The Informational Role of Crowdfunding*

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Abstract

The recent rise of crowdfunding begs the question of what unique value the crowd brings to entrepreneurs compared with sophisticated intermediaries. This paper proposes an answer to this question by focusing on the informational role of crowdfunding. I argue that a distinct role of crowdfunding is the provision of early feedback to entrepreneurs that facilitates their learning. Using a large dataset from Kickstarter, I first document that entrepreneurs adjust their expectations about their projects based on feedback from the crowd, and that such adjustments are stronger when entrepreneurs face higher uncertainty or when the crowd is more experienced. The crowd's feedback affects entrepreneurs' subsequent continuation decisions and project choices, and influences the aggregate entry pattern of future entrepreneurs on the platform. I then establish the learning advantage of crowdfunding leveraging the entry decisions of heterogeneous entrepreneurs. I show that, when crowdfunding becomes more costly relative to alternative financing (bank borrowing), entrepreneurs choosing crowdfunding shift to those that benefit particularly from early feedback, i.e., those facing high uncertainty or high fixed costs. These results suggest that crowdfunding is not merely a financing tool, but also a learning device that improves the information environment faced by entrepreneurs.

Keywords: entrepreneurship, crowdfunding, learning, feedback, financial disintermediation

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The financing of entrepreneurs is traditionally dominated by intermediaries such as banks and venture capital firms. In recent years, this scenario has been disrupted by the direct participation of the general public. Crowdfunding, a new financing method for entrepreneurs, grew thirty two-fold globally from a market size of $0.5 billion in 2009 to that of $16.2 billion in 2014, and is expected to reach $34.4 billion in 2015 (Massolution 2015). With now about 1,250 platforms in more than 50 countries, crowdfunding has drawn major attention (see Figure A1) as well as debates. While many tout its potential to democratize access to finance, others regard it as "dumb money", doubting the value it brings to entrepreneurs[1]. Indeed, given that the crowd is neither deep-pocketed nor experienced compared with intermediaries, the rise of crowdfunding seems surprising. What is the comparative advantage of crowdfunding relative to traditional financiers? What unique role does it play in the entrepreneurial process besides providing finance? This paper attempts to advance our knowledge along this direction.

In this paper, I uncover a distinct role of crowdfunding: the provision of early feedback to entrepreneurs that facilitates their learning. Using a comprehensive dataset from the world's largest crowdfunding market, Kickstarter, I show that entrepreneurs update beliefs about their projects based on feedback from the crowd and adjust their funding targets, project choices, as well as entry decisions accordingly. I then establish the learning advantage of crowdfunding leveraging the entry decisions of heterogeneous entrepreneurs. I show that, when crowdfunding becomes more costly relatively to alternative financing (bank borrowing), entrepreneurs choosing crowdfunding shift to those that benefit particularly from early feedback. These results suggests that crowdfunding can improve the information environment faced by entrepreneurs who lack access to traditional financial market feedback.

The informational role of crowdfunding stems from the fact that the crowd collectively has information unknown to the entrepreneurs, and that entrepreneurs can learn from the crowd. I argue that crowdfunding provides *better* and *earlier* feedback to entrepreneurs compared with traditional financiers. Unlike VC and angels, which are only available to a small fraction of the entrepreneurs in the economy, crowdfunding is more accessible,

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[1] See, for example, *The Economist*, 2012 Jun 16th, "The new thundering herd"; *The Wall Street Journal*, 2013 Jan 31st, "Inventive funding deserves creative regulation"; *The Wall Street Journal*, 2015 Nov. 6th, "The Uberization of money"; *Forbes*, 2013 Nov. 3rd, "Do you really want dumb money?"; *Financial Times*, 2012 Nov. 26, "The unexpected cost of success"; *Inc.*, 2013 Nov 1st, "The dark side of equity crowdfunding".

especially at an early stage when feedback is most valuable.[2] As the main financier for entrepreneurs, banks base their lending decisions largely on entrepreneurs' personal credit conditions, as opposed to the product market viability of their ideas. Crowdfunding, on the other hand, leverages the collective information production of the crowd, who, through their funding decisions, have "skin in the game" to provide valuable feedback to entrepreneurs. Such feedback helps resolve entrepreneurs' uncertainty over their ideas or abilities, and can improve their decisions. Crowdfunding can therefore serve as a learning tool for entrepreneurs beyond providing finance.

This paper tests the informational role of crowdfunding using two approaches. I first focus on the *ex-post* learning behaviors of entrepreneurs and ask whether and how they learn from the crowd, as well as whether such learning has effect on their subsequent decisions. I then examine whether the *ex-ante* learning value of crowdfunding is reflected in entrepreneurs' choice between crowdfunding and the main financing alternative, bank borrowing.

I employ a novel dataset from the world's largest reward-based crowdfunding platform Kickstarter to conduct the above tests. On Kickstarter, an entrepreneur posts a project pitch with a funding target she wishes to achieve within a funding window. Backers pledge money in small amounts in return for in-kind rewards. A project is funded if the total pledged amount equals or exceeds the funding target by the end of the funding window, in which case the entrepreneur gets all the pledged money;[3] otherwise the project is unfunded and no money is transferred to the entrepreneur. Importantly, and also common to all crowdfunding markets, Kickstarter features rich social components that allow entrepreneurs and backers to communicate and interact online. My dataset contains the universe of projects launched on the platform between April 2009 and April 2014, involving 137,371 projects (both funded and unfunded) and 12 million entrepreneur-backer links.

I first examine whether and how entrepreneurs adjust beliefs about their projects in response to feedback from the crowd. Employing a sample of repeat entrepreneurs that have launched multiple projects on the platform, I use an entrepreneur's initial funding target as

[2] In U.S., less than 0.5% newly created firms have raised capital from VCs, and less than 5% have raised capital from angel investors (estimated based on data from U.S. Census Bureau, Small Business Administration, PWC Money Tree, and CVR Angel Report).
[3] Less 5% fee charged by Kickstarter.

a measure of her prior expectation about the amount her project can attract. I then use the actual amount pledged by the crowd as a measure of the crowd's feedback. Such a feedback reflects the crowd's interests in the project or their belief about the entrepreneur's ability to deliver it. I use the funding target of the same entrepreneur's next similar project as a proxy for her posterior expectation.[4] I find that entrepreneurs' posteriors are positively associated with their priors and the feedback from the crowd.[5] Further, entrepreneurs place more weight on the crowd's feedback and less weight on their priors when they face higher uncertainty or when the crowd is more experienced, consistent with basic Bayesian updating. These results are robust to accounting for sample selection, alternative definition of similar projects, as well as subsample analyses on larger or more tech-oriented projects. To shed light on whether learning is more about project or ability, I first show that the crowd's feedback is unrelated to the funding target of an entrepreneur's next project if the project is in a different project type, suggesting that learning about one's general ability does not drive my results. Second, I show that the learning results do not interact with the extent to which the entrepreneur is featured in a project pitch. Together, these findings are consistent with entrepreneurs learning from the crowd about the product market viability of their projects.

Next, I study whether feedback from the crowd has consequences for entrepreneurs' subsequent decisions such as entry and project choice. I find that, more positive feedback from the crowd, measured by higher pledge ratio (pledged amount divided by funding target) or higher number of comments posted per backer, is associated with a higher likelihood of an entrepreneur re-entering the platform and, conditional on re-entry, a higher likelihood of launching a project similar to her previous project. I further show that such feedback can be picked up by entrepreneurs not yet on the platform through observational learning and influences the future entry pattern on Kickstarter. I find that past funding outcomes in a project category positively predicts future entry into this category relative to other categories. This effect is driven by the most successful projects in the recent past, consistent with entrepreneurs reacting to the most salient information. Such information spillover is unique to crowdfunding due to the public nature of its funding activities. The informational benefits of crowdfunding can therefore reach beyond entrepreneurs that launches a crowdfunding

[4] The main definition of "similar projects" are projects in the same project type. Kickstarter categorizes projects into 51 refined project types and 13 project categories based on the contents of the projects.

[5] With a slight abuse of terminology, in the rest of the paper, I use prior to refer to prior expectation and posterior to refer to posterior expectation for simplicity.

campaign.

In the second part of the paper, I take an *ex-ante* perspective and ask whether crowdfunding commands extra learning value compared with bank borrowing, the main financing alternative for early-stage entrepreneurs, and whether such an advantage is reflected in entrepreneurs' choices between the two financing alternatives. To this end, I study how the composition of crowdfunding entrepreneurs changes in response to changes in the relative cost of crowdfunding vis-à-vis bank borrowing. I demonstrate in a simple model that, when local borrowing costs decrease so that crowdfunding is relatively more costly, the average uncertainty and fixed costs faced by entrepreneurs *choosing* crowdfunding will increase if and only if crowdfunding provides more precise feedback than banks.[6] Using instrumented local housing price movements and local small business loan supply shocks as exogenous changes to the relative cost of crowdfunding, I first confirm that crowdfunding and bank borrowing are indeed substitutes in providing finance: demand for financing on Kickstarter drops in response to cheaper local credits. I then find that, as local borrowing becomes cheaper, entrepreneurs entering Kickstarter shift to those that derive higher learning value from early feedback, i.e. those facing more uncertainty or proposing projects with higher fixed costs. I also find that such entrepreneurs engage in more learning ex post. These results are consistent with crowdfunding having additional value of learning compared with bank financing.

Lastly, I address the potential concern that feedback is endogenous to entrepreneurs' decisions due to omitted unobservables. To this end, I make use of Kickstarter's weekly newsletters that are sent to all subscribers and feature three projects each week. I exploit strong and discontinuous changes in attention shocks received by projects presented in different positions in emails. Specifically, projects presented first in emails received much higher attention and subsequent funding than projects presented second and third, while the differences between the last two groups are insignificant. This is consistent with the presence of a primacy effect (Krosnick (1987)). Importantly, Kickstarter states that they do not rank the projects in email based on any preference, and a comparison of various ex-ante

[6] The intuition is that, the relative option value of crowdfunding vis-à-vis bank borrowing will be positive and increasing in project uncertainty if and only if the crowd's feedback is more precise than that of the banks. Since lower borrowing costs drive up the average relative option value faced by crowdfunding entrepreneurs, I would observe an increase in their underlying project uncertainty if and only if the relative option value is positive.

characteristics confirms that projects in all three positions are observationally equivalent. I therefore compare the subsequent decisions of entrepreneurs with first-presented projects with those with second-presented projects to obtain causal inferences. The results support my main findings.

The main contribution of this paper is to empirically document the informational role of crowdfunding as well as its implications for entrepreneurs' real and financial decisions. Compared with managers of listed firms who can access rich feedback from financial markets, entrepreneurs face a poor information environment. Decisions to commit significant resources often have to be made with little information about future returns. This paper suggests that crowdfunding can be a solution to entrepreneurs' information problem. By democratizing access to early feedback, crowdfunding resolves uncertainty and helps improve entrepreneurs' decisions. The value of crowdfunding therefore goes beyond providing finance.

This paper adds to the nascent literature on crowdfunding. Most existing studies focus on the financing side of crowdfunding as well as incentives and mechanisms on crowdfunding platforms.[7] This paper departs from the literature by looking at the informational role of crowdfunding. This paper also builds on several recent studies that document the wisdom of the crowd. Iyer, Khwaja, Luttmer, and Shue (2015) find that lenders in a debt-based crowdfunding platform predict a borrower's likelihood of default with 45% greater accuracy than the borrower's exact credit score (unobserved by the lenders), highlighting the crowd's advantages in producing soft-information. Mollick and Nanda (2015) compare crowd and expert judgment in funding Kickstarter theatre projects and find a high degree of agreement between their funding decisions. Mollick (2013) finds that entrepreneurial quality is assessed in similar ways by VCs and crowdfunders. Golub and Jackson (2010) model learning and information aggregation in a network and show that the crowd's opinion will converge to the truth as long as the influence of the most influential agent vanishes as the network grows. This paper studies whether, given the wisdom of the crowd, entrepreneurs take cues from

[7] Agrawal, Catalini, and Goldfarb (2014) study how geographical distance affects investors' funding patterns; Zhang and Liu (2012), Mollick (2014), Kuppuswamy and Bayus (2014), and Li and Duan (2014) study funding dynamics on crowdfunding platforms; Duarte, Siegel, and Young (2012), Ahlers, Cumming, Guenther, and Schweizer (2013), Marom and Sade (2013), Li and Martin (2014), and Bernstein, Korteweg, and Laws (2015) examine the determinants of funding decisions and outcomes in crowdfunding markets; Wei and Lin (2013) and Cumming, Leboeuf, and Schwienbacher (2015) study funding mechanism in debt-based and reward-based crowdfunding market respectively; Hildebrand, Puri, and Rocholl (2014) examine player incentives in peer-to-peer lending. See Agrawal, Catalini, and Goldfarb (2013) for a more detailed review of the literature.

the crowd's feedback and adjust their decisions accordingly.

This paper also relates to the literature on the informational role of financial markets (Edmans, Goldstein, and Bond (2012)). Financial market prices typically contain information that managers do not have, and through managers' learning, can guide their decisions such as investments (Chen, Goldstein, Jiang (2007)), acquisitions (Luo (2005), Edmans, Goldstein, Jiang (2012)), and governance (Edmans (2009, 2013)). Relatedly, the literature on prediction market shows that markets provide better predictions than polls and other devices (Wolfers and Zitzewitz (2004)). This paper shows that, by shifting early-stage financing from intermediaries to markets, crowdfunding can improve the information environment faced by entrepreneurs.

Lastly, this paper contributes to a recent literature that views entrepreneurship as experimentation. In their review paper, Kerr, Nanda, and Rhodes-Kropf (2014) argue that entrepreneurship is about experimentation because the probabilities of success are low and unknowable. Experimentation resolves uncertainty and creates real option value. The costs and constraints on the ability to experiment therefore impacts entry into entrepreneurship (Hombert, Schoar, Sraer, and Thesmar (2014)) as well as associated returns (Manso (2014)). This paper suggests that, by increasing the feedback value of experimentation, crowdfunding can encourage entrepreneurship through a channel other than relieving financing constraints.

