer 0 if you do not think it should be funded. Assume you have enough budget to fully fund all of the projects in the survey.” We also asked judges to list the best and worst projects of those that they had seen.

We generated a stratified random sample of theater projects that attempted to raise at least \$10,000 on the Kickstarter platform between May 2009 and June 2012. We focused our attention on projects that were raising money for a specific performance, as opposed to efforts such as fund-raising for building a new theater. Again, this was to match the types of proposals typically seen in national grant competitions.

There were 257 projects that met our criteria, from which we randomly selected 120. Specifically, we created 20 “sets” of six projects each, where each set was made up of three projects that failed to reach their funding goal, two projects that achieved their goal, and one project that exceeded its funding goal.<sup>3</sup> Hence, our stratified random sample consisted of 60 failed projects (from a total of 141 failed projects), 40 projects that just met their goal (from a total of 85 such projects) and 20 projects that exceeded their goal (from a total of 31 such projects). Each set of six projects was then randomly assigned to a judge, who evaluated the six projects on a range of criteria described above.

It is worth pointing out that since projects were randomly assigned to sets, and judges were randomly assigned, our objective was to ensure that once a judge agreed to evaluate the projects, he or she did a diligent job in evaluating (rather than to ensure a high “response rate” in terms of judges agreeing to evaluate our projects, as might be a standard concern in other surveys). We incentivized judges with a \$50 gift certificate for completing the survey, helping us gain the participation of the high-quality experts we required for our test. The quality of the responses is measurable in a number of ways. First, we note that there were virtually no missing values in the responses from the judges, so that there is no response bias in our results.<sup>4</sup> Second, half the sets (that is, 60

<sup>2</sup> Judges have served on a mean of five panels each for national theater prizes and awards. All judges were also involved in theater, either as critics, artistic directors, dramaturges, theater managers, or some other role. In addition to the NEA, judges had been part of panels for the Mellon Foundation, the Doris Duke Charitable Trust, and other major theater prizes and grant-making bodies.

<sup>3</sup> We defined *exceeding* the funding goal as raising over 10% more than the ideal goal.

<sup>4</sup> One judge omitted some fields on one of the six projects that was evaluated.



projects) were randomly assigned to a second judge for evaluation. Using a squared weighting scheme appropriate for subjective scoring (Cohen 1968), the kappa statistic that measures the interrater agreement for these judges was 0.44. The Z-statistic was 7.14, strongly rejecting the hypothesis that the scores were generated at random. Although the kappa statistic of 0.44 suggests moderate agreement among the judges, it is worth noting that theater projects have an inherent element of subjectivity to them. Given this, we are reassured that there is a strong and consistent signal that seems to emerge from the judges' evaluations of the projects. Also, as will be discussed, we use a variety of methods of measuring a judge's responses to proposed projects, and we find the decisions to be robust across these approaches.

Overall, our research design aims to combine the expertise of real judges for traditional grant-making bodies with a sample of applications from a crowd-funding platform that reduces, if not eliminates, many of the concerns about selection that were outlined above. On a qualitative dimension, feedback from our survey participants suggested that there was reasonable overlap in the types of projects applying for funding through Kickstarter and the types that they had judged for in the past. In addition, many judging bodies, including the National Endowment for the Arts, are moving toward a system where judges have electronic access to applications, in part to be able to view videos that provide much richer information on the application in a short amount of time. This reduces concern that the mode of information dissemination is foreign to the judges, although we cannot rule out that specific projects were presented in a mode that was alien to judges. We address this specific issue in §5 and §6 below.

We also conducted a second survey in which we contacted the creators of the 60 successful projects in our sample to determine the longer-term outcomes of their project. We used a modified version of a previously applied questionnaire (Mollick and Kuppawamy 2016), and asked for a variety of qualitative and quantitative outcomes, including information about the audience of play as well as critical reviews. We supplemented this information with additional online searches, using Factiva and Google, to find other reviews of the productions funded through Kickstarter. Together, this material provides rich data on project outcomes along a variety of dimensions.

#### 4. Data

Since 10 sets of projects were evaluated by two judges each and the other 10 evaluated by one judge, we have a total of 180 evaluations for the 120 projects.

For each response, we have basic information on the background of judges, such as their main affiliation with the theater community (academic, actor, critic, director, writer, or other) and the number of national grant-making institutions they have judged for in the past. For each project in the set that the judge evaluates, we have information on the judge's familiarity with the project, his or her rating of the project's novelty, relevance to the community, quality, feasibility, and commercial viability. We also provide the judges with the funding goal of the project and ask them how much they would be willing to allocate to the given project, assuming they were not constrained in terms of the total funding they needed to allocate.

These 180 responses form the core of the data we use for this paper. However, we have two other sets of data that we match to the 120 projects. First, we have data on the attributes of the projects and their fundraising process on Kickstarter. For example, we know the location of the individual raising the funds, the number of individuals who pledged funding, and the total amount that was pledged (even when the goal was not successful), as well as the number of distinct reward levels that were developed to induce participation by the crowd. We also coded the number of videos and photographs the project displayed. Second, we have aimed to collect long-term outcome information on the projects, both through the survey of project founders and through Web searches. The objective here is to try and codify the degree to which the individuals themselves, as well as external observers, deemed these projects to be commercial and artistic successes. These data are much more likely to be present for projects that were successful, so our main comparison is between projects that were funded by the crowd and were rated highly by experts and those that the crowd funded but were rated poorly by the experts. Our follow-up survey of the Kickstarter projects that were successful yielded a 53% response rate (32 of the 60 projects), of which 28 completed all of the needed data, a high rate for Web-based surveys (Kriauciunas et al. 2011). Furthermore, we find no observable differences in the attributes of the projects for which there was a response and for which there was none. We use these survey responses to compare the longer-term outcome of these funded projects. In addition to the survey results, we have attempted to code the degree of artistic success for these projects, using critical reviews in the press.

#### 5. Results

We start by outlining descriptive statistics on the projects in Table 1. Table 1 compares the evaluations of projects that achieved their funding goal on Kickstarter with those that did not succeed. The judges

**Table 1** Descriptive Statistics on Projects

	All	Reached or exceeded funding goal on Kickstarter	Did not reach funding goal on Kickstarter	<i>t</i> -Test for difference
Number of projects	120	60	60	
Number of evaluations from judges	180	90	90	
Probability judge was familiar with project	6.1%	7.7%	4.4%	0.35
Average score	3.0	3.1	2.8	0.01***
Average novelty	2.8	3.0	2.6	0.02**
Average relevance	2.7	2.9	2.6	0.04**
Average quality	3.0	3.2	2.7	<0.01***
Average feasibility	3.4	3.6	3.2	<0.01***
Average reach	2.8	2.9	2.7	0.09*
Probability ranked as “Best” among set of projects evaluated	17%	22%	11%	0.05**
Probability ranked as “Worst” among set of projects evaluated	17%	9%	24%	<0.01***
Average funding share proposed by judges	44%	52%	35%	<0.01***

*Notes.* This table reports descriptive statistics on the sample of 120 Kickstarter projects that were grouped into 20 sets of six projects each. Each set comprised three successful and three unsuccessful projects that were then randomly assigned to experts who regularly review applications for the theater arm of institutions such as the National Endowment for the Arts. The specific questions each judge was asked to answer about each project are reported in the appendix. Each set of six projects was evaluated by at least one judge, and half the sets were evaluated by two judges. Interrater reliability for these judges was 0.45. This table reports descriptive statistics on the expert evaluations of the projects, broken down by whether the project successfully raised funding on the Kickstarter platform.