The rest of the paper proceeds as follows. Section 2 introduces crowdfunding and Kickstarter and describes the data. Section 3 examines whether and how entrepreneurs update beliefs about their projects based on feedback from the crowd and how they adjust their subsequent decisions. Section 4 examines the ex ante learning value of crowdfunding. Section 5 addresses the endogeneity of feedback. Section 6 provides further discussions and section 7 concludes.

2. Setting and Data

2.1. Crowdfunding

Crowdfunding is the practice of openly funding a project or venture by raising small amounts of money from a large number of people, typically via an online platform. As a new financial phenomenon, crowdfunding is reshaping the entrepreneurial finance landscape and has garnered great public attention.[8] The global crowdfunding market has grown tremendously in recent years from $0.5 billion in 2009 to $16.2 billion in 2014, with now around 1250 platforms in more than 50 countries (Massolution 2015). Regulators around the world have also been keeping up with the change by passing various regulations to assist the growth of crowdfunding. Crowdfunding platforms fall largely into three categories: debt-based, reward-based, and equity-based.[9] Debt-based crowdfunding, also known as peer-to-peer lending, are typically used to fund personal expenditures or debt consolidations, with a small portion going to small business finance. Reward-based crowdfunding gives investors in-kind rewards in return for their funding, with no financial securities issued. So far, it has the second largest volume after debt-based crowdfunding. Equity-based crowdfunding gives investors equity shares and is the most complex and nascent of the three. In U.S., the Jumpstart Our Business Startups (JOBS) Act signed by President Obama in 2012 legalized equity-based crowdfunding and was recently implemented by the Securities and Exchange Commission.

An important distinction of crowdfunding from traditional entrepreneurial finance is the lack of intermediation. Due to high information asymmetry and uncertainty associated with early-stage ventures, traditional entrepreneurial financing is heavily intermediated. Both banks and venture capitalists rely on close relationships with entrepreneurs to acquire private information and to monitor. In crowdfunding, platforms mainly provide a market place for investors and entrepreneurs to match. They engage in none to a very limited amount of intermediation, and are not actively involved in the screening, pricing, or ex-post monitoring of projects. Information asymmetry in these markets is mainly mitigated by the crowd's collective information production, while transparency and reputation costs help curtail moral hazards. Further, investors are able to achieve substantial diversification thanks to the low costs of search and investing online, which greatly improves risk-sharing. These mechanisms, essentially enabled by internet technologies, sustain the functioning of

[8] See Figure A1 in Appendix V for a comparison of trends in Google search interests for crowdfunding and venture capital.

[9] Prominent examples of reward-based crowdfunding platforms include Kickstarter (US), Indiegogo (US), and Crowdfunder (UK); examples of debt-based crowdfunding platforms include LendingClub (US), Prosper (US), and Zopa (UK); examples of equity-based platforms include Seedrs (UK), Crowdcube (UK), EquityNet (US), EarlyShares (US), and ASSOB (Australia).

crowdfunding markets.

2.2. Kickstarter

Kickstarter is the world's largest reward-based crowdfunding platform. It was founded in April 2009 and has since grown rapidly (see Figure 1). As of July 2015, Kickstarter is open to entrepreneurs from 18 countries and backers from 224 countries.[10] More than 243,000 projects have been launched on the platform, receiving $1.8 billion pledged funds from 9 million backers. Prominent projects funded on Kickstarter include Pebble Watch (a smartwatch), Oculus (a virtual reality gaming goggle), the movie Veronica Mars, and Coolest Cooler (a multi-function cooler).[11]

On Kickstarter, an entrepreneur posts a project pitch that typically includes information on product, team, traction, use of funds, relevant risks, and promised rewards (see Figure 2 for a sample project page). She also sets a funding target as well as a funding time window (typically 30 days). After the project is launched, backers start to pledge money in small amounts in return for the promises of rewards. Rewards vary across projects, ranging from gifts, early samples, product parts, to the final product eventually produced by the project. Rewards are also structured into tiers, with different tiers corresponding to different contributing amounts. Funding follows an all-or-nothing rule: a project is funded if, by the end of the funding window, the total pledged amount reaches or exceeds the funding target, in which case the entrepreneur gets all the pledged money; otherwise it is unfunded and no money is transferred to the entrepreneur. Kickstarter takes 5% of the successfully raised funds. The platform mainly provides a market place for entrepreneurs and backers to match, and does not engage in active screening, pricing, or advising, nor does it guarantee returns or arbitrate disputes between entrepreneurs and backers.[12]

Kickstarter features various social components that allow users to communicate with each other and share information. For example, backers can post comments on a project's wall and raise questions in the Q&A section. The entrepreneurs is then able to reply to those

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[10] Most of the projects come from U.S., with U.K. and Canada coming second and third.

[11] These project achieved great funding success on Kickstarter and subsequently received further financing from angel or VC investors. In a recent prominent deal, Oculus was acquired by Facebook for $2 billion.

[12] Kickstarter does do a simple vetting of submitted projects to make sure they are within Kickstarter's basic requirements and mandates before releasing them for launch. Kickstarter also periodically features some projects on its front page and in the weekly newsletters it sends to subscribers.

comments and questions, and post updates on the project. Users can also follow each other on Kickstarter and observe the backing activities of their friends in their social network. Most of these social interactions are publicly observable, and are permanently archived online. These features, coupled with the involvement of the crowd, greatly facilitate information production on the platform and provide the infrastructure for participants' learning.

In reward-based crowdfunding, backers can be considered as a type of trade creditors to whom an entrepreneurs owes a liability in the form of "goods deliverable". Failure to deliver the promised rewards is a violation of contract and may results in legal actions taken against them by backers.[13] However, ex ante, backers do not always seek financial returns when making funding decisions. Backers' funding decisions are largely driven by their personal interests in the proposed projects, and can be sometimes based on non-pecuniary or even altruistic considerations.[14]

2.3. Data and descriptive statistics

Kickstarter claims no ownership over the projects and the information they produce. The web pages of projects launched on the site are permanently archived and are accessible to the public. After funding is completed, projects and uploaded contents cannot be edited or removed from the site. This allows me to observe all historical information. To construct my dataset, I use web crawling scripts to collect information from all project pages, including both funded and unfunded projects. I also extract entrepreneurs' biographies and project-backer network. The final dataset contains the universe of projects launched on Kickstarter from its inception in April 2009 to April 2014, with 137,371 project pages, 118,214 entrepreneurs, 12 million entrepreneur-backer links, and 3 million comments posted by backers. To my knowledge, this is the most comprehensive reward-based crowdfunding database compiled so far.

I first present some descriptive statistics to help understand the data. Figure 1 plots the aggregate volume growth of Kickstarter over my sample period April 2009 to April 2014. We see a tremendous growth in both the number of projects and the aggregate funding

[13] Among funded projects, only about 9% of projects failed to deliver (Mollick (2015)).
[14] Though backers' funding decisions can sometimes be donation-based, Kickstarter explicitly states that "projects can't promise to donate funds raised to a charity or cause, and they can't offer financial incentives like equity or repayment."

amounts. About 43% of projects are successfully funded and the success rate is fairly stable over time. Most unfunded projects received very little pledging so the aggregate funding amount represents a majority of the aggregate pledged amount. Figure 3 shows the geographic distribution of funding demands on Kickstarter across U.S. Metropolitan/Micropolitan Statistical Areas. We see that funding activities on Kickstarter are very geographically dispersed, and are more concentrated in areas that are traditionally associated with high entrepreneurial activities, such as the Bay Area, Seattle, Houston, Boston, and New York City.

Table 1 Panel A tabulates the summary statistics of key variables for all projects, funded projects, and unfunded projects. The average funding target is $22,669 and the median is $5,000. The funding target amount is very skewed with a long tail in projects with large funding needs. Funded projects have much lower funding target than unfunded projects. The median pledge ratio for a funded project is 1.13, while the mean is 3.77, suggesting a small number of projects were extremely successful and received very high pledge ratios. For unfunded projects, most of them have very low pledge ratio, with a median of 0.04 and a mean of 0.11. On average, a project attracts around 100 backers. This number is much higher for funded projects (202 backers) than for unfunded projects (22 backers). The average pledged amount per backer is $72, and is slightly higher for funded projects ($82) than for unfunded projects ($63). Funding window is typically about one month.

Comparing funded and unfunded projects, we can get a rough idea of what project and entrepreneur characteristics are likely associated with funding success. Successfully funded entrepreneurs typically have longer project pitch, provide more reward choices, and employ more videos and images on their project page. They also seem to be more active online than unfunded entrepreneurs: having more websites and Facebook friends, posting more frequent project updates, and creating and backing more projects on Kickstarter. In return, funded projects received much more comments and questions from backers. Further, female and better educated entrepreneurs seem to have higher success rates. Overall, the statistics suggest that having a reasonable funding target, communicating well in project pitch, and being socially active online are important for funding success on Kickstarter.

Panel B breaks down the projects by their top category. Kickstarter defines 13 top categories that covers a variety of projects. A large part of the projects are in creative arts, with another sizable share in hardware and design, food, apparel, games, technology, and publishing. Technology projects typically have the largest funding amounts, while dance and music projects have the smallest. Success rates also differ across project categories. Apparel, publishing, and technology have the lowest success rates, while dance, theatre, and music have the highest.

About 24% of the projects on Kickstarter are launched by entrepreneurs who crowdfund more than once on the platform and they on average show up 2.5 times. Table A1 in Appendix II compares the initial projects launched by these repeat entrepreneurs and the projects launched by one-time entrepreneurs. There is no significant differences in the size, pitch length, novelty, or fixed costs of the projects initially launched by the two groups of entrepreneurs. Although the initial success rate is lower for repeat entrepreneurs, the average pledge ratio is slightly higher. Importantly, repeat entrepreneurs do not seem to be more experienced than one-time entrepreneurs, both in terms of the length of their biographies and an experience index constructed from analysing the content of these biographies.[15] However, they do seem to be more active online, backing more projects by other entrepreneurs and having more Facebook friends.

3. Learning by Entrepreneurs

3.1. Adjustment of beliefs about projects

In this section, I examine whether and how entrepreneurs learn from the crowd. To this end, I first outline a simple Bayesian learning framework to guide my empirical predictions. I then discuss empirical measures and tests.

3.1.1. A simple learning framework

An entrepreneur comes to the crowdfunding platform with a prior about the amount of funding her project can attract. This amount depends on the market demand for the project as well as the entrepreneur's ability to implement it. Through crowdfunding, the entrepreneur accumulates information from the crowd and uses this information to update her prior. Following earlier work (Javanovic (1979) and Gibbons et al. (2005)), I assume the

[15] See Appendix I for detailed definition of some of the variables.

entrepreneur's prior belief μ is normally distributed with expectation μ_0 and precision h_0: $\mu \sim N\left(\mu_0, \frac{1}{h_0}\right)$. The crowd provides a feedback f that represents an imperfect signal of μ with precision h_c: $f|\mu \sim N\left(\mu, \frac{1}{h_c}\right)$. The entrepreneur then update her prior based on the crowd's feedback to form a posterior. Following DeGroot (1970), under Bayesian updating, the entrepreneur's posterior expectation would take on a simple expression: a weighted average of the prior expectation μ_0 and the feedback f:

$$\mu_f = E(\mu|f) = \frac{h_0}{h_0+h_c} \times \mu_0 + \frac{h_c}{h_0+h_c} \times f. \qquad (1)$$

The posterior variance is $Var(\mu|\varepsilon) = \frac{1}{h_0+h_c}$, which is smaller than the prior variance $Var(\mu) = \frac{1}{h_0}$, meaning learning reduces uncertainty faced by the entrepreneur. Equation (1) generates the following hypothesis.

Hypothesis 1: *An entrepreneur's posterior expectation* (μ_f) *is positively associated with her prior expectation* (μ_0) *and the crowd's feedback (f). Further, she will places more weight on the information with relatively higher precision if the she updates in a Bayesian way.*

To test this hypothesis, I make use of a sample of entrepreneurs that have launched multiple projects on Kickstarter.[16] I use the funding target of an entrepreneur's initial project as a measure of her prior expectation about the amount her project can attract.[17] I then use the actual amount pledged by backers in that funding round to represent the feedback from the crowd. This feedback reflects backers' interests in the proposed product as well as their belief about the entrepreneurs' ability to complete such a project. We do not directly observe the entrepreneur's posterior, but can infer it from the funding target of her next similar project, with similarity defined as being in the same project type categorized by Kickstarter.[18]

[16] About 24% of projects on Kickstarter are launched by repeat entrepreneurs. On average, an entrepreneur's two consecutive projects are launched 7 months apart from each other. Entrepreneurs typically make meaningful project improvements in their subsequent funding attempts and sometimes switch to an entirely different project.
[17] The all-or-nothing funding rule gives entrepreneurs incentives to estimate the amount their projects expect to attract: a target too high will reduce the chance of raising any money, while a target too low will drive away backers who fear the risk of backing an undercapitalized project (Cumming et al. (2015)). In addition, backers tend to stop funding a project after it has reached its target (Mollick (2014), Kuppuswamy and Bayus (2014)). This further curtails entrepreneurs' incentives to strategically lower the target in order to achieve funding success.
[18] Kickstarter categorizes projects into 51 refined project types. In robustness test in Table A2 Appendix II, I apply a more stringent definition of similarity by comparing the project pitches of an entrepreneurs' two consecutive projects.

The idea is that, an entrepreneur's updated expectation about backers' interests as well as her ability with respect to a type of project should carry over to her next similar project. The new funding target would therefore correlate positively with her updated posterior expectation.

My main proxy for the precision of entrepreneurs' prior is the cosine similarity score between the word vector of a project's pitch and the combined word vector of all projects' pitches within the same project type. A lower value of this measure means a project is more atypical and innovative compared with an average project of the same type. Entrepreneurs of such projects therefore face more uncertainty and have less precise priors due to the lack of relevant information out there to inform potential returns. My alternative measure of prior precision is the inverse of the logarithmic length of the "Risks and Challenges" section on project page, where entrepreneurs are required to discuss the potential risks and the challenges associated with their projects. The inverse of this measure captures the amount of subjective uncertainty perceived by an entrepreneur regarding her project. However, it is only available for projects launched after September 2012 when Kickstarter starts to mandate such disclosure.[19] To proxy for the precision of the crowd's feedback, I use the average number of prior projects backers have backed on the platform to capture the experience of a project's backer base. The idea is that backers will collectively provide more reliable feedback if they are on average more experienced with backing projects on Kickstarter. As an alternative measure, I also use the average number of months a projects' backers have been on the platform to capture backers' experience. Appendix I provides more details on the construction of these measures.

Using the above measures, I perform the following tests of Hypothesis 1:

$$\widetilde{posterior} = \alpha + \beta \times prior + \gamma \times feedback + \varphi X + \varepsilon, \tag{2}$$

$$\widetilde{posterior} = \alpha + \beta \times prior + \gamma \times feedback + \rho \times prior\ precision$$
$$+ \theta_1 \times prior \times prior\ precision + \theta_2 \times feedback \times prior\ precision + \varphi X + \varepsilon, \tag{3}$$

[19] To validate these two prior precision measure, I sort the projects into quintiles based on each of the two measures and tabulate the mean and standard deviation of funding outcome (log pledge ratio) for each quintile. As shown in Table A4 in Appendix II, funding outcomes exhibit lower means and higher variations for projects in quintiles with lower *Prior precision* and lower *Prior precision_alt*. This is consistent with the fact that, for projects with higher uncertainty, risk-averse backers are more cautious in providing funding and tend to disagree more in their funding decisions, leading to lower mean and higher standard deviation in funding outcomes.

$$\widetilde{posterior} = \alpha + \beta \times prior + \gamma \times feedback + \tau \times \ feedback\ precision +$$
$$\theta_3 \times prior \times feedback\ precision + \theta_4 \times feedback \times feedback\ precision + \varphi X + \varepsilon, \quad (4)$$

where *prior* is the funding target of an entrepreneur's current project, *feedback* is the pledged amount of the current project, $\widetilde{posterior}$ is the funding target of the same entrepreneur's next same-type project and is a positive affine function of the unobserved true posterior (i.e., $\widetilde{posterior} = \rho \times posterior + \epsilon$ and $\rho > 0$), *prior precision* and *feedback precision* are the precision measures introduced above, and X is a vector of control variables that include characteristics of the next same-type project as well as dummies for its associated year-quarter and project type. If entrepreneurs learn from the crowd's feedback, we should expect $\beta > 0$ and $\gamma > 0$ in equation (2). Further, if such learning occurs in a Bayesian way, we should expect $\theta_1 > 0$ and $\theta_2 < 0$ in equation (3), and $\theta_3 < 0$ and $\theta_4 > 0$ in equation (4).

3.1.2. Results

Table 2 Panel A presents the main results. Column 1 reports the result of the baseline specification in equation (2), regressing the funding target of each entrepreneur's next same-type project (posterior expectation) on the funding target of her current project (prior expectation) and the pledged amount of the current project (feedback). Consistent with entrepreneurs learning from the crowd's feedback, the posterior depends positively on both the prior and the feedback (column 1), with both coefficients significant at the 1% level. Columns 2 and 3 further show that such learning occurs within both funded and unfunded projects. Column 4 tests equation (3), interacting prior and feedback with the precision of entrepreneur's prior, which is measured by the cosine similarity score between a project's pitch and all project pitches within that project type. Column 5 tests equation (4), interacting prior and feedback with the feedback precision, which is measured as the average number of prior projects backed by the current project's backers. Column 6 combines both sets of interactions from columns 4 and 5.[20] In all three columns the interaction terms are statistically significant and their signs are consistent with Hypothesis 1: Entrepreneurs place less weight on their priors and more weight on the crowd's feedback when their priors are less precise or when the crowd's feedback is more precise. In terms of magnitude, a one-standard-deviation increase in prior precision increases the weight on prior by 4.1% and

[20] All precision measures are standardized in interactions to facilitate the interpretation of magnitudes and to minimize potential multicollinearity.

decreases the weight on feedback by 21.1%, while a one-standard-deviation increase in feedback precision decreases the weight on prior by 7.2% and increases the weight on feedback by 32.4%.

Panel B presents the results using alternative measures of prior and feedback precisions. In column 1, prior precision is measured as the inverse log length of the risk disclosure section of the project page. In column 2, feedback precision is proxied by the average number of months a project's backers has been on the platform before backing this project. The results are similar to those obtained in Panel A.[21]

Table 3 conducts additional analyses on entrepreneurs' learning. I first explore how learning differs across different types of entrepreneurs. Prior literature suggests that men are more overconfident than women—they tend to overestimate the precision of their information, especially in tasks perceived to be masculine or risky (Lundeberg, Fox and Puncochar (1994), Barber and Odean (2001)). In activities such as entrepreneurship, men may therefore overweight the importance of their priors and be less responsive to feedback than female entrepreneurs. Column 1 in Panel A confirms this finding. I interact prior and feedback with *Male*, a dummy variable indicating the gender of an entrepreneur.[22] The sample is conditioned on individual entrepreneurs that are not registered as firms on Kickstarter. The result shows that, compared with female entrepreneurs, male entrepreneurs place on average 8% more weight on their priors and 28% less weight on the crowd's feedback. In column 2, I compare entrepreneurs with difference levels of education. *Education* is a dummy variable equal to one if the entrepreneur is identified as having a bachelor or above bachelor degree from its biography. I find that, more educated entrepreneurs place less weight on the crowd's feedback and more weight on their own priors (albeit insignificant) compared with less educated entrepreneurs. This is consistent with the fact that more educated entrepreneurs are more informed about their pursuits and are able to form more precise beliefs.

[21] The sample size is smaller in columns 1 and 3 because the risk disclosure section is only available for projects launched after September 2012.

[22] Following Greenberg and Mollick (2014), I algorithmically identify the gender of entrepreneurs by their first names using the *genderize.io* name database. The database contains 208,631 first names from 79 countries and 89 languages. For each name, the database assigns a probability that a specific name-gender attribution is correct in the population of a country. An entrepreneur is identified to be of a specific gender if the associated probability exceeds 70%. In 94.6% of the matched cases, the probability exceeded 95%, suggesting a high degree of accuracy.

To shed further light on what entrepreneurs learn from the crowd, I first conduct a placebo test relating a project's funding target and pledged amount to the funding target of the entrepreneur's next project in a *different* project type. In Panel B of Table 3, I fail to find any relation between the crowd's feedback and the funding target of an entrepreneurs' next different-type project. This suggests that learning about one's general ability as an entrepreneur does not drive my results, because such information carry over to an entrepreneur next project regardless of project type. To gauge whether adjustment in funding targets mainly reflects learning about one's project-specific ability, I interact the baseline results with a variable, *Jockey*,[23] measuring the extent to which the entrepreneur is featured in a project pitch (Marom and Sade (2013)). If learning is primarily about project-specific ability, belief updates should be stronger for projects that rely more on the entrepreneur than on the idea/product. In Panel C of Table 3, I find that the *Jockey* measure does not interact significantly with entrepreneurs' priors or the crowd's feedback, suggesting learning about project-specific ability is not dominant in my sample. Overall, the results are most consistent with entrepreneur learning from the crowd about market interest or demand for their projects.

3.1.3. Robustness tests

My test on entrepreneurs' Bayesian learning relies on the sample of entrepreneurs that launched at least two projects of the same type on Kickstarter. A possible concern is that the estimates may be biased due to sample selection, i.e., repeat entrepreneurs may have unobserved characteristics that also correlate with their subsequent funding targets. To address this, I employ a two-stage Heckman model to control for selection. For identification, I use the local density of repeat entrepreneurs as an instrument in the first stage. The instrument, *Peer propensity*, is the proportion of Kickstarter entrepreneurs in a ZIP code (excluding the focal entrepreneur) that have repeatedly participated on the platform. It positively predicts selection into my sample due to the well-documented peer effects in entry into entrepreneurship (Ginannetti and Simonov (2009), Nanda and Sørensen (2010), Lerner and Malmendier (2013)). I focus on ZIP code as this is the geographic level where social

[23] See Appendix I for detailed definition. The name *Jockey* is borrowed from Kaplan, Sensoy, and Stromberg (2009), where they compare the idea or the business to "the horse" and the entrepreneur to "the jockey". I validate this measure in Panel B of Table A4 in Appendix II by sorting the 13 project categories according to the average of *Jockey*. Consistent with our intuition, projects in "Music", "Dance", and "Theater" have the highest values in *Jockey*, whereas projects in "Games", "Technology", and "Hardware and design" have the lowest values.

interactions and therefore peers effects most likely take place. An entrepreneur is more likely to become a repeat entrepreneur if her local peers are more likely to do so. Local peers' participation decisions, however, should not directly affect the funding target of a specific entrepreneur, especially after controlling for her previous funding target.

Table A2 in Appendix II presents the results under this two-stage model. The results are very similar to those in Table 2 Panel A. The first-stage coefficient on the instrument is significantly positive at the 1% level. Coefficient on the inverse Mills ratio and the log likelihood comparison test suggest a positive selection effect: entrepreneurs that launched multiple same-type projects are ex ante more likely to choose higher funding targets. This selection bias, however, have quantitatively very small effects on my estimated coefficients.

I further show that my results are robust to the use of different alternative samples. In Table A3 Panel A, I apply a more stringent definition of "next similar" projects, restricting to the same entrepreneur's two consecutive projects that are not only in the same project type, but also highly similar in content (having a pitch text similarity score of at least 0.95 on a scale of 0 to 1).[24] In Panel B, I focus on projects in more traditional sectors, such as those in "Hardware and design", "Fashion and apparel", "Food and restaurant", "Games", "Publishing", and "Technology". These projects more closely resemble the type of projects commonly pursued by entrepreneurs or self-employed individuals. In Panel C, I remove very small projects and focus on projects with funding targets of at least $10,000. In all these samples, my main results continue to hold.

3.2. Learning and entrepreneurs' continuation decisions

The above analysis on Bayesian learning conditions on entrepreneurs that have launched multiple same-type projects on Kickstarter in order to observe the evolvement their beliefs. However, the decisions to participate again and to launch the same type of project may themselves be an outcome of learning. Do entrepreneurs make these continuation decisions based on what they learnt? If so, how? This section investigates these questions.

If launching crowdfunding campaigns involves fixed costs, only entrepreneurs with high enough posteriors, i.e., those who have received very positive feedback, will participate again on the platform. Entrepreneurs who have received negative feedback would correct

[24] See footnote 26 for details on the construction of this score.

down their beliefs about their projects, and, if the correction is large enough, may decide not to enter again. Similarly, conditional on participating again, launching a different type of project involves switching costs. An entrepreneur would only do it if she believes the crowd's interests in her original project is very low, so that even improving upon it would not generate enough funding. My second hypothesis therefore is:

Hypothesis 2: *Entrepreneurs who have received more positive feedback from the crowd will be more likely to stay on the platform and crowdfund again, and conditional on crowdfunding again, will be more likely to launch a project of the same type as (or similar to) their previous project.*

I use two measures to capture the positivity of feedback. The first measure, log pledge ratio, is the log ratio between the pledged amount and the funding target, and captures how much of the entrepreneur's initial funding expectation is met by backers' pledge.[25] My second measure is the logarithm of the average number of comments posted per backer. Popular projects typically see their backers actively posting comments, questions, or suggestions on project page that indicate their interests and enthusiasm. This measure therefore captures how well-received a project is. I then relate the probability of re-entering Kickstarter and, conditional on re-entering, the probability of launching a same-type or similar project to these two measures of feedback positivity.

Before formally testing Hypothesis 2, I first explore the non-parametric relationship between feedback positivity and entrepreneurs' continuation decisions. In Figure 4A, I use kernel regression to estimate the relation between the probability an entrepreneur launches a second project (on y-axis) and the rank of the current project's pledge ratio (on x-axis). I use the rank of pledge ratio (scaled between 0 and 1) to properly fit observations on the x-axis as the raw pledge ratio is heavily skewed to the right. We see that within both funded and unfunded projects, there is a generally positive relation between the pledge ratio and the probability of launching another project. However, the comeback probability drops discontinuously around the funding success threshold where pledge ratio is equal to one (indicated by the dashed line). This is because entrepreneurs are much less likely to come back again once funded if they do not have further supply of projects. To deal with this

[25] I use the logarithm of the ratio because the distribution of the ratio is very skewed: a small number of projects achieved very high amounts of funding that greatly exceed their funding targets.

mechanical change in comeback probability that is unrelated to learning, I will only exploit the variation in pledge ratio within funded and unfunded projects in my regression analysis.

Figure 4B looks at the probability of launching a project of same type as the previous project conditional on the entrepreneur coming back to Kickstarter. Similar to Figure 4A, within both funded and unfunded projects, there is a strong positive relation between feedback positivity and the probability of continuing with the same project type. Because previously unfunded entrepreneurs are more likely to improve on their original project rather than switching to a new one compared with funded entrepreneurs, we observe a similar probability drop around the funding success threshold. Again, I will only exploit the variation in pledge ratio within funded and unfunded projects in my subsequent analysis.

Figure 4C and 4D present the results using an alternative measure of feedback positivity: the log number of comments posted per backer, which captures the interests from the backers, i.e., how well-received the project is. Similar to Figure 4A and 4B, I estimate the non-parametric relationship between the two continuation probabilities and the log number of comments per backer. There is a positive relation between backer interests and the two continuation probabilities.

Table 4 presents OLS regressions controlling for project and entrepreneur characteristics as well as fixed effects. Panel A measures feedback positivity with log pledge ratio and Panel B with log number of comments per backer. In addition to discrete project type change, in the last column of both panels, I also use *Project similarity*, a text similarity score, to capture continuous change in projects.[26] The regression results are similar to those obtained from the non-parametric analysis. Together, these results suggests that feedback from the crowd does affect entrepreneurs' subsequent continuation decisions as well as project choices.