\*, \*\*, and \*\*\* refer to significance at 10%, 5%, and 1%, respectively.

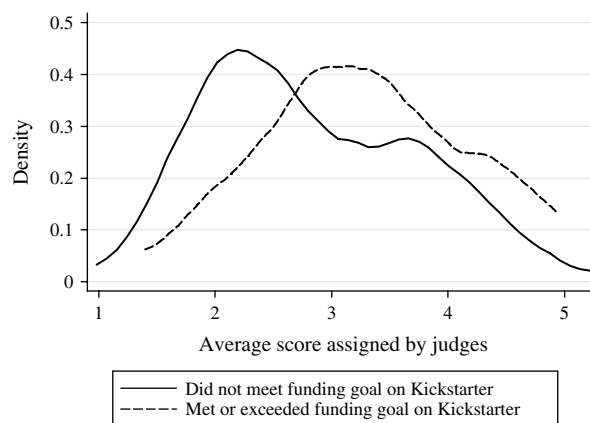
seem to consistently rate the successful projects higher than those that did not achieve their funding goal. Since there are six projects in each set, the probability that one of them will be ranked either the best or the worst is 1/6. However, Table 1 shows that projects that were funded by the crowds were twice as likely to be ranked as the best project, whereas those that were unsuccessful were more than two times as likely to be ranked as the worst project by judges. Finally, even though judges were told they should provide a hypothetical funding as if they were unconstrained in allocating funds to projects, they greatly favored projects supported by the crowd, allocating an average of 1.5 times more funds to successful projects than those that were unsuccessful.

There are two patterns that emerge from Table 1, which can be seen most clearly in Figure 2, which graphs the distribution of the judges combined scores for both successful and unsuccessful projects. First, there seems to be a strong and systematic positive correlation between the judgment of crowds and of experts: projects funded on Kickstarter are systematically evaluated as being better by experts. Second, this strong correlation does not tell the full story—the scores and the funding amounts proposed by the experts are not as stark as the decision about whether or not to fund projects, suggesting that there are projects that are funded on Kickstarter that do not seem to be highly rated by experts and others that raised funding but were not as highly rated by experts. We probe these two patterns further in Table 2.

In Table 2, we investigate the robustness of the positive correlations between expert evaluations and

crowdfunding, using the results from the first judge who responded for each project. Columns (1)–(3) report the coefficients on ordinary least squares (OLS) regressions, where the dependent variable is the average score assigned to a project by the judges. The main variable of interest is an indicator variable that takes a value of 1 for projects that either met or exceeded their funding goal. Column (1) of Table 2 reports the average scores of the two types of successful projects relative to the unsuccessful ones. Column (2) adds covariates related to the background of the judges, their experience with judging for grant-making foundations, and their prior familiarity with the specific projects in the survey they were asked to evaluate. Column (3) adds judge fixed effects to

**Figure 2** Kernel Density Plots of Average Scores Assigned to Projects by Experts



*Note.* Kernel = Epanechnikov; bandwidth = 0.3512.

**Table 2** Correlation Between Judge Evaluations and Kickstarter Success

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Average score from judges			Funding share proposed by judges		
<i>Reached or exceeded goal on Kickstarter</i>	0.564*** (0.171)	0.559*** (0.177)	0.551*** (0.189)	0.212*** (0.062)	0.211*** (0.064)	0.209*** (0.068)
<i>Constant</i>	2.597*** (0.106)	2.422*** (0.184)	2.584*** (0.092)	0.308*** (0.053)	0.220*** (0.071)	0.306*** (0.032)
Controls	No	Yes	Yes	No	Yes	Yes
Judge fixed effects	No	No	Yes	No	No	Yes
Number of observations	120	120	120	120	120	120
<i>R-squared</i>	0.12	0.15	0.34	0.12	0.19	0.33

*Notes.* This table reports the results of OLS regressions, where the dependent variable is either the average score that the judge assigned a project or the share of funding goal that the judge proposed the project should get. Columns (2), (3), (5), and (6) control for the background of the judges, including the number of times they have evaluated grant applications for theater projects, their affiliation with the theater industry, their familiarity with specific projects, and the time they took to complete the survey. Columns (3) and (6) further add individual fixed effects for each judge. The key coefficients of interest are related to indicator variables for whether the project either reached or exceeded its goal on Kickstarter. These coefficients are estimated relative to the category of projects that did not reach their goal on Kickstarter. We report robust standard errors that are clustered by judge.

\*, \*\*, and \*\*\* refer to significance at 10%, 5%, and 1%, respectively.

control for other fixed differences across judges, such as their average leniency or harshness, a bias in favor of or against theater projects raising money from the crowds, or a specific objective function they have for theater projects.

Moving across columns (1)–(3) of Table 2 provides a very consistent picture of the strong correlation between the evaluation of judges and crowds. The inclusion of covariates and judge fixed effects increases the *R*-squared of the regressions considerably, implying these control variables add significant explanatory power to the regressions. Yet the coefficient on the indicator variables for success remains remarkably stable.<sup>5</sup> The magnitudes on the coefficients are intuitive and relate to the magnitudes reported in Table 1. Unsuccessful projects score approximately 2.6 out of 5 on average, whereas those that reach or exceed their funding goals score about 3.2.<sup>6</sup> Columns (4)–(6) repeat the same regressions but where the dependent variable is now the funding share proposed by the experts for projects. They validate the results shown in columns (1)–(3).

Table 2 therefore shows that, on average, the evaluation of equivalent projects by crowds and experts has

a strong positive correlation. Moreover, it also documents that projects that exceed their goals are not the result of “the madness of crowds.” Rather, if we use the expert evaluations as a benchmark of quality, it points to the fact that, on average, crowds do a good job of evaluating projects and screening the good from the bad.

The number of observations in the regressions in Table 2 is 120 rather than 180 because, although we have two sets of evaluations per project for half the projects, we have only included the first evaluation from each judge in order to provide consistency in terms of the weight given to each project in the regression. This leads to the question as to whether our results are sensitive to the choice of judge.

To address the question of the sensitivity of results to our choice of judge, we start by noting that since we have 10 sets of projects with two judges each, 10 projects only had one judge each, we have  $2^{10}$  (or 1,024) possible combinations of judges for the 10 sets.<sup>7</sup> To understand the role of the choice of judges, we look at all 1,024 combinations rather than just at the result of regressions from any one of these 1,024 combinations. This provides us with more confidence that we are not arbitrarily choosing a combination that happens to be statistically significant. We find the magnitude of the average score for successful projects ranges from 0.35 more than the unsuccessful to 0.7 more (with a mean of 0.52 larger). In all but two of

<sup>5</sup> This is also reassuring because it shows us that the patterns we see are not driven by some judges “picking at random” and others who might be “peeking” at the outcomes and thereby providing results that were systematically correlated with project outcomes. We should note also that we explicitly asked judges whether they were familiar with projects and in only 2 instances out of 180 did they respond that they were very familiar with a particular project.

<sup>6</sup> In unreported regressions, we find that although the point estimates for the projects that exceed their goal is always higher, a Wald test for the difference in the coefficient between the two types of successful projects cannot reject the hypothesis that they are the same.

<sup>7</sup> As a simpler example, suppose we only had four sets and had two sets that were sent to two judges (set 1 to judges A and B and set 2 to judges C and D) and two sets that we sent only to one judge (set 3 to judge E and set 4 to judge F). In this case, we would have  $2^2$ , or four, unique combinations of judge evaluations across 24 projects: ACEF, ADEF, BCEF, and BDEF.

the 1,024 combinations, the  $p$ -value is below 0.05. The largest  $p$ -value is 0.06, providing us with greater confidence that the results documented in Table 2 are statistically significant and robust to any of the other 1,023 combination of judges we might have picked in reporting our results. Similarly, the funding share results range from 0.18 more to 0.26 more for the projects that are successful on Kickstarter, and they are always significant at the 5% significance level. Our results therefore document that there is a strong positive correlation between the evaluation by crowds and experts on projects.

Despite these positive results about the wisdom of crowds *on average*, it does not necessarily mean that they can perfectly substitute for experts in every instance—it is this heterogeneity between crowds and experts that we turn to next.

### 5.1. Heterogeneity in Expert and Crowd Evaluations

To examine heterogeneity in crowd and expert evaluations, we segment each of our 120 projects into one of four mutually exclusive categories: (1) those that are funded by both experts and crowds, (2) those that are funded by neither, (3) those funded only by experts, and (4) those funded only by crowds. Although we have outcome data on whether the crowd funded a project or not, we do not have actual funding decisions from experts. Rather, we have survey responses to a question asking them how much of the goal they would fund, assuming their grant-making budget was not constrained.

Our categorization of whether a judge hypothetically funded a project is thus based on our mapping of their responses to a hypothetical funding decision, one that is dependent on two factors. The first factor is the harshness of the screen we use—that is, whether we deem a project to be funded by a judge only if the judge funds the project a 100% or if we are willing to deem the project to be funded by experts when they only want to fund, say, 50% or 75% of the goal. Although it may seem like we only want to use 100% as the funding threshold (just like with the funding criterion on Kickstarter), our discussions with experts suggest that they routinely give projects that seem viable less money than requested, and hence we do not necessarily want to use the most harsh screen when deemed projects as hypothetically funded by experts. Second, as above, since half the projects are evaluated by two judges, the question of whether the project was funded by experts potentially depends on which expert's funding choice we use.

Although in theory these different empirical strategies can make large differences, in practice we find that the distribution of projects across buckets and the overall patterns we show in the subsequent tables

are quite insensitive to the specific categorization we choose. To help put this in perspective, in Table 3(a) we document how the distribution of the 120 projects across these four categories changes for the 1,024 different permutations outlined above across three different screens. The first two columns correspond to a categorization scheme where we assumed that a project would only be viable if the judge allocated 100% of the funding goal to the project. The next two correspond to a screen where the funding threshold is 75%, and finally, the last two columns correspond to a screen where the funding threshold is 50%.

Within each funding screen, we first report the degree of agreement between experts and crowds—that is, the percentage of cases where they either both fund a project or both do not fund a project. The first row reports the average agreement for a given screen across all 1,024 combinations of judges. As can be seen from columns (1), (3), and (5), there is a strong degree of agreement between experts and the crowds—about 59% on average and ranging from 56.7% to 65%.

We demonstrate the strength of this correlation in two related ways. First, we compare the extent of agreement in Table 3(a) to a hypothetical case where a judge funds projects at random (with a 50% probability). The simulations show that the percentage of agreement needs to be approximately 55.5% or more before we can conclude that agreement is not due to a random process at the 90% confidence interval and needs to be 57.5% or more before we can conclude that agreement is not due to random process at the 95% confidence level. As can be seen from Table 3(a), the minimum level of agreement using each screen is always greater than 55.5% and almost always greater than 57.5%.

The second way we demonstrate the strength of the positive correlation is to run a regression where the dependent variable takes a value of 1 if there is agreement between the experts and crowds and the key explanatory variable is where the project was successful on Kickstarter. The coefficient on the key variable of interest can be stated as  $\rho = E[Y_i | C_i = 1] - E[Y_i | C_i = 0]$ , where  $Y_i$  is an indicator that takes the value of 1 if the judge funds the project  $i$ ,  $C_i = 1$  if the crowd funded the project, and  $C_i = 0$  if the crowd did not fund the project. If the judge funds a project each time the crowd does and does not fund the project each time the crowd does not, then  $E[Y_i | C_i = 1] = 1$  and  $E[Y_i | C_i = 0] = 0$ , leading the difference to be +1 (which, as one would like it to be, is perfect positive correlation). On the other hand, if the expert rejects a project each time the crowd funds it and funds the project each time the crowd does not, then  $E[Y_i | C_i = 1] = 0$  and  $E[Y_i | C_i = 0] = 1$ , leading the difference to be -1 (which,



**Table 3(a) Level of Agreement Between Crowds and Experts**

	(1)	(2)	(3)	(4)	(5)	(6)
	Funding threshold is 100% of goal		Funding threshold is 75% of goal		Funding threshold is 50% of goal	
	Share of cases where experts and crowd agree on funding outcome (%)	Share of disagreement cases where crowd funds but experts do not (%)	Share of cases where experts and crowd agree on funding outcome (%)	Share of disagreement cases where crowd funds but experts do not (%)	Share of cases where experts and crowd agree on funding outcome (%)	Share of disagreement cases where crowd funds but experts do not (%)
Mean	58.8	80	58.8	76	62.1	57
Minimum	56.7	71	56.7	68	59.2	44
25th percentile	57.9	78	57.9	74	60.8	52
Median	58.8	80	58.8	76	62.1	57
75th percentile	59.6	82	59.6	78	63.3	58
Maximum	60.8	89	60.8	84	65.0	68