3.3. Information spillover through observational learning

So far I have shown that entrepreneurs adjust expectations and decisions in response

[26] I use the Bigram string comparison algorithm to construct the text similarity score. The Bigram algorithm compares two strings using all combinations of two consecutive characters within each string. For example, the word "bigram" contains the following bigrams: "bi", "ig", "gr", "ra", and "am". The Bigram comparison function returns a value between 0 and 1 computed as the ratio of the total number of bigrams that are in common between the two strings divided by the average number of bigrams in the strings. The higher the score, the more similar two strings are.

to feedback generated from their own crowdfunding attempts. Such feedback, although directed towards a specific entrepreneur, can be also picked up by other entrepreneurs both on and off the platform through observational learning. Such information spillover is possible due to the public nature of crowdfunding and the transparency of crowdfunding platforms. In contrast, information produced by intermediaries such as VCs and banks are largely held within the intermediary (Kaplan (2006), Breton (2011), Dang, Gordon, Holmström, and Ordonez (2014)). The informational benefit of crowdfunding therefore reaches beyond those who directly participate in a crowdfunding campaign.

To test for the presence of information spillover, I examine how past crowdfunding outcomes on the platform affects the aggregate entry pattern of future entrepreneurs on the platform. Specifically, by observing what is happening on Kickstarter today, entrepreneurs who are not yet on the platform are able to infer the crowd's interests across different categories of projects, and can therefore adjust their future entry decisions accordingly. At the aggregate level, this should lead to a positive relation between past funding outcomes and future entry volumes across project categories. I therefore posit the following hypothesis.

Hypothesis 3: *Past funding outcomes in a project category positively predicts the entry of future entrepreneurs into this category relative to other categories.*

Table 5 Panel A presents the results. In column 1 (column 3), the dependent variable is the number (total funding target amount) of projects launched each month in each project category. In column 2 (column 4), the dependent variable is, for each month, the proportion of projects (total funding target amount) in each project category. The independent variables are the log of average pledge ratio in a project category as well as that in all other categories in each of the past two months. We see that past average funding outcome in a project category positively predicts entry into that category and negatively predicts entry into other categories. In Panels B and C, I replace the average pledge ratio with the 50^{th} and 95^{th} percentiles of the pledge ratios within a project category. Interestingly, I find that the effects in Panel A are driven entirely by the most successful projects rather than the median funding outcome in a project category. These "hot" projects typically attract great public attention, and are more easily noticed by potential entrepreneurs. Moreover, current entry pattern react more strongly to funding outcomes in the previous month than those two months before. Such recency and saliency effects are consistent with limited attention in observational learning, while are inconsistent with shifts in fundamentals, which tend to occur at a longer horizons and do not exhibit a saliency effect.

Overall, based on all the results in Section 3, I conclude that crowdfunding does provide feedbacks to entrepreneurs. Such feedbacks prompt entrepreneurs to adjust their funding expectations, continuation decisions, and project choices accordingly. Further, crowdfunding feedbacks can spill over to other entrepreneurs through observational learning, therefore influencing the entry pattern of future entrepreneurs.

4. The Ex-ante Learning Advantage of Crowdfunding

In this section, I take a step back and ask whether crowdfunding has additional learning value *ex ante* compared with traditional early-stage financing methods and whether such a learning advantage is reflected in entrepreneurs' financing choices.

4.1. Why crowdfunding provides better and earlier feedbacks

I argue that crowdfunding provides *better* and *earlier* feedbacks to entrepreneurs than do traditional entrepreneurial financiers.

First, crowdfunding features low information production costs and can leverage the wisdom of the crowd. Relying on internet technology, crowdfunding platforms lower the participation cost of the crowd, each of whom brings his/her own piece of information. Through online social interactions, different pieces of information can be quickly aggregated, updated, and disseminated. These interactions also facilitate the production of soft information that is critical to early-stage financing (Iyer, Khwaja, Luttmer, and Shue (2015), Lin, Prabhala, and Viswanathan (2013), Morse (2015)). Disintermediated online market therefore provides rich feedbacks to entrepreneurs by capitalizing on the collective information production of the crowd ("wisdom of the crowd") (Golub and Jackson (2010), Mollick and Nanda (2015), Mollick (2013)). In reward-based crowdfunding, such feedbacks are especially helpful, as backers are also potential consumers who can provide unique product market information unavailable from other traditional financiers.

Feedbacks from crowdfunding also come at an earlier stage than those from traditional financiers. The removal of fixed intermediation costs on crowdfunding markets lowers optimal transaction size, so that smaller investments can be financed than is possible with intermediaries.[27] At the same time, online investing enables investors to diversify across a large number of projects, achieving substantial risk-sharing. It is the smaller and riskier nature of crowdfunding that make it accessible to entrepreneurs at a much earlier stage than traditional financing sources.[28] As such, feedbacks from crowdfunding are more likely to arrive before entrepreneurs' key decisions such as manufacturing or commercialization, thereby commanding extra real option value.

On the other hand, although VCs (and perhaps angels) have advantages in mentoring and monitoring, they are inaccessible to most entrepreneurs in the economy, especially at a very early stage. In U.S., less than 0.5% newly created firms have raised capital from VCs, and less than 5% have raised capital from angel investors.[29] Bank credit is the dominant external financing source for entrepreneurs (Robb and Robinson (2014) and Cosh, Cumming, Hughes (2009)). Banks, however, provide relatively poor feedbacks on entrepreneurs' projects. Most of the lendings to entrepreneurs are either in personal loans or in business loans heavily collateralized or guaranteed by personal assets (Avery, Bostisc, and Samolyk (1998), Robb and Robinson (2014), Meisenzahl (2014)).[30] These lending decisions are therefore largely based on entrepreneurs' personal credit conditions, such as credit score or the availability of collateral, rather than the product market potential of their projects. Further, in banks, lending decisions are typically delegated to a loan officer, while the market engages many investors with diverse opinions. Markets are therefore more suitable than banks to finance and provide feedback to projects that are subject to more disagreement (Allen and Gale (1999)). Lastly, the opacity of banks with respect to the information they produce (Kaplan (2006), Breton (2011), Dang, Gordon, Holmström, and Ordonez (2014)) limits the extent to

[27] The average fundraising size on Kickstarter is about $23,000, much smaller than that provided by banks, angles, or venture capitalists. In 2013, U.S. Small Business Administration reports an average small business loan amount of $330,000. CrunchBase data shows that the median angel investment amount is $450,000 while the median venture capital round is $4.5 million.

[28] On Kickstarter, more than 80% of the entrepreneurs are not yet formally incorporated. Among incorporated ventures, the median age is 1.5 years old. According to CrunchBase data, the average age of firms receiving angel financing is 2 years old and the average age of firms receiving venture capital funding is 4.5 years old.

[29] Based on data from U.S. Census, Small Business Administration, PWC Money Tree, and CVR Angel Report.

[30] Early-stage entrepreneurs that haven't registered their businesses can only borrow through personal loans. For sole proprietorships or partnerships, unlimited liability blurs the difference between business and personal loans. Even for corporations, small business lenders typically requires the posting of personal guarantees or personal collaterals, effectively circumventing entrepreneur's limited liability (Avery, Bostisc, and Samolyk (1998), Mann (1998), Moon (2009)).

which its feedback can benefit other entrepreneurs compared with crowdfunding.

4.2. Empirical Methodology

If crowdfunding provides better and earlier feedbacks, then coupled with entrepreneurs' ability to learn, it should command higher learning value compared with traditional early-stage financing such as bank borrowing.

The ideal setting to test this conjecture is a direct comparison of crowdfunding and traditional financing methods. However, there is no exogenous geographic expansion of crowdfunding that allows for such a comparison. I overcome this by instead identifying the learning advantage of crowdfunding using shocks to entrepreneurs' selection into crowdfunding. I exploit a setting where entrepreneurs choose between crowdfunding and bank borrowing, the most common alternative traditional financing source. When local borrowing costs decrease, crowdfunding becomes relatively more expensive. If crowdfunding provides higher learning value thank banks, then entrepreneurs that do not benefit particularly from the crowd's feedback will switch to bank borrowing, driving up the average learning value derived by those that remain using crowdfunding.

I demonstrate this methodology in a theoretical framework built on the Bayesian learning model in Section 3.1.1. Entrepreneur i chooses between bank borrowing and crowdfunding. When borrowing from the bank, she makes her commercialization decision without any feedback.[31] Bank borrowing gives the entrepreneur an ex-ante value of

$$V_i^B = Max\left[0,\ E(\mu)\right] - R_i^B, \tag{5}$$

which is the larger of the expected return $E(\mu)$ based on her prior and the outside option (assumed to be zero), minus bank borrowing cost R_i^B. If the entrepreneur uses crowdfunding, she makes commercialization decision *after* receiving feedback from crowdfunding, i.e., maximizing between outside option and the *updated* expected return $E(\mu|f)$. She also pays a

[31] In Appendix IV, I relax this condition and allow both bank and crowdfunding to provide feedback. I show that my theoretically prediction continues to hold: average uncertainty and fixed costs faced by crowdfunding entrepreneurs will increase in response to increases in the relative cost of crowdfunding, if and only if feedback provided by crowdfunding is more precise than that provided by bank borrowing.

crowdfunding cost of R_i^C.[32] Crowdfunding therefore gives her an ex-ante value of

$$V_i^C = E_f\{Max[0,\ E(\mu|f)]\} - R_i^C. \tag{6}$$

I further assume that the return to the project is equal to an uncertain gross profit (revenue minus variable cost), s, minus a constant fixed cost, I: $\mu = s - I$, where $s \sim N\left(\mu_s,\ \frac{1}{h_0}\right)$ and $\mu_s = \mu_0 + I$ to be consistent section 3.1.1. The entrepreneur chooses crowdfunding if $V_i^C > V_i^B$, i.e.,

$$O_i = E_f\{Max[0,\ E(s|f) - I]\} - Max[0,\ E(s) - I] > R_i^C - R_i^B. \tag{7}$$

It can be shown that

i) $O_i \geq 0$;

ii) O_i increases in $\frac{h_c}{(h_0+h_c)h_0}$;

iii) O_i increases in I as long as $I < \mu_s$, i.e., $\mu_0 > 0$.

The left hand side of inequality (7) O_i is the option value of crowdfunding relative to bank borrowing. By Jensen's inequality, it is strictly positive as long as feedback f is not completely uninformative ($h_c = 0$). This additional option value O_i comes from both the informativeness of the crowd's feedback as well as the feedback's earlier timing relative to the commercialization decision. Intuitively, O_i increases in the precision of crowd's feedback (h_c) and decreases in the precision of entrepreneur's prior (h_0). It also increases in the fixed costs of the project as long as the expected return to the project is positive.

The average option value derived by entrepreneurs that *choose* crowdfunding is $E_i[O_i|O_i > R_i^C - R_i^B]$, which increases when R_i^B *weakly* decreases. This means that entrepreneurs choosing crowdfunding on average derive higher option value from learning when local borrowing cost decreases. This is because, as crowdfunding becomes relatively more costly, only entrepreneurs that benefit enough from learning will select into crowdfunding. In other words, cheaper local borrowing attracts away entrepreneurs who crowdfund mainly for money and helps to tease out those who crowdfund for feedback. I therefore posit the following hypothesis:

Hypothesis 4: *When local financing cost decreases so that crowdfunding becomes relatively*

[32] This cost includes, among other things, the 5% fee to Kickstarter, 3%-5% payment processing fees to Amazon, overheads from preparing for the campaign, costs of procuring, producing, and shipping the rewards, as well as the discount of reward price relative to the market value of rewards.

more costly, entrepreneurs that remain using crowdfunding derive higher option value on average (i.e., face higher uncertainty or launch projects with higher fixed costs) and engage in more learning ex post.

My first measure of shocks to local financing cost is instrumented MSA-level housing price movements. Robb and Robinson (2014) document that entrepreneurs rely predominantly on collateralised personal debt to finance their new ventures. Meisenzahl (2014) documents the pervasiveness of private residences as entrepreneurial collateral. Consistent with this evidence, Harding and Rosenthal (2013), Adelino, Schoar, and Severino (2014), and Schmalz, Sraer, and Thesmar (2015) show that local housing price appreciation leads to more entrepreneurial activities through relieving collateral constraints. A positive local housing price shock should therefore lower the costs of bank borrowing.[33] At the same time, it should not affect the financing cost on Kickstarter as crowdfunding requires no collateral. This makes crowdfunding relatively more costly. In a "difference-in-difference" setting, I can therefore compare two regions—one with housing price increases and one without—and look at the differential shifts in the composition of entrepreneurs entering Kickstarter. The region that experienced housing price increases should produce crowdfunding entrepreneurs who face higher uncertainty, propose projects with higher fixed costs, and engage in more learning ex post.

It is worth noting that the above identification does not require every individual to react to changing housing prices. For example, renters, wealthy individuals, and those who are severely priced out by the banks may not experience any change in their access to finance when housing price changes. As long as *some* individuals face lower borrowing costs and switch from crowdfunding to banks (i.e., R_i^B *weakly* decreases), we should observe a change in the *average* option value derived by the remaining entrepreneurs.

One potential concern with this methodology is that the effect of housing prices on entrepreneurial activities on Kickstarter may be driven by shifts in local demands. For example, local housing price appreciations may increase the wealth of local consumers and

[33] Constrained borrowers faces infinitely high borrowing costs at the desired borrowing amount. The relief of borrowing constraints is therefore equivalent to a reduction in borrowing costs at each borrowing amount, i.e., a downward shift in the pricing schedule.

hence their demand for products produced by Kickstarter entrepreneurs.[34] To address this, I first compare entrepreneurs that are likely renters with those that are likely home owners. I do not observe the exact home ownership status of the entrepreneurs in my sample. However, the coordinates of their addresses allow me to proxy for the likelihood of an entrepreneurs' home ownership with the average home ownership rate in her ZIP-code. Because renters and home owners in the same region face the same local conditions, such a comparison helps to "difference out" unobserved changes in local demands. I further show that my results are robust to excluding projects that may face predominantly local demands. A second concern is that higher housing prices may relieve entrepreneurs' financial constraints through a wealth effect in addition to the collateral channel (Jensen, Leth-Peterson, and Nanda (2014), Kerr, Kerr, and Nanda (2014)). Although my identification uses collateralised bank borrowing as a financing alternative to crowdfunding, it can be easily extended to include both bank borrowing and personal wealth as alternatives to crowdfunding, in which case both the wealth effect and the collateral effects imply higher relative cost of crowdfunding when local housing price increases. As a result, my empirical strategy and the interpretation of results are unaffected. Finally, there is a possibility that my results may be explained by changing risk-aversion of entrepreneurs if higher housing prices make them wealthier and less risk-averse. However, existing literature does not find a significant effect of wealth changes on changes in risk aversion or risk taking (Brunnermeier and Nagel (2008)). Schmalz, Sraer, and Thesmar (2015) show that firms started by wealthier homeowners are not riskier than firms started by poorer individuals. They also document that housing prices appreciation increases entrepreneurship only for full home-owners and not for partial home-owners though both groups experience the same amount wealth shock, suggesting access to more valuable collateral does not increases risk-taking.