*Notes.* This table reports the degree to which experts and crowds agree on which projects to fund, and the extent to which the disagreement is driven by projects funded by the crowd and not experts versus those funded by experts but not the crowd. We create three funding thresholds for experts (100%, 75%, and 50%) so that a project is deemed funded by an expert only if the expert allocated more than that threshold for the given project. We then look at all 1,024 possible combinations of judges, and for each combination, we calculate the extent to which the experts would have agreed with the crowd's funding decision, given the different funding thresholds. Columns (1), (3), and (5) report the degree of agreement between experts and crowds and different percentiles of the distribution across the 1,024 combination of judges. For example, the average degree of agreement at the 75% funding threshold was 58.8%. Columns (2), (4), and (6) further report the extent to which the disagreement is driven by crowds funding the projects the experts would have rejected, or vice versa. They show that most of the disagreement comes from projects funded by the crowd but rejected by the experts. For example, 76% of the projects where experts and crowds did not agree at the 75% funding threshold were ones where the crowd funded the project but experts did not. Hence, only 24% of the disagreements in this example were due to projects funded by experts but rejected by the crowd.

**Table 3(b) Level of Agreement Between Crowds and Experts**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Funding threshold is 100% of goal		Funding threshold is 75% of goal		Funding threshold is 50% of goal	
<i>Reached or exceeded goal on Kickstarter</i>	0.167** (0.073)	0.167** (0.077)	0.183** (0.073)	0.183** (0.077)	0.250*** (0.083)	0.250** (0.087)
<i>Constant</i>	0.108 (0.077)	0.167*** (0.039)	0.138 (0.095)	0.183*** (0.039)	0.218* (0.110)	0.317*** (0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Judge fixed effects	No	Yes	No	Yes	No	Yes
Number of observations	120	120	120	120	120	120
<i>R</i> -squared	0.1	0.19	0.13	0.29	0.12	0.27

*Notes.* This table reports the results of OLS regressions, where the dependent variable is an indicator variable that takes the value of 1 if the crowds and experts agree on the funding decision. Columns (1) and (2) run specifications where the expert is deemed to have funded the project when the funding threshold is 100%, columns (3) and (4) refer to the funding threshold of 75%, and columns (5) and (6) refer to the funding threshold of 50%. The key coefficient of interest is an indicator variable for whether the project either reached or exceeded its goal on Kickstarter. These coefficients are estimated relative to the category of projects that did not reach their goal on Kickstarter. We report robust standard errors that are clustered by judge.

\*, \*\*, and \*\*\* refer to significance at 10%, 5%, and 1%, respectively.

as one would like it to be, is perfect negative correlation). Furthermore, note that if the judge funds projects at random, then  $E[Y_i | C_i = 1] = E[Y_i | C_i = 0]$ , and hence the correlation between the crowd and expert evaluation is zero. The requirement for the conditional expectations to be equal is that the projects be funded at random, rather than the specific probability of, say, 50%. For example, a judge who used a stacked coin that funded every third project would still be as likely to fund a project that was funded by the crowd (1/3) as a project that was not funded by the crowd (still 1/3). This is because with a random

coin flip that is unrelated to whether the crowd did or did not fund the project,  $E[Y_i]$  is independent of  $C_i$ , leading  $E[Y_i | C_i = 1] = E[Y_i | C_i = 0]$ . Therefore, under the null of random funding by the judges (at any approval rate), we should expect the coefficient in our regression to be zero.

We report the result from these regressions in Table 3(b), where, as with Table 2, we pick the first judge who responded to each set in our survey. The results from Table 3(b) show that there is in fact a strong positive correlation between judge and crowd evaluations, rejecting the null hypothesis that this

could be due to random at the 5% confidence interval. Of course, as with Table 2, we can check that our specific combination of judges is representative of the findings reported in Table 3(b). We find that in every case our coefficients are significant at the 10% confidence interval, and in nearly 90% of the cases, they are also significant at the 5% confidence interval.

Despite these differences in categorization of projects, it can be seen that there is strong agreement between judges and crowds. Regardless of the screen used, we can almost always reject the hypothesis that the agreement was purely due to chance at the 95% confidence interval, and we can always reject it at the 10% confidence interval. This confirms the broad patterns we documented in Tables 1 and 2. However, Table 3(a) also documents that the “off-diagonals”—the projects where the crowds and judges disagreed about the funding decision—represent about 40% of the projects and that these disagreements are most often made up of projects that were rejected by experts but funded by the crowd. That is, among the projects where there is a disagreement, an overwhelming share—about three-quarters of the projects, on average—are ones where the crowd chose to fund them but the experts did not.

In subsequent tables, we focus on two questions related to this heterogeneity. First, are there systematic differences in the attributes of the projects that are funded by only the crowd and only the experts? The second question arises from the fact that the majority of disagreements are constituted by projects funded by the crowd but rejected by experts. Given that many projects were funded by the crowd, but not by experts, are the results of these projects systematically different from those where experts and the crowd agreed? Since these projects were successfully funded on Kickstarter, we are able to examine real outcomes to study this issue. These questions get to the heart of how the difference in the organization of crowds from that of experts may lead to different types of projects being funded.

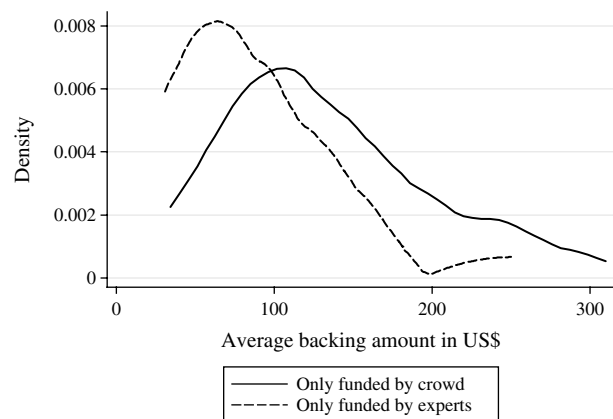
In Table 4, we first examine whether there are systematic differences in the characteristics of projects that were funded only by the crowds compared with those funded only by experts.<sup>8</sup> To do so, we run OLS regressions, where the dependent variable is the specific characteristic we are examining, and the main right-hand-side variables are indicators for whether the project fell in one of the four mutually exclusive categories outlined above. The projects that were funded by neither the crowd nor the experts are

treated as the omitted reference category, so all coefficients can be interpreted as deviations from this baseline. The specific screen we use for these regressions is one where the funding threshold is 75%. All regressions include judge fixed effects and the set of control variables used in Table 2. We report robust standard errors that are clustered by judge.

Table 4 shows some interesting patterns. First, projects that were not liked by either the crowds or the judges had larger funding goals than any of the other three categories. Projects that were funded had systematically lower funding goals, although a large funding goal does not account for why the crowd did not fund the subset of projects that the experts liked that were unsuccessful on Kickstarter. Columns (2)–(6) provide an explanation for why this may be the case. Column (2) documents that projects that were ultimately funded (rows (a) and (c)) have significantly larger average funding amounts than those that were funded only by the experts (row (b)). A Wald test for the difference in coefficients shows that these differences are also statistically significant. That is, it seems that although the funding goals were not different, projects that the crowds liked had significantly larger average funding amounts compared with those that were not funded. Note that the average funding size is a relevant metric since Kickstarter collects and keeps data on all those who commit funding to projects even when the project is unsuccessful in meeting its goal. This is because commitments are made in a continuous manner but are only “drawn upon” when the project has met its goal. Thus, we still have instances where some individuals have committed funding to unsuccessful projects. In these instances, we find that the average funding amounts are significantly lower. This is most easily seen by looking at Figure 3.

The pattern seen in Figure 3 could be for two reasons. First, those who were successful could be

Figure 3 Kernel Density Plots of Average Funding Amounts



Note. Kernel = Epanechnikov; bandwidth = 27.6448.

<sup>8</sup> From this point on, we now focus on the combination of judges that were used in the regressions in Tables 2 and 3(b) that have been shown to be quite typical of the 1,024 possible combinations of judges we might have used.

**Table 4** Differences in the Characteristics of Projects Funded by Judges and Crowds

Dependent variable	Log of goal (1)	Average investment size (2)	Reward levels (3)	Number of updates (4)	Number of pictures (5)	Number of videos (6)	Formal language (7)	Log number of Facebook friends (8)	Located in NY or CA (9)
(a) <i>Funded by both</i>	−0.185 (0.148)	24.911* (13.649)	1.358 (1.116)	5.003*** (1.853)	−0.002 (0.101)	−0.032 (0.078)	−0.654 (1.133)	0.735 (0.874)	−0.103 (0.126)
(b) <i>Only experts</i>	−0.410* (0.220)	−12.623 (13.870)	−1.096* (0.573)	−0.588 (0.780)	−0.184*** (0.056)	−0.122** (0.048)	2.636 (1.737)	−0.047 (1.096)	−0.148 (0.167)
(c) <i>Only crowd</i>	−0.239** (0.120)	49.755*** (12.898)	1.738** (0.860)	3.065*** (1.002)	0.053 (0.090)	0.062 (0.080)	−0.330 (0.992)	0.399 (0.682)	0.148 (0.090)
<i>Constant</i>	9.866*** (0.089)	84.747*** (7.900)	8.551*** (0.487)	2.224*** (0.574)	0.184*** (0.056)	0.122** (0.048)	25.284*** (0.657)	2.394*** (0.444)	0.694*** (0.067)
<i>p-value for the difference between (b) and (c)</i>	0.42	<0.01***	0.06*	<0.01***	0.01**	0.01**	0.09*	0.76	0.14
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Judge fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	120	120	120	120	120	120	120	120	120
<i>R-squared</i>	0.057	0.146	0.053	0.189	0.060	0.029	0.007	0.007	0.065

*Notes.* This table reports the results of OLS regressions, where the dependent variables refer to a number of characteristics of the projects. Each of the 120 projects is divided into one of four categories: (1) those that were funded by the crowd and were deemed good enough to receive at least 75% of their funding goal by experts, (2) those that were given at least 75% of their funding goal by experts but not funded by the crowd, (3) those that the crowd funded but were not highly funded by experts, and (4) those that did not reach their goal either from the crowd or from the experts. The first three coefficients are estimated relative to the fourth category. We report robust standard errors that are clustered by judge.

\*, \*\*, and \*\*\* refer to significance at 10%, 5%, and 1%, respectively.

connected to a wealthier network, so that they are able to get larger commitments from their backers and hence more easily reach their goal. This might be particularly true because studies of crowdfunding suggest that friends and family are often a critical base for campaigns (Agrawal et al. 2010).<sup>9</sup> The second explanation is that there are systematic differences in the ways in which the two groups approach fund-raising on Kickstarter and that the differences in commitments are an indication of the skill associated with raising money from crowds.<sup>10</sup> Of course, these are not mutually exclusive explanations, and both could be true. The evidence presented in Table 4 is certainly consistent with theory that there are differences in fund-raising approaches, and it provides some suggestive evidence that networks may also be important. Columns (3) and (4) of Table 4 show that projects that successfully raise money from crowds provide a greater number of reward levels for the crowds and also more commonly post “updates” about their

project within the first three days after launch. This is equally true for rows (a) and (c), but we can see that row (b) is significantly different. Moreover, columns (5) and (6) document that the projects that were rated highly by experts but did not raise money from crowds also did not provide as many pictures or videos as those that were successful. In addition, column (7) suggests that the language in the projects that were funded only by experts tended to be more formal<sup>11</sup> than those funded by only the crowd, suggesting that crowds may have a disposition to less formal language. Together, columns (3)–(7) paint a consistent picture: raising money from the crowd seems to involve a skill that may be independent of the quality of the project (in much the same way as raising money from experts requires skill). Those who do not pitch to the crowd in an appropriate way may not be successful in raising money, even if the quality of the underlying project is high.<sup>12</sup>

<sup>9</sup> In our follow-up survey of successful projects, project creators suggested that friend and family support was important but probably not the provider of the majority of funding. In a five-point Likert scale ranging from “strongly disagree” to “strongly agree,” the mean answer to the question “My backers were mostly friends and family” was 3.7; sd = 1.1.

<sup>10</sup> Note that there is also the possibility that projects that offered a higher consumption utility (say, because people wanted to watch the play) raised higher amounts through ticket sales. As we note later, this was not the case, so we do not focus on this possible mechanism.

<sup>11</sup> Our measure of formality in this context is the share of words in the proposal that were longer than six letters, as studies have shown that longer word length in a body of text is correlated with the level of formality in that text (Brooke et al. 2010, Karlgren and Cutting 1994). We also have some qualitative evidence that proposals that used swear words were less likely to be funded by experts, suggesting that informality may be punished.