To further ameliorate any lingering concerns with the use of housing prices as a shifter of local borrowing costs, I employ a second measure that captures the supply shocks to local small business lendings. To this end, I turn to the small business loan data that banks report under the Community Reinvestment Act (CRA). The granularity of this bank-county

[34] Housing price appreciations may also increase the wealth of local backers on Kickstarter. However, this should not affect my results given the geographic dispersion of investors on crowdfunding platforms compared with off-line investing. In my sample, the average distance between an entrepreneurs and her backers is 2,600 miles. In another reward-based crowdfunding platform, Agrawal et al. (2011) find that the average distance between entrepreneurs and investors is about 3,000 miles.

level data enables me to decompose local lending growth into bank-level supply shocks and county-level demand shocks by essentially comparing the differential changes in banks' lendings to the same counties. The decomposition method follows Amiti and Weinstein (2013), Flannery and Lin (2015), and Greenstone, Mas, and Nguyen (2015), which is an improved variation of the fixed effect estimator used in studies such as Khwaja and Mian (2008), Jiménez, Ongena, Peydro, and Saurina (2012), and Schnabl (2012) to control for credit demand.[35] I construct county-level lending supply shocks as weighted averages of bank-level shocks based on banks' lending shares in each county. The estimation procedure is elaborated in Appendix III. Because this measure reflects local supply shocks that originate from the bank-level, it is uncorrelated with local economic conditions, and thus serve as a useful alternative to housing prices as a shifter of local borrowing costs.

4.3. Results

I first validate my assumption that crowdfunding and bank borrowing are substitutes in providing finance. I examine how the demand for finance on Kickstarter changes in response to shocks to local housing prices or small business loan supply. If bank borrowing is a viable alternative to crowdfunding, a decrease in local borrowing cost should trigger an outflow of entrepreneurs from Kickstarter to bank borrowing and hence generate a decrease in demand on Kickstarter. Table 6 confirms this. In Panel A, the dependent variable *MSA-level demand for finance on KS* is the logarithm of quarterly aggregate funding target amount on Kickstarter at the Metro/Micropolitan Statistical Area (MSA) level.[36] The independent variable *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) from the Federal Housing Financing Agency (FHFA). I also follow Cvijanovic (2014) and instrument HPI with the interaction of MSA-level land supply elasticity (Saiz (2010)) and national real estate prices (the S&P/Case-Shiller Home Price Index). The sample is at the MSA-quarter level covering 287 MSAs and 20 quarters from April 2009 to March 2014. In Panel B, the dependent variable *County-level demand for finance on KS* is the logarithm of

[35] This approach imposes additional adding-up constraints on estimation of bank supply shocks. In particular, a county cannot borrow more without at least one bank lending more, and a bank cannot lend more without at least one county borrowing more. Amiti and Weinstein (2013) show that ignoring these adding-up constraints could produce estimates of bank lending growth that are widely different from the actual growth rates.

[36] I use the crosswalk files from the U.S. Department of Housing and Urban Development (HUD) to map ZIP codes to CBSA (Core Based Statistical Area) codes, which is the collective of all Metropolitan Statistical Areas and Micropolitan Statistical Areas, and FIPS (Federal Information Processing Standard) county codes.

quarterly aggregate funding target amount on Kickstarter at the county level. The independent variable *Local SBL supply shock* is the county-year level weighted average shocks to bank small business loan supply (see Appendix III for details on the construction of this variable). The sample covers 2,144 counties and 20 quarters from April 2009 to March 2014. In both Panels A and B, I also control for local level unemployment rate, population, and income per capita.

In both Panels A and B, I find a significantly negative relationship between access to local credit and demand for finance on Kickstarter. A one standard deviation increase in *Local housing price index* (*Local SBL supply shock*) reduces demand on Kickstarter by 11% to 22% (4% to 11%) from its mean. This suggests that bank credit and crowdfunding can indeed be substitutes in financing projects. Cheaper access to local credit therefore increases the relative cost of crowdfunding.

I then test how the relative cost of crowdfunding affects the option value and thus the uncertainty and fixed costs faced by entrepreneurs choosing crowdfunding. I use two measures to proxy for uncertainty. The first measure, *Project Novelty*, is one minus the cosine similarity score between the text a project's pitch and the pooled text of all projects' pitches within the same project type. A higher value of *Project Novelty* means a project is more atypical and innovative compared with the average project of the same type. Entrepreneurs of these projects therefore face higher uncertainty due to the novelty of the projects and the lack of existing information out there to inform potential returns. My second measure, *Experience Index,* is constructed from text analysing entrepreneurs' biographies and measures how much professional or entrepreneurial experience an entrepreneur has.Holding constant the project, less experienced entrepreneurs should face more uncertainty. These two measures complement each other by capturing uncertainty from the project side and the entrepreneur side, respectively.[37] The option value from learning should therefore be higher for projects with higher *Project Novelty* or for entrepreneurs with lower *Experience Index*. To measure fixed costs involved in a project, I follow Cumming et al (2015) and construct a

[37] To further validate these two measure, I sort the projects into quintiles based on each of the two measures and tabulate the mean and standard deviation of funding outcome (log pledge ratio) for each quintile. As shown in Table A4 in Appendix II, funding outcomes exhibit lower means and higher variations for projects in quintiles of higher *Project Novelty* and lower *Experience Index*. This is consistent with the fact that, for projects with higher uncertainty, risk-averse backers are more cautious in providing funding and tend to disagree more in their funding decisions, leading to lower mean and higher standard deviation in funding outcomes.

variable *Fixed Costs* by counting the mentioning of fixed costs-related words in the project's project pitch. A higher value of *Fixed Costs* means a project is likely associated with higher initial investment costs and therefore derive higher option value from early feedback. Detailed definition of these three variables can be found in Appendix I.

Table 7 presents the results. I find that, when local borrowing cost drops, as proxied by higher local housing prices (Panel A) and positive small business loan supply shocks (Panel C), entrepreneurs entering Kickstarter are less experienced, choose riskier projects and projects involving higher fixed costs. This is consistent with the prediction that, in equilibrium, higher relative cost of crowdfunding leads to higher option value faced by entrepreneurs choosing crowdfunding over bank borrowing.

To ensure that the relation between housing prices and entrepreneurial activities on Kickstarter is not driven by local demands, in Panel B of Table 7, I interact *Local housing price index* with *High home ownership*, a dummy variable indicating that the ZIP code in which an entrepreneur resides has above median home ownership rate. The main results in Panel A are significantly stronger for entrepreneurs that are likely home owners than those that are likely renters. Further, in Panel A of Table A4 in Appendix II, I show that my results continue to hold after dropping projects in "Food and restaurant", "Fashion and apparel", "Dance", and "Theatre", which may face predominantly local demands. In addition, I show in Panel B of Table A4 that my results are robust to focusing on projects in more traditional sectors.

Lastly, I examine how entrepreneurs' ex-post learning on Kickstarter is affected by the relative cost of entering into crowdfunding. I embed local borrowing costs into the Bayesian learning framework from Section 3.1. Specifically, following Table 2, I interact proxies of local borrowing costs with entrepreneur's prior and feedback measures. Lower local borrowing costs and thus higher relative cost of crowdfunding should in equilibrium lead entrepreneurs to engage in more learning ex post, i.e., placing more weight on feedback and less weight on prior in updating beliefs. Table 8 presents the results. I find that entrepreneurs' posteriors are more responsive to feedback and less responsive to their priors when local housing prices are higher or when there is a positive supply shock of local small business loans. This suggests that entrepreneurs choosing crowdfunding despite cheaper local credit do engage in more learning ex post.

In summary, the results from Table 7 and 8 are consistent with crowdfunding presents greater learning value to entrepreneurs compared bank borrowing.

5. Addressing the Endogeneity of Feedback

In the last part of this paper, I address potential endogeneity concerns with respect to the feedback from crowdfunding. Funding outcomes as a feedback do not happen randomly, and can correlate with unobservables such as entrepreneurs' personal traits that also influence their subsequent decisions. To this end, I make use of a sample of projects featured in Kickstarter's weekly newsletters and exploit the order in which they are presented in the newsletters. Each week, Kickstarter features three projects in the email it sends to all subscribers. I hand-collect these projects from 185 newsletters (555 projects) and categorize into three groups based on the order they are presented in the newsletters. Kickstarter states that they do no rank the projects or order them based on any preferences, meaning projects presented first in the email are not preferred or necessarily better than those presented second and third. A comparison of various project characteristics confirms this – projects in all three positions are observationally equivalent (Table 9 Panel A). Further, none of these characteristics predicts selection into the three positions (Table 9 Panel B). However, in terms funding outcome, projects presented first received much higher funding than those presented second and third, while the difference is not significant between the last two groups (Table 9 Panel A and Figure 5). This is consistent with the presence of a primacy effect when options are presented visually (Krosnick (1987)). Due to backers' limited attention, projects showing up first in the emails receive much higher attention from subscribers, and therefore attract more clicks and subsequent funding. I therefore exploit this discontinuous change in funding outcomes over negligible to no change in the underlying project quality to obtain causal inference.

In Panel C of Table 8, I compare the subsequent decisions of entrepreneurs whose projects were presented first in emails with those whose projects were presented second. The key independent variable *Treat* indicates projects in the first group. Entrepreneurs in the first group (treatment) received exogenously better feedback from the crowd than those in the second group (control). I examine three outcome variables. In column 1, *Launch again* indicates whether an entrepreneur comes back to the platform again and launches a second project. Column 2 conditions on those that come back again and have a matched control or treatment project, and examines the similarity between the current and the next project. Column 3 examines the log funding target amount of the next project.[38] All regressions control for the log funding target amount of the current project. The results are consistent with the main results in section 3.1 and 3.2.

6. Further Discussion

The use of platform data in this paper calls for a discussion of the generalizability of my results. First, what type of entrepreneurs are represented on Kickstarter? Schoar (2010) highlights the heterogeneity of entrepreneurs in the economy and points to the distinction between subsistence and transformational entrepreneurs. Subsistence entrepreneurs have no intention to grow or innovate, and most start their businesses as a means of living. Transformational entrepreneurs seek to grow through innovation, and would professionalize their businesses down the road. Like their counterparts in the economy, entrepreneurs on Kickstarter also exhibit great heterogeneity. However, the overall population resembles transformational entrepreneurs more than subsistence ones. First, Kickstarter places great emphasis on creative projects, meaning that entrepreneurs on Kickstarter do intend to innovate. Indeed, innovativeness is an important factor in attracting funding on Kickstarter. Some projects are even patented or have filed for patents. Second, the fact that Kickstarter entrepreneurs are willing to seek funding and attention from the public means that they do intend to grow instead of remaining small and quiet. Nevertheless, most of these entrepreneurs are still at a very early stage of their pursuits and have yet to achieve the type of professionalism and success associated with VC-backed entrepreneurs. Overall, Kickstarter entrepreneurs can be described as the precursors to transformational entrepreneurs. Studying their learning behaviors thus has important implications for understanding the group of entrepreneurs that are economically significant.

Second, can the results on reward-based crowdfunding be generalized to other types of crowdfunding? Despite their differences, crowdfunding platforms share common features that contribute to the formation of rich learning opportunities. These features include the

[38] Due to very limited sample size, I am unable to further condition on next projects in the same project type.

involvement of the crowd, online social interactions, and accessibility at a very early-stage. Nevertheless, the type of contract offered to investors will affect the kind of feedback generated in the funding process. In reward-based crowdfunding, backers are trade financiers and potential customers at the same time, so their feedback is more product market-oriented. In equity-based crowdfunding, funders hold equity stakes in projects, and are therefore more long-term oriented. Equity crowdfunders also care about the financial viability of a project in addition to its product-market potentials. These incentive differences will in turn be incorporated into the feedback generated in the funding process, and affect what entrepreneurs will learn about. However, the basic learning mechanisms and the key distinguishing features of crowdfunding remain the same across different crowdfunding types. Therefore, the results in this paper can speak to crowdfunding as a new financing method in general.

7. Conclusion

In recent years, entrepreneurial finance is experiencing a gradual disintermediation caused by the rise of crowdfunding, which, for the first time in history, enables entrepreneurs to directly raise financing from the general public. Our understanding of this new financing method is still very limited. What's the distinguishing feature of crowdfunding? Does it provide any benefit to entrepreneurs other than financing? This paper advances our knowledge about crowdfunding by uncovering an important informational role it plays in the entrepreneurial process: the provision of early feedbacks to entrepreneurs. Using a comprehensive dataset from Kickstarter, I show that entrepreneurs update beliefs about their projects based on feedback from the crowd and adjust their funding targets, project choices, and subsequent continuation decisions accordingly. I further establish the ex ante learning advantage of crowdfunding leveraging the entry decisions of heterogeneous entrepreneurs. Overall, my results highlight the potential for crowdfunding to improve the information environment faced by entrepreneurs. My paper suggests that, feedback from financial markets, traditionally only available to public firms, can become accessible to entrepreneurs of new ventures as early-stage financing is disintermediated by the involvement of the crowd.

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Figure 1. Kickstarter Growth

This figure plots Kickstarter's volume growth from its inception in April 2009 to April 2015. Red (blue) bar represents the cumulative number of funded (unfunded) projects. Green (yellow) line represents the cumulative amount of pledged (raised) money in U.S. dollars.

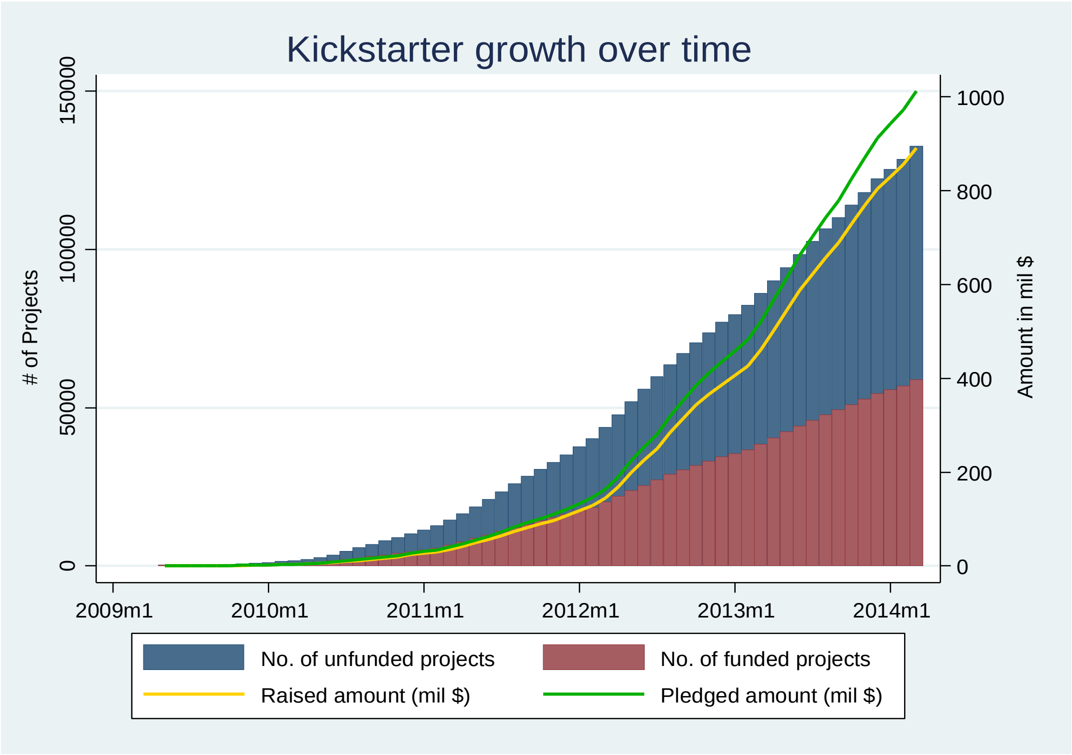

Figure 2. A Sample Kickstarter Page

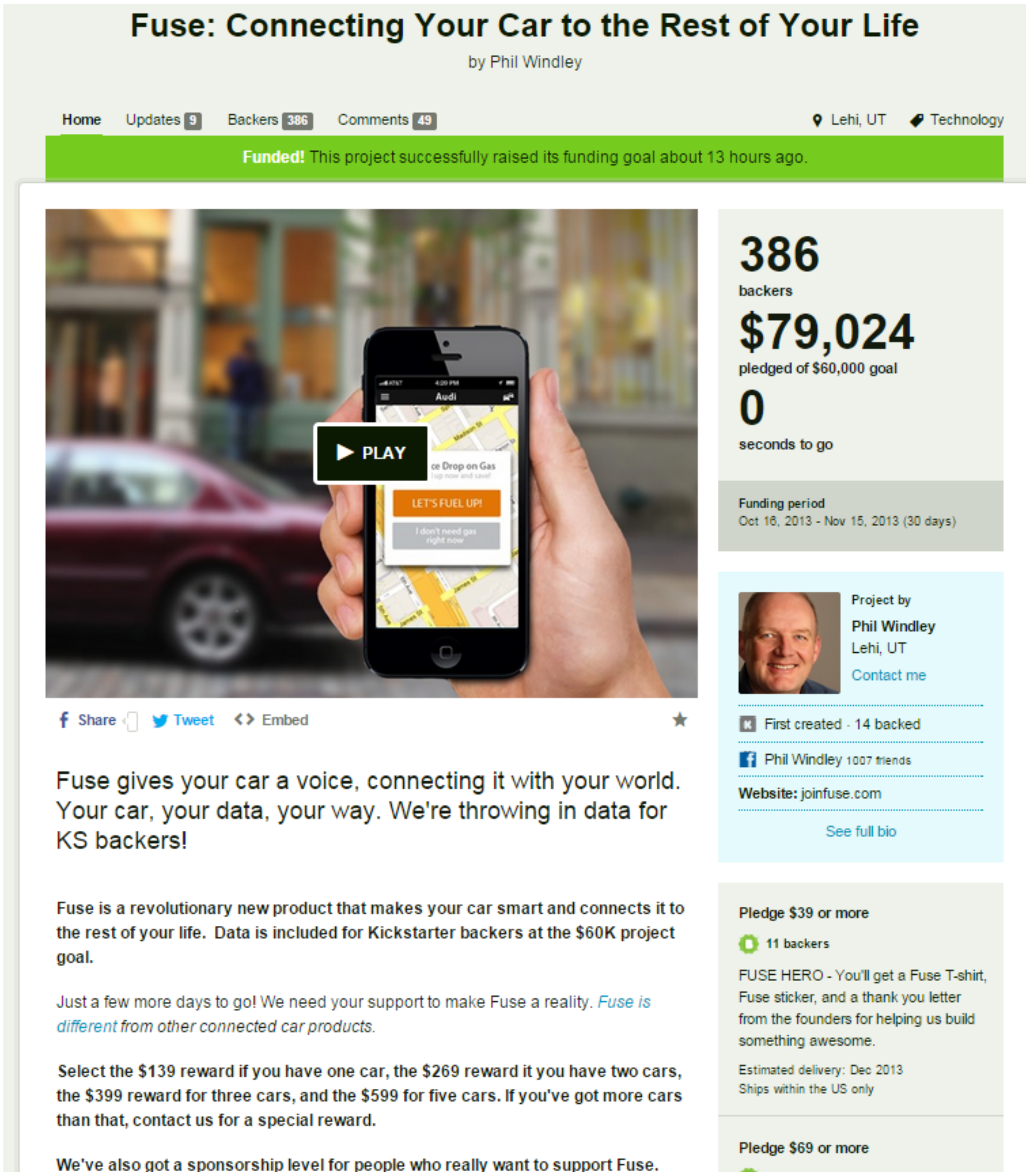

Figure 3. Geographic Distribution of Funding Demands on Kickstarter in U.S.

This figure plots the distribution of funding demand on Kickstarter in U.S. across Metropolitan/Micropolitan Statistical Areas based on data from April 2009 to April 2014. Projects are assigned to each of the MSAs based on the longitudes and latitudes of the locations of the entrepreneurs. Funding target amounts are then aggregated to the Metropolitan/Micropolitan Statistical Area level and plotted on the map, with darker areas representing higher amounts. White areas on the map represents regions that do not belong to the MSA system. Alaska, Hawaii, Puerto Rico, and other territories are omitted to fit in the map.

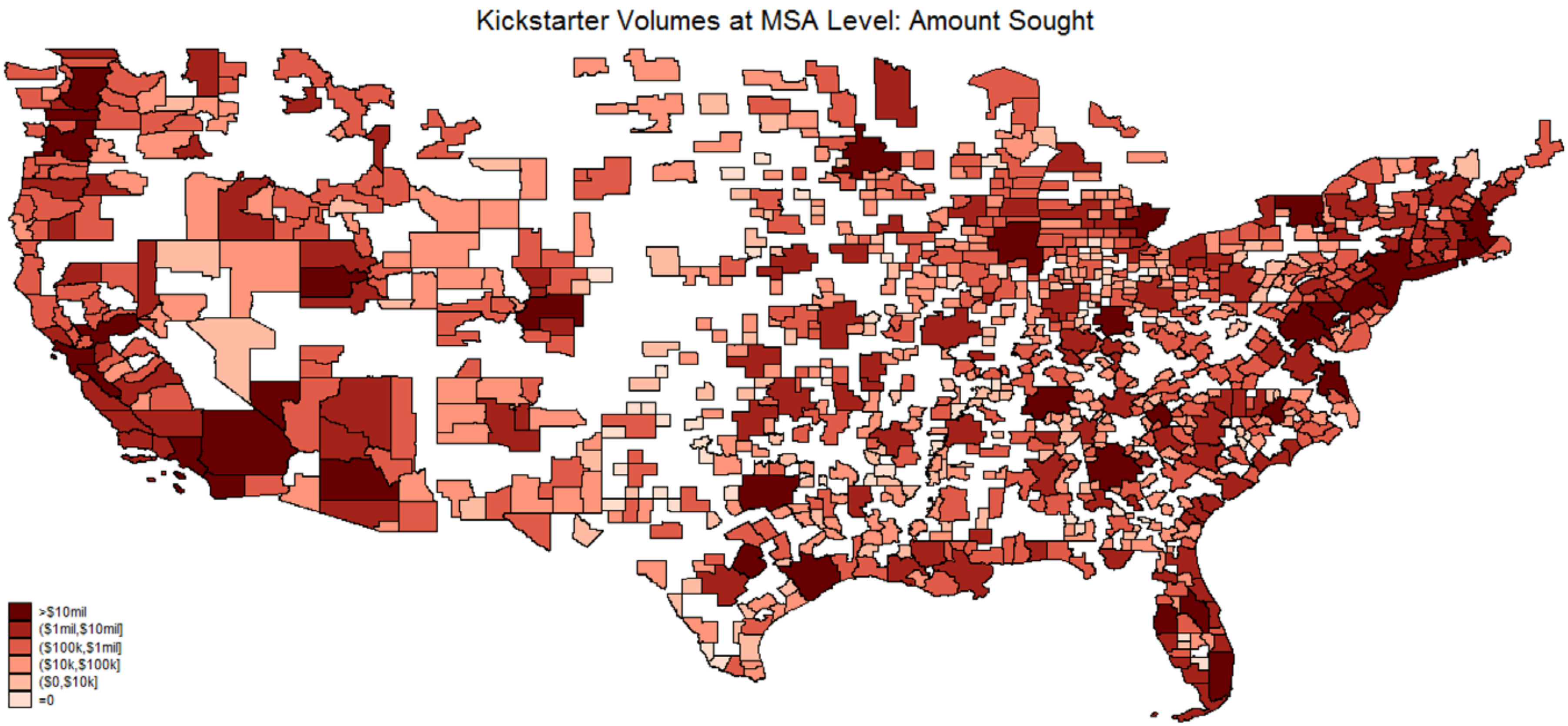

Figure 4. Non-parametric Relation between Feedback Positivity and Continuation Probability

This panel of figures plot the non-parametric relation between the positivity of feedback received in the current project and an entrepreneur's subsequent continuation decisions. In all figures, the dark line corresponds to point estimates from kernel regression and the grey area indicates the associated 95% confidence band. The vertical axis in Figures 4A and 4C is the probability an entrepreneur launches another project on Kickstarter after the current project. The vertical axis in Figures 4B and 4D is the probability an entrepreneur's next project is of the same type as her current project conditional on launching a next project. In all panels the horizontal axis is the positive level of feedback that an entrepreneur receives in her current project. In Figures 4A and 4B, feedback positivity is measured as the rank of pledge ratio (scaled between 0 and 1). The vertical dashed line indicates funding success threshold where pledge ratio is equal to one. In Figures 4C and 4D, feedback positivity is measures as ln(1+number of comments per backer). The sample in Figures 4A and 4C includes all projects launched before May 2013 (to allow for one year to observe entrepreneurs' comeback decisions). The sample in Figures 4B and 4D includes all projects launched after entrepreneurs' initial projects. All kernel regressions use a local linear specification with 50 bins.