<sup>12</sup> These factors of the pitch tend to be established prior to the launch of a crowdfunding campaign. For updates, we follow Mollick (2014) and only measure whether projects were updated in the first three days after launch, reducing the risk that updates are a reaction to success. At the same time, we cannot rule out that these

**Table 5** Evaluation of Projects Funded by Judges and Crowds

Dependent variable	(1) Combined average score	(2) Novelty	(3) Relevance	(4) Quality	(5) Feasibility	(6) Commercial viability
(a) <i>Funded by both</i>	1.557*** (0.202)	1.587*** (0.278)	1.729*** (0.263)	1.864*** (0.301)	1.350*** (0.189)	1.252*** (0.260)
(b) <i>Only experts</i>	1.024*** (0.187)	1.005*** (0.284)	0.964*** (0.295)	1.342*** (0.225)	0.751*** (0.249)	1.052*** (0.235)
(c) <i>Only crowd</i>	0.309 (0.209)	0.266 (0.220)	0.306 (0.248)	0.436* (0.225)	0.216 (0.246)	0.312 (0.270)
<i>Constant</i>	2.271*** (0.089)	1.369*** (0.100)	1.777*** (0.103)	2.155*** (0.112)	3.481*** (0.102)	2.576*** (0.115)
Number of observations	120	120	120	120	120	120
R-squared	0.58	0.53	0.55	0.52	0.47	0.41

*Notes.* This table reports the results of OLS regressions, where the dependent variable is the average score that the judge assigned a project along a range of different dimensions. All specifications include individual judge fixed effects and controls outlined in Table 2. Each of the 120 projects is divided into one of four categories: (1) those that were funded by the crowd and were deemed good enough to receive at least 75% of their funding goal by experts, (2) those that were given at least 75% of their funding goal by experts but not funded by the crowd, (3) those that the crowd funded but were not highly funded by experts, and (4) those that did not reach their goal either from the crowd or from the experts. The first three coefficients are estimated relative to the fourth category. We report robust standard errors that are clustered by judge.

\*, \*\*, and \*\*\* refer to significance at 10%, 5%, and 1%, respectively.

Columns (8) and (9) examine the hypothesis that those who are successful in raising money from crowds may have better or wealthier networks. Column (8) shows that those who were successful had the same network size, as proxied by the number of Facebook friends. A difference in funding commitment for a similar-sized network could be consistent with wealthier friends and family, although it could also proxy for the skill in approaching the crowd. In column (9), we show that those projects that only the crowd liked were somewhat more likely to be based in New York or California; this could proxy for the wealth of the local network or, again, could proxy for savviness with social media and running crowd-funding campaigns. Alternatively, it could also be due only to the degree of diffusion of the Kickstarter platform in these two states. On balance, we find the strongest evidence for systematic differences in raising crowdfunding as stemming from skill in running such campaigns, although we cannot rule out that this was also due to differences in networks. Further evidence of the role of skill in crowdfunding stems from the fact that the attributes of projects funded by both the crowd and experts (row (a)) are more similar to those funded by only the crowd (row (c)) than each of these is to those funded only by experts (row (b)).

Next, we consider how judges rate projects that are supported by the crowd alone compared with those that are not. Table 5 provides the differences in scores attributed to these projects by our experts. The specifications run in Table 5 are identical to those in Table 4, with the exception that the dependent variables are

dimensions along which the experts were asked to evaluate the projects. The high scores associated with rows (a) and (b) are mechanical, in that these are projects that the experts would have funded. Nevertheless, it is worth noting that the projects that the crowd and experts funded rank higher than those funded only by experts, again reinforcing the notion that the projects where both crowds and experts agree to fund are likely to be extremely high quality.

Looking at row (c) is also instructive since it shows that the point estimates are consistently higher than the omitted category, although they are often imprecisely estimated so that the differences are not statistically significant. That is, there is a subset of projects that the crowd funded that the experts found no better than the omitted category (those that neither the crowd nor experts liked). Indeed, our survey of the successful Kickstarter projects suggests that this was also true to experts in general: the subset that only the crowd funded raised an average of \$1,900 from institutional sources prior to the campaign compared with \$4,850 for those that the experts and crowds funded. That is, our finding that experts did not rate these projects as highly seems to be broadly representative of how other experts may have also viewed these projects. Nevertheless, it is interesting that the one column where there is a statistically significant difference between row (c) and the omitted category is that of the quality of the project. That is, among projects that the experts chose not to fund, those that were funded by the crowd were deemed by the experts to be higher-quality projects than those that the crowd did not fund (although, of course, they were also ranked as lower quality than rows (a) and (b)). Again, this supports the notion that even when there is

factors could be changed in reaction to the crowd and are careful, therefore, not to push a causal explanation for these differences.



disagreement between crowds and experts on the funding decision, there still seems to be some level of congruence in terms of the broad sense of which projects are higher quality.

Next, we turn to qualitative evidence about the longer-term outcomes of projects. We relied on survey data for information on both audience size and the degree to which projects succeeded or failed at meeting their audience goals. We also asked respondents to provide links or excerpts from reviews. In all cases, we also attempted to locate reviews ourselves by searching for the project on Factiva and on Google. To be conservative, we classified projects in one of four ways: we considered projects to be failures if they received only bad reviews and did not run for their full length.<sup>13</sup> Successes made up the vast majority of projects. These were projects that ran for their intended length but did not earn rave reviews from national publications, though they may have received good local press. This category contains a wide range of projects, some much more successful than others, as indicated by the qualitative data in the tables. Finally, we categorized projects as commercial hits if they had substantially extended runs in front of large crowds and as critical hits if they either received rave reviews from national publications or else won prestigious theater awards.

First, we look at the long-term outcome of the projects that both crowds and experts funded. (A detailed table of these results, labeled Table 6, is provided in the online appendix, available at <http://dx.doi.org/10.1287/mnsc.2015.2207>.) We have survey responses that include self-reported outcome data on 11 of the 22 such projects. Using our conservative coding regime, none of these projects failed, and one turned into a commercial hit. Examining the more detailed qualitative data, it is apparent that there were a wide variety of critical and commercial outcomes but a relative dearth of either clear failures or runaway successes. Though these results are tentative, most projects selected by both the crowd and experts appeared to deliver on their promise, with some variation in the critical and commercial acclaim achieved.

We recreate this for projects that the crowd funded but which the experts did not. (A detailed table of these results, labeled Table 7, is available in the online appendix.) Here, we have self-reported outcome data on 17 of the 38 productions. Remarkably, we find quite a similar pattern, with the vast

majority of projects achieving the same level of success as the projects endorsed by the experts. To the extent that there are differences, there is one failure among the crowd-selected projects and four projects that we could consider hits. Two of these hits are critical, rather than commercial, successes—an ironic outcome, given that these performances were rejected by the expert critics but embraced by the crowd in the funding stage. We find that the broad picture is one where 94% of the funded projects supported by the crowd alone had at least moderate success, and 24% were extremely successful, some artistically and some commercially. This compares to a 100% success rate from the projects backed by both crowds and experts, of which 9% were extremely successful.<sup>14</sup>

We also endeavored to examine the outcomes of the 11 projects selected by experts but not funded by the crowd. We were able to determine that seven of these projects were ultimately staged. All seven would be considered minor successes, but none achieved high levels of critical notice, or substantial commercial success.

Although we hesitate to draw broad conclusions from the limited data, we find it interesting that within the bucket of projects unfunded by experts, the experts do seem to give higher ratings to projects that were ultimately more successful. This suggests that the screen used by the crowd is somewhat lower but not entirely without merit (although the crowd also funded the only project to fail dramatically). These results are suggestive of a case where the crowd selects some projects with greater variability in potential outcome than do experts, resulting in more failures but more breakout hits than the experts, similar to findings about how the structure or the number of participants in screening can generate more high-quality or low-quality ideas (Sah and Stiglitz 1986, Terwiesch and Ulrich 2009, Terwiesch and Xu 2008).

A possible alternative explanation of the ability of the crowd to pick successful projects is that the crowd

<sup>13</sup> One concern about crowdfunding has been that some projects may fail to deliver entirely, either because of malicious intent or else failure on the part of the project creators. We found only one example of this sort of project, in this case as a result of the death of a project creator, adding to research suggesting fraud on Kickstarter is uncommon (Mollick 2014).

<sup>14</sup> Although we did not have survey results for the remaining 32 projects, we did seek to establish whether or not critical reviews of the projects indicated any substantial deviation from that observed in the projects for which we had survey results. We did not locate any indication of a systematic difference. Of the 11 projects that did not answer the survey but which were supported by the crowd and the experts, 10 appeared to be successes, with 1 project failing as a result of the death of a key member of the theater troupe. Of the 21 projects that were funded only by the crowd, at least 1 was a critical success, winning a prestigious theater award, and 2 others appeared to win less prestigious theater honors. Additionally, two were partial failures, having delivered some of the performances promised in their campaign but not all, although both projects promised to finish delivery in 2014 or 2015 and still appeared to enjoy backer support. These results align with those from the survey group, suggesting that there does not appear to be large hidden biases in Tables 6 and 7, but that, if anything, the crowd seems to be associated with slightly more variance in outcomes.

might serve as the factor that makes these products succeed. By prepurchasing tickets through Kickstarter (one of many potential rewards offered by artists), they may be ensuring the success of these shows. Using our survey data, we examined the 14 projects that provided us with estimates of total ticket sales. Together, these projects sold 25,779 tickets overall, of which 961, or less than 4%, were presold through Kickstarter. Presales on Kickstarter did not seem to account for the success of these shows based on this measure. Furthermore, presales would not be predictive of critical acclaim, which also seemed to accrue disproportionately to projects backed by the crowd alone.

## 6. Discussion

Given the rise of crowds as a vital part of decision making in areas ranging from product design to entrepreneurship, the question of how the judgment of crowds compares with that of experts is of great importance. Although there have been some signs that crowds could act wisely, most examples of crowd wisdom either include experts that ultimately exercise final judgment, as in crowdsourcing (Afuah and Tucci 2012, Poetz and Schreier 2012), or compare aggregated predictions to those of individuals (Budescu and Chen 2014, Larrick and Soll 2012, Wolfers and Zitzewitz 2004). Crowdfunding, similar to other emerging areas where crowds act without intermediaries or secondary markets, operates differently, heightening the risk that the crowd could be “mad”—subject to irrational exuberance, follies of group decision making, or other collective pitfalls. Furthermore, even if crowds are not directly irrational, they could still only express idiosyncratic or popular tastes, ignoring proposals that would normally be supported by experts.

The first contribution of our work is to document strong congruence in the judgment of crowds and experts in a highly subjective environment such as theater, even outside of prediction markets or forecasting competitions. These results were robust to many kinds of measurement. Furthermore, we see no signs that, for those decisions where crowds and experts diverge, that the decisions supported by the crowd alone perform systematically worse than those of the experts. The projects selected by the crowd succeeded 93% of the time, whereas those selected by crowds and experts succeeded 100% of the time. However, among the successes, the crowds also seemed associated with bigger hits, suggesting more variability in the outcomes rather than a lower mean.

Our results also shed light on the differences between crowd and expert judgment. The biggest differences we found between projects that the crowd alone

supported versus those supported by experts seemed to be in the style of presentation, rather than the quality of the actual project itself. The more “crowdfunding friendly” a quality proposal was—taking advantage of the Internet by using videos and pictures, including many rewards for backers, and so on—the more it seemed to appeal to the crowd. Similarly, experts also seem to have signals that they look for—for example, the degree of formality of a proposal or the presence of swear words. Our results suggest that these differences in tastes can have meaningful, real outcomes, in that the crowd seems willing to fund projects that experts are not, even when experts are given unlimited funds, and similarly, the crowd seems to systematically miss projects that experts like because they are not pitched in a “crowdfunding-friendly” format.

In this sense, our paper provides evidence of the important role crowdfunding can have in democratizing entry among projects that experts might have rejected. For example, crowdfunding provides the possibility of funding to individuals who would not otherwise have access to funds because of the potential challenges of applying for NEA grants: they may not have experience or knowledge of grant writing, may have the wrong skill set to apply, or may be proposing programs that are not within the NEA guidelines.<sup>15</sup> Based on this evidence, the change from a hierarchical expert-led system to a mixed expert and crowd-based one may have large positive effects on the types of innovations that the system produces (Sah and Stiglitz 1986), as allowing more ideas to come to fruition has been shown to lead to increased innovation quality (Kornish and Ulrich 2011, Terwiesch and Ulrich 2009). Similarly, a more diverse pool of individual innovators can further increase innovation (Østergaard et al. 2011).

It is important to note that, although we find encouraging evidence for the value of crowd decision making, this does not devalue the role of experts. For example, some discussions with experts showed more willingness to fund more artistically challenging work that may not appeal to the crowd. Experts may also be less swayed by the salesmanship of the pitch, as evidenced by the lower importance they appeared to place on the multimedia in the pitch itself. Our results are consistent with, and indeed support, the notion that in a crowd-based decision regime there is still

<sup>15</sup> As noted above, there are some suggestions in the data that the crowd may be more willing to take a chance on projects with higher variance outcomes than experts might be comfortable with. Though it is not statistically testable, we find that the crowd funded a higher percentage of hits (27%) than did the experts (7%), as well as the only project that failed because of a quality issue. Increasing the number of high variance projects may lead to more breakthrough ideas.

a critical place for expert judges. In fact, we aim to stress that our setting and research design does not allow us to speak definitively to the important and pertinent policy question of what would happen to theater projects if we shifted from a purely expert-funded model to a purely crowd-funded one. This is because we are focused on projects that applied to a crowdfunding site rather than the universe of artistic projects that might be available.<sup>16</sup> For example, some have argued that the growing importance of Kickstarter in the funding of the arts reduces the need for the government to provide funding to such endeavors through the NEA, which has an annual operating budget of about \$150 million. Although our results suggest that crowdfunding can play an important role to complement such organizations, we are less well positioned to speak to questions related to how a decrease in theater grants from the NEA would impact the nature and style of theater productions in the United States, especially theater produced by underrepresented groups or works that are artistically challenging.