Figure 4A

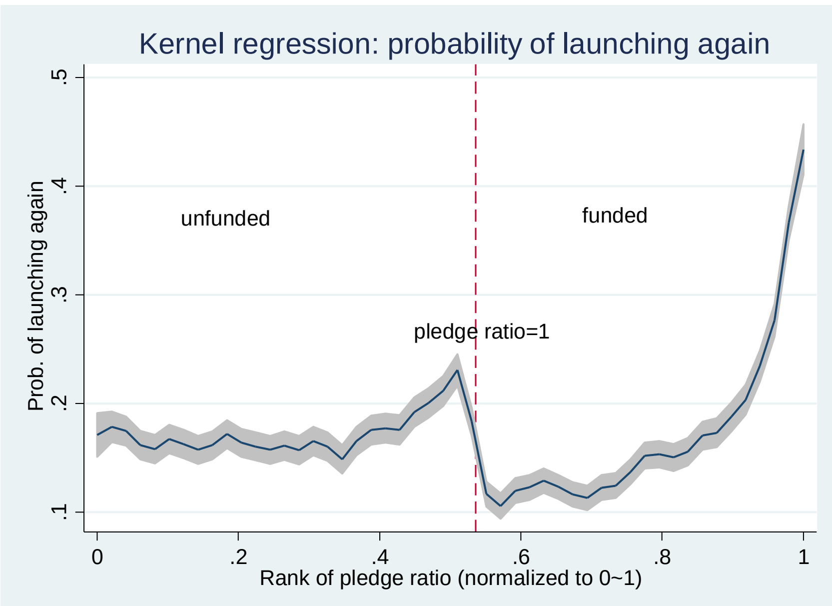

Figure 4B

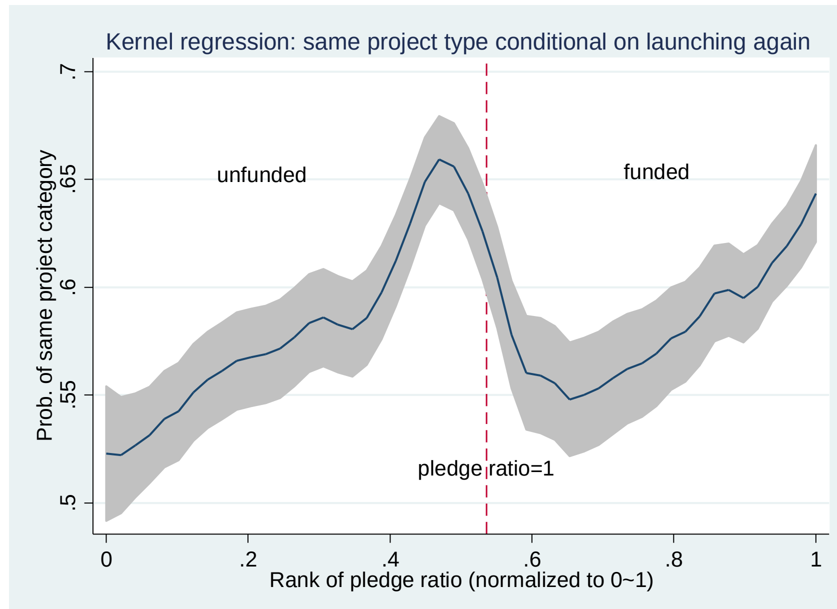

Figure 4C

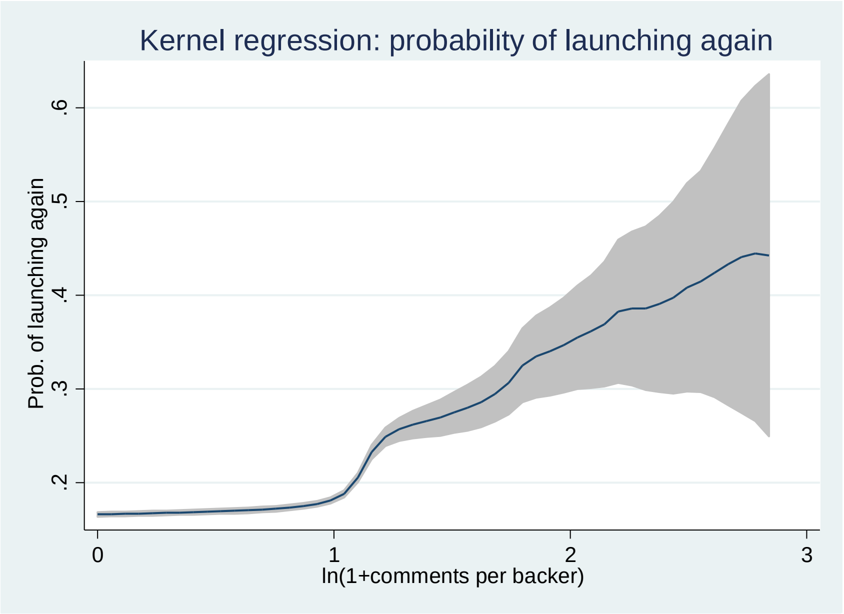

Figure 4D

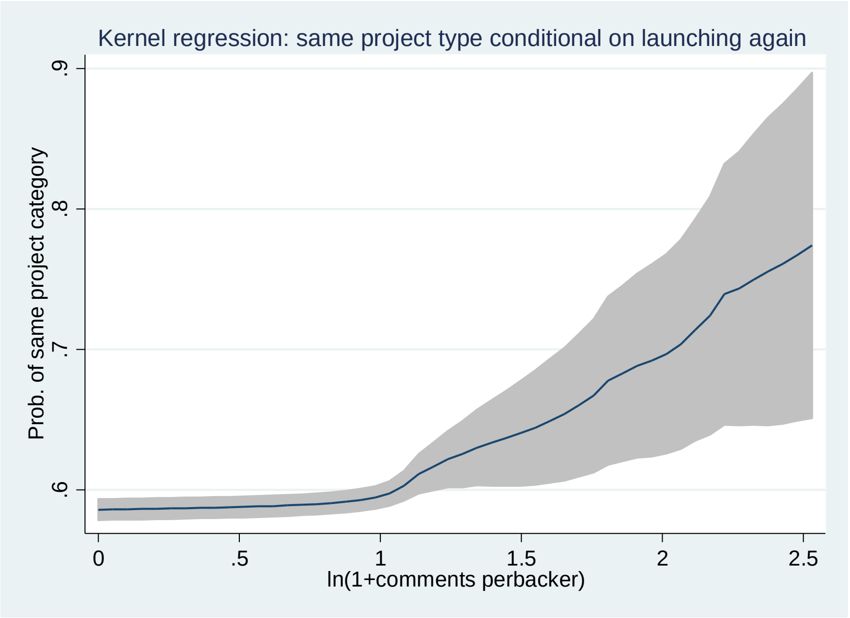

Figure 5. Comparing funding outcomes of projects presented in different positions in Kickstarter weekly newsletters

This panel of figures compares the density of funding outcomes for projects presented first (Group 1), second (Group 2), and third (Group 3) in Kickstarter's weekly newsletter emails. Figures 5A and 5C compare projects in Group 1 and Group2 in terms of their ln(pledge ratio) and ln(pledged amount), while Figures 5B and 5D compare projects in Group 2 and Group3 in these two funding outcomes. The lines correspond to the Epanechnikov kernel density of the related funding outcome. P-values of the Kolmogorov-Smirnov tests of equality of distributions are reported in the bottom of all figures.

Figure 5A

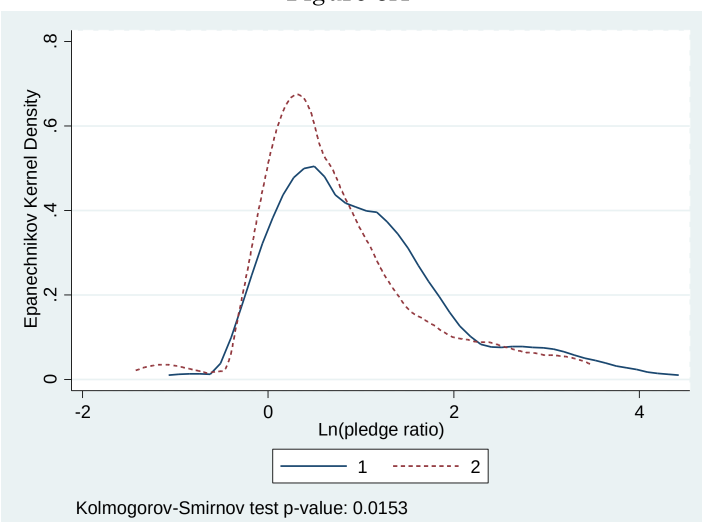

Figure 5B

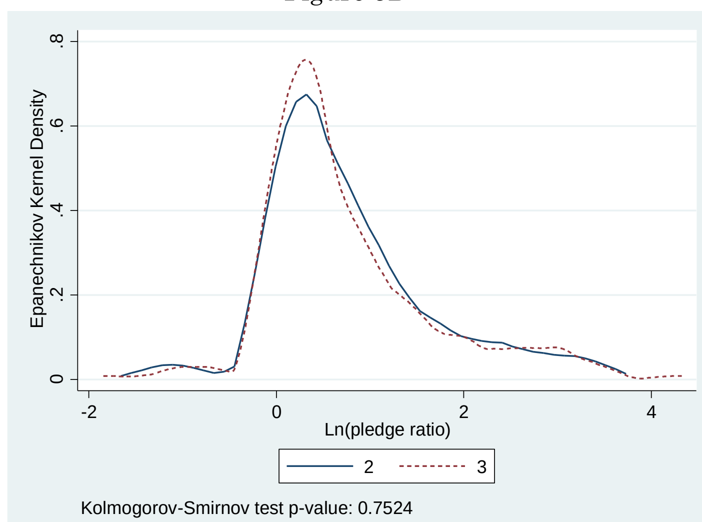

Figure 5C

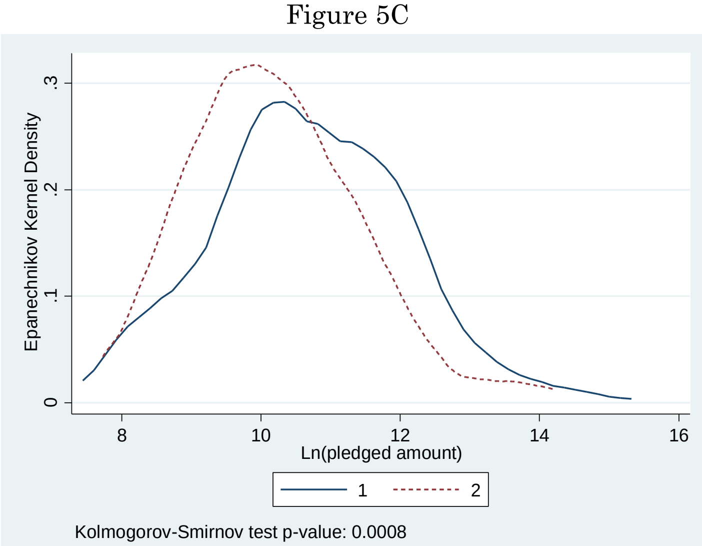

Figure 5D

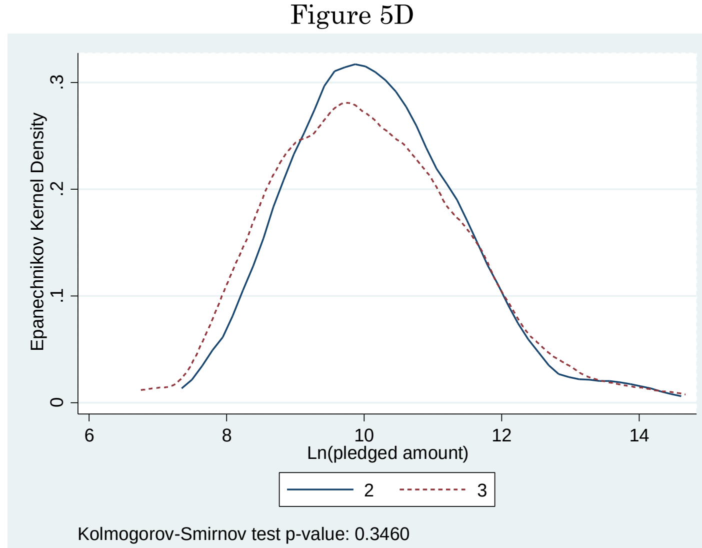

Table 1. Summary Statistics

This table presents descriptive statistics for my data. Panel A presents the mean and median of key variables for three samples: all projects (137,371 projects), funded projects (78,216 projects), and unfunded projects (59,155 projects). All variable definitions are detailed in Appendix I. Panel B presents the breakdown of projects into 13 top categories and tabulates the number of projects, share of total pledged amount, average funding target, and average success rate for each top category.

Panel A

	All projects		Unfunded projects		Funded projects	
Variable	Mean	Median	Mean	Median	Mean	Median
			Project characteristics			
Target amount	22,669.01	5,000.00	33,593.87	7,000.00	8,223.92	3,500.00
Pledged amount	7,336.25	1,139.00	1,602.79	212.00	14,917.16	4,250.00
Pledge ratio	1.69	0.30	0.11	0.04	3.77	1.13
Funded	0.43	0.00	1.00	1.00	0.00	0.00
Number of backers	99.49	21.00	21.62	6.00	202.45	63.00
Pledged amount per backer	72.33	50.48	63.38	40.00	82.35	61.64
Funding window (in days)	35.63	30.00	37.22	30.00	33.53	30.00
No. of words in project pitch	553.99	404.00	531.78	378.00	583.35	435.00
No. of words in risk disclosure	66.81	0.00	69.09	26.00	63.80	0.00
No. of videos	0.98	1.00	0.92	1.00	1.07	1.00
No. of images	3.78	0.00	3.54	0.00	4.11	0.00
Has website	0.83	1.00	0.79	1.00	0.87	1.00
No. of reward tiers	8.69	8.00	7.99	7.00	9.60	8.00
Average log(reward price threshold)	3.60	3.67	3.55	3.61	3.67	3.72
No. of Q&As	0.59	0.00	0.43	0.00	0.81	0.00
No. of updates	4.37	2.00	1.62	0.00	8.02	5.00
No. of comments	29.06	0.00	2.97	0.00	63.54	2.00
No. of comments per backer	0.09	0.00	0.08	0.00	0.09	0.03
			Entrepreneur characteristics			
No. of projects created	1.68	1.00	1.55	1.00	1.85	1.00
No. of projects backed	2.51	0.00	1.57	0.00	3.74	0.00
No. of Facebook friends	466.31	138.00	393.44	81.00	562.65	263.00
Has Facebook	0.58	1.00	0.56	1.00	0.59	1.00
No. of words in biography	119.61	78.88	117.29	76.57	122.69	82.01
Male	0.71	1.00	0.75	1.00	0.65	1.00
Education	0.29	0.00	0.27	0.00	0.30	0.00
			Other variables			
Prior precision	0.34	0.33	0.32	0.32	0.35	0.35
Feedback precision	1.60	1.27	1.80	1.50	1.38	1.13
Prior precision_alt	0.22	0.21	0.21	0.20	0.23	0.23
Feedback precision_alt	4.71	3.40	4.71	3.20	4.71	3.58
Jockey	2.86	2.97	2.77	2.86	2.99	3.06
Peer propensity	0.12	0.11	0.12	0.11	0.12	0.11
Project Novelty	0.66	0.67	0.68	0.68	0.65	0.65
Experience Index	1.57	1.61	1.54	1.61	1.62	1.61
Fixed Costs	1.98	2.00	1.97	2.00	1.99	2.00
Local housing price index	1.94	1.96	1.91	1.90	1.97	2.01
Local SBL supply shock	-0.07	-0.17	-0.08	-0.17	-0.06	-0.16

Panel B

Top category	No. of projects	Share of total pledged amount	Avg. funding target ($)	Success rate
Art	12,265	3.7%	24,803	47%
Comics	3,802	2.5%	8,720	48%
Dance	1,802	0.6%	6,142	69%
Hardware and design	7,158	14.5%	25,266	37%
Fashion and apparel	5,560	3.0%	13,103	29%
Film and video	33,546	19.7%	35,818	40%
Food and restaurant	5,666	3.8%	18,071	39%
Games	9,071	21.5%	43,521	34%
Music	27,956	10.4%	9,115	55%
Photography	4,184	1.3%	10,447	36%
Publishing	16,588	4.9%	11,373	32%
Technology	4,006	11.8%	63,590	33%
Theater	5,767	2.3%	12,365	64%

Table 2. Adjustment of Beliefs by Entrepreneurs

This table presents results from tests on entrepreneurs' belief adjustments. The key independent variables are the log funding target of an entrepreneur's current project (capturing prior expectation) and the log pledged amount the project receives (capturing feedback). The dependent variable is the log funding target of the same entrepreneur's next same-type project and captures the entrepreneur's posterior expectation. In Panel A, *Prior precision* is the cosine similarity score between the word vector of a project's pitch and the combined word vector of all project pitches in that project type. *Feedback precision* is the average number of prior projects a project's backers have backed. Columns 2 and 3 examine learning within initially funded and unfunded entrepreneurs, respectively. Panel B is analogous to columns 4 - 6 in Panel A, using alternative precisions measures. *Prior precision_alt* is the inverse of the logarithmic word count of the risk disclosure section and is only available for projects launched since September 2012. *Feedback precision_alt* is the average site age of the project's backers. All precision measures are standardized (removing sample mean and divided by sample standard deviation) in the regressions. Across all specifications I control for project type dummies, year-quarter dummies, characteristics of the entrepreneur's next same-type project (funding window (in days), web site dummy, number of reward tiers, average log reward threshold, project pitch length, number of images, and number of videos), and entrepreneur characteristics (number of Facebook friends, entrepreneur's biography length, and entrepreneur's Experience Index). Detailed variable definitions are in Appendix I. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

Dependent var: Ln(next target amount)	(1)	(2)	(3)	(4)	(5)	(6)
Ln(target amount)	0.393***	0.442***	0.417***	0.392***	0.388***	0.387***
	[0.013]	[0.029]	[0.024]	[0.013]	[0.012]	[0.012]
Ln(pledged amount)	0.075***	0.081***	0.085***	0.076***	0.068***	0.068***
	[0.008]	[0.026]	[0.021]	[0.008]	[0.008]	[0.008]
Ln(target amount) × Prior precision				0.016**		0.016**
				[0.007]		[0.007]
Ln(pledged amount) × Prior precision				-0.016***		-0.016***
				[0.004]		[0.004]
Ln(target amount) × Feedback precision					-0.028***	-0.027***
					[0.008]	[0.008]
Ln(pledged amount) × Feedback precision					0.022***	0.022***
					[0.006]	[0.006]
Prior precision				-0.002		-0.002
				[0.060]		[0.058]
Feedback precision					0.218***	0.216***
					[0.067]	[0.067]
Project type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	13,038	5,850	7,188	13,038	13,038	13,038
Adjusted R^2	0.529	0.609	0.522	0.530	0.534	0.535

Panel B. Alternative precision measures

Dependent var: Ln(next target amount)	(1)	(2	(3)
Ln(target amount)	0.436***	0.483***	0.438***
	[0.014]	[0.012]	[0.011]
Ln(pledged amount)	0.068***	0.091***	0.063***
	[0.009]	[0.007]	[0.008]
Ln(target amount) × Prior precision_alt	0.026**		0.033***
	[0.011]		[0.010]
Ln(pledged amount) × Prior precision_alt	-0.026***		-0.028***
	[0.007]		[0.007]
Ln(target amount) × Feedback precision_alt		-0.018**	-0.021**
		[0.008]	[0.010]
Ln(pledged amount) × Feedback precision_alt		0.011**	0.039***
		[0.004]	[0.006]
Prior precision_alt	-0.016		-0.064
	[0.095]		[0.080]
Feedback precision_alt		0.132**	0.024
		[0.066]	[0.086]
Project type FEs	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes
No. of observations	4,549	13,038	4,549
Adjusted R^2	0.578	0.530	0.594

Table 3. Adjustment of Beliefs by Entrepreneurs – Additional Analyses

Panel A examines differences in learning between different types of entrepreneurs. *Male* indicates that the gender of an entrepreneur is male. *Education* a dummy equal to one if an entrepreneur is identified as having a bachelor or above bachelor degree from her biography. The sample includes all entrepreneurs that are not registered as firms on Kickstarter. Panel B conducts a placebo test examining the effect of an entrepreneur's prior and the crowd's feedback on the funding target of the entrepreneur's next *different-type* project. Panel C interacts entrepreneurs' learning with the variable *Jockey*, which measures the extent to which the entrepreneur is featured in a project's pitch. Details on the construction of *Male*, *Education*, and *Jockey* are provided in Appendix I. Control variables are the same as in Table 2. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Heterogeneity of learning

Dependent var: ln(next target amount)	(1)	(2)
Ln(target amount)	0.381***	0.400***
	[0.013]	[0.011]
Ln(pledged amount)	0.079***	0.084***
	[0.009]	[0.007]
Ln(target amount) × Male	0.031**	
	[0.015]	
Ln(pledged amount) × Male	-0.022***	
	[0.008]	
Male	-0.091	
	[0.131]	
Ln(target amount) × Education		0.018
		[0.018]
Ln(pledged amount) × Education		-0.024**
		[0.012]
Education		0.251*
		[0.151]
Project type FEs	Yes	Yes
Year-quarter FEs	Yes	Yes
Other controls	Yes	Yes
No. of observations	10,548	10,548
Adjusted R^2	0.513	0.532

Panel B. Placebo test

Dependent var: Ln(next target amount)	(1)
Ln(target amount)	0.308***
	[0.017]
Ln(pledged amount)	-0.008
	[0.008]
Project type FEs	Yes
Year-quarter FEs	Yes
Other Controls	Yes
No. of observations	4,004
Adjusted R^2	0.420

Panel C. Interact with "Jockey" measure

Dependent var: Ln(next target amount)	(1)
Ln(target amount)	0.393***
	[0.013]
Ln(pledged amount)	0.074***
	[0.008]
Ln(target amount) × Jockey	0.002
	[0.003]
Ln(pledged amount) × Jockey	-0.002
	[0.002]
Jockey	-0.016
	[0.026]
Project type FEs	Yes
Year-quarter FEs	Yes
Other Controls	Yes
No. of observations	13,038
Adjusted R^2	0.526

Table 4. Learning and Continuation Decisions

This table examines the effect of feedback positivity on entrepreneurs' continuation decisions: whether to launch a next project after the current one, and conditional on launching again, whether to launch a project of the same type as or similar to the current project. The dependent variable *Launch again* is a dummy equal to one if the entrepreneur has launched another project after the current one before May 2013 (allowing for one year before the end of the sample period to observe entrepreneurs' comeback decisions). The dependent variable *Same-type project* is a dummy equal to one if an entrepreneur's next project is of the same type as her current project. The dependent variable *Project similarity* is the Bigram text similarity score between the project pitch of an entrepreneur's next project and that of her current project. The Panel A measures feedback positivity with *Ln(pledge ratio)*. Panel B measures feedback positivity with *Ln(1+comments per backer)*. All columns include project type fixed effects, year-quarter fixed effects, controls for current project characteristics (ln(target amount)), funding window (in days), web site dummy, number of reward tiers, average log reward threshold, project pitch length, number of images, number of videos), and controls for entrepreneur characteristics (number of Facebook friends, log length of entrepreneur's biography, and entrepreneur's Experience Index). Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Launch again	Same-type project (cond. on launching again)	Project similarity (cond. on launching again)
Ln(pledge ratio) × Unfunded	0.0025**	0.0354***	0.0107***
	[0.0013]	[0.0046]	[0.0005]
Ln(pledge ratio) × Funded	0.1230***	0.0293**	0.0076***
	[0.0037]	[0.0104]	[0.0016]
Funded	-0.0654***	-0.0962***	-0.0204***
	[0.0046]	[0.0218]	[0.0024]
Project type FEs	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
No. of observations	94,037	18,972	18,972
Adjusted R^2	0.043	0.078	0.067

Panel B

	Launch again	Same-type project (cond. on launching again)	Project similarity (cond. on launching again)
Ln(1+comments per backer)	0.1243***	0.1021***	0.0085***
	[0.0268]	[0.0183]	[0.0023]
Project type FEs	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
No. of observations	94,037	18,972	18,972
Adjusted R^2	0.037	0.064	0.030

Table 5. Observational Learning: Past Funding Outcomes and Future Entry Patterns on Kickstarter

This table examines how current entry pattern on Kickstarter depends on past funding outcomes on the platform. The sample is at the month-project category level (there are 13 project categories). The dependent variables are the same in all panels: *Ln*(*no. of projects*) is the log number of projects launched in each project category in each month; *% of projects* is the number of projects launched in a category-month divided by the total number of projects launched in that month; *Ln*(*volume*) is the log total target amount sought by projects launched in each category-month; *% of volume* is the total target amount in a category-month divided by the total target amount in that month. The independent variables in Panel A are the log of the mean pledge ratio for projects that ended funding in each of the previous two months in the same category as the dependent variable as well as in all other categories. The independent variables in Panel B and C are analogously defined as in Panel A except focusing on the 50th and 95th percentiles of pledge ratios rather than the mean pledge ratio. All regressions include project category fixed effects and monthly fixed effects. Standard errors are clustered at the project category level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Ln(no. of projects)	% of projects	Ln(volume)	% of volume
	(1)	(2)	(3)	(4)
Ln(mean pledge ratio)_samecat (t-1)	0.0820***	0.0032**	0.1130**	0.0065*
	[0.0210]	[0.0012]	[0.0475]	[0.0035]
Ln(mean pledge ratio)_samecat (t-2)	0.0444	0.0019	0.0724	0.0002
	[0.0365]	[0.0017]	[0.0464]	[0.0032]
Ln(mean pledge ratio)_othercat (t-1)	-0.0836	-0.0219***	-0.0955	-0.0227**
	[0.0600]	[0.0053]	[0.1253]	[0.0101]
Ln(mean pledge ratio)_othercat (t-2)	-0.1671*	-0.0250***	-0.1750	-0.0418
	[0.0800]	[0.0056]	[0.1520]	[0.0330]
Project category FEs	Yes	Yes	Yes	Yes
Monthly FEs	Yes	Yes	Yes	Yes
No. of observations	719	719	719	719
Adjusted R^2	0.930	0.907	0.883	0.744

Panel B

	Ln(no. of projects) (1)	% of projects (2)	Ln(volume) (3)	% of volume (4)
Ln(p50_pledge ratio)_samecat (t-1)	0.0019	-0.0011	-0.0063	0.0005
	[0.0233]	[0.0015]	[0.0527]	[0.0032]
Ln(p50_pledge ratio)_samecat (t-2)	0.0046	-0.0003	0.0336	0.0015
	[0.0241]	[0.0014]	[0.0571]	[0.0034]
Ln(p50_pledge ratio)_othercat (t-1)	-0.2690	-0.0236	-0.2950	-0.0174
	[0.233]	[0.0256]	[0.2461]	[0.0133]
Ln(p50_pledge ratio)_othercat (t-2)	0.0579	-0.0057	0.1230	0.0075
	[0.209]	[0.0142]	[0.3734]	[0.0176]
Project category FEs	Yes	Yes	Yes	Yes
Monthly FEs	Yes	Yes	Yes	Yes
No. of observations	719	719	719	719
Adjusted R^2	0.926	0.899	0.879	0.737

Panel C

	Ln(no. of projects) (1)	% of projects (2)	Ln(volume) (3)	% of volume (4)
Ln(p95_pledge ratio)_samecat (t-1)	0.0635***	0.0034**	0.0947***	0.0052*
	[0.0143]	[0.0012]	[0.0305]	[0.0024]
Ln(p95_pledge ratio)_samecat (t-2)	0.0504	0.0032*	0.0796**	0.0037*
	[0.0283]	[0.0016]	[0.0344]	[0.0018]
Ln(p95_pledge ratio)_othercat (t-1)	-0.1790	-0.0200	-0.5060	-0.0306
	[0.240]	[0.0202]	[0.349]	[0.0234]
Ln(p95_pledge ratio)_othercat (t-2)	-0.2170	-0.0171	-0.3550	-0.0216
	[0.2383]	[0.0165]	[0.480]	[0.0303]
Project category FEs	Yes	Yes	Yes	Yes
Monthly FEs	Yes	Yes	Yes	Yes
No. of observations	719	719	719	719
Adjusted R^2	0.933	0.908	0.889	0.744

Table 6. Substitution between Bank Borrowing and Crowdfunding

This table validates the assumption that crowdfunding and bank credit are substitutes in providing finance. In Panel A, the sample is at the MSA-quarter level covering 287 MSAs and 20 quarters from April 2009 to March 2014. The dependent variable *MSA-level demand for finance on KS* is the logarithm of quarterly aggregate funding target amount on Kickstarter at the Metro/Micropolitan Statistical Area (MSA) level. The independent variable *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) from the Federal Housing Financing Agency (FHFA). Following Cvijanovic (2014), I instrument *Local housing price index* with the interaction of MSA-level land supply elasticity (Saiz 2010) and national real estate prices (the S&P/Case-Shiller Home Price Index). In Panel B, the sample is at the county-quarter level covering 2,144 counties and 20 quarters from April 2009 to March 2014. The dependent variable *County-level demand for finance on KS* is the logarithm of quarterly aggregate funding target amount on Kickstarter at the county level. The independent variable *Local SBL supply shock* is the weighted average shock to banks' supply of small business loans in each county-year (see Appendix III for detailed definition). In Panel A (Panel B), I also include MSA-level (county-level) *Unemployment rate*, *Population*, and *Income per capita* as local controls. Standard errors are clustered at the MSA level in Panel A and at the county level in Panel B. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

Dependent variable:	MSA-level demand for finance on KS	
	OLS	IV
	(1)	(2)
Local housing price index	-0.032***	-0.069**
	[0.009]	[0.033]
First stage:		
Land supply elasticity ×national real estate price		-0.129***
		[0.0271]
Local controls	Yes	Yes
MSA FEs	Yes	Yes
Year-quarter FEs	Yes	Yes
No. of observations	5,740	5,740
Adjusted R^2	0.723	0.721

Panel B

	County-level demand for finance on KS
	(1)
Local SBL supply shock	-0.335***
	[0.124]
Local controls	Yes
Year-quarter FEs	Yes
No. of observations	42,880
Adjusted/Pseudo R^2	0.118

Table 7. Local Borrowing Costs and the Learning Value of Crowdfunding

This table examines the effect of local borrowing cost and thus the relative cost of crowdfunding on the ex-ante uncertainty faced by entrepreneurs