Although our analysis was conducted for theater projects, we feel that our key result—that experts demonstrate a strong congruence with projects funded by the crowd—is likely to generalize to other settings where the crowd is an end user for the product being financed and hence might be well positioned to judge the project. Although this is likely to be true for many aspects of the arts, such as film, music, and dance, we believe that there are also aspects of technological innovation where crowds can play a key role in complementing experts as sources of capital. Kickstarter has proven to be an influential source for innovations in areas such as gaming and consumer-facing Internet technologies, as well as more specialized areas such as wearable computing and three-dimensional printing. Indeed, a number of start-ups that have raised funding on Kickstarter have gone on to raise institutional venture capital, suggesting the growing role that the crowd can play in providing validation of “traction” for experts.<sup>17</sup>

<sup>16</sup> Consider the following example: Say, of 10 projects, p1–p10, the crowd would fund p1–p3, neither crowds nor experts would fund p4, and experts would fund p5–p10. If a study sample contained only projects p1–p6—say, because p7–p10 were not conducive to being listed on a crowdfunding site—then showing that a majority p1–p6 were funded by the crowd does not tell us anything about whether the crowd-only or expert-only system is better. In this example, if one were to choose between a crowd-funded or expert-funded system, the expert-based one would fund six projects compared with only three under a purely crowd-funded system, even though the sample in question had a lower share of projects funded by experts. This is why one would need the *universe* of projects, together with project fixed effects, to effectively address this policy question. We thank a referee for clarifying this issue.

<sup>17</sup> For example, Kerr et al. (2014) document the difficulty that even professional investors have in predicting which investments

Our research has some limitations and strengths. One limitation is our study stems from the research design: we chose to restrict our analysis to a set of projects where, *ex ante*, we believed there to be overlap in the types of projects that were funded by the crowd and the types of projects our experts would evaluate in other settings, such as when reviewing for the NEA or foundations. We thus restricted our study to theater projects seeking at least \$10,000. Although we believe that theater offers a conservative test of crowd wisdom, given its subjective nature and the divide between critics and customers, we cannot necessarily generalize these findings to all other forms of crowd judgment. Furthermore, our results speak to crowdfunding behavior conditional on the funding size we studied. If projects seeking much smaller funding, even within theater, are more frivolous or associated with different crowdfunding motivations, our findings will not apply to them. Second, although our outcome data are strongly suggestive of similar outcomes between the crowd-only and the expert- and crowd-backed projects, they are circumstantial in nature and hard to measure directly. Third, we focus only on projects that applied for crowdfunding rather than the universe of all theater projects, which implies that we are limited in our ability to speak to which screening regime (crowds versus experts) is better suited to the projects applying for funding or to address the question of how a shift from one funding regime to another might impact which projects are commercialized.

Despite these limitations, however, our approach also has strengths. A key strength is that by using panels of expert judges to evaluate existing projects, we were able to avoid many of the endogeneity concerns that might otherwise arise in such studies. Further, the opinions of judges on projects are robust to judge fixed effects, suggesting that our results are not purely the result of idiosyncratic views of some judges. Additionally, we were able to use field data representing actual crowd decisions from the largest crowdfunding platform, observing both successful and failed projects.

## 7. Conclusion

Our study offers the first detailed comparison of crowd and expert judgment, an issue of increasing relevance in a world where crowdfunding, crowdsourcing, crowdscience, and related concepts are increasing in popularity and where billions of dollars are being

are likely to be successful. Indeed, there seems to be a growing move among early-stage investors to demonstrate traction with customers, as is demonstrated by platforms such as AngelList profiling these metrics for potential investors.



deployed through crowdfunding platforms. In particular, we can effectively address the extent to which experts agree or disagree with the funding decisions of the crowd and thereby use this as a benchmark for the wisdom of crowds. We find that the crowd is more wise than mad, generally agreeing with the experts, and that, on average, the projects selected by the crowd alone seem to do as well as those selected by experts. For academics, our work highlights the need to better understand the ways in which crowd decisions are made and the circumstances under which the crowd, experts, or a combination of the two should be deployed to address particular needs. In practical terms, this paper suggests that crowdfunding may be a viable source of entrepreneurial financing for both cultural projects and traditional start-ups. The crowd has the potential to increase innovation, lower barriers to entry, and democratize the entrepreneurial process by allowing more ideas to compete in the marketplace, particularly as a complement to expert judgment.

### Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/mnsc.2015.2207>.

### Acknowledgments

Authorship is alphabetical; both authors contributed equally in developing this paper. The authors are grateful to Xiang Ao, Ajay Agrawal, Teresa Amabile, Ronnie Chatterji, Jing Chen, Chuck Eesley, Avi Goldfarb, Brent Goldfarb, Mukti Khaire, Josh Lerner, Matt Marx, Matthew Rhodes-Kropf, Antoinette Schoar, and Tavneet Suri for helpful conversations and feedback, and to the participants of the Economics of Entrepreneurship and Innovation Conference at Queens School of Business. The authors thank John Galvin and Andrew Marder at Harvard Business School for their help in implementing the survey. The authors also thank the editors and three anonymous reviewers for their very helpful comments. Support was provided by the Kauffman Foundation's Junior Faculty Fellowship and Harvard Business School's Division of Research and Faculty Development.

### Appendix. Survey Procedure and Questions

Judges were contacted from among the list of experts who had previously acted as judges for major theater competitions and grants (the National Endowment for the Arts, Drama Desk Awards, New York Drama Critics' Circle, Pulitzer Prize for Drama, Theatre World Award, and Tony Awards).

Judges were electronically asked to score six projects using the criteria below. All questions asked on a 1–5 point Likert scale, with 1 being “strongly disagree” and 5 being “strongly agree.”

#### Novelty

This project displays a high degree of artistic ingenuity.  
Assuming it was completed as planned, this project would advance the art form.  
This project is original.

#### Quality

The proposal for the project is of high quality.  
The video added to the proposal in a meaningful way.  
The artistic vision of the proposal is clear.

#### Feasibility/Realism

The artistic and/or commercial goals of this project are achievable.  
The individual or group proposing this project is qualified to complete the project.  
This project can be implemented with the resources in the proposal.

#### Stakeholders and Reach

This project would reach a diverse audience.  
This project would attract a wide range of potential funders and stakeholders.  
This project would be commercially viable/profitable.

#### Relevance

Assuming it was completed as planned, this project would advance a cultural, political, or artistic dialogue.  
This project promotes a high sense of audience engagement.  
I feel personally excited about this project.

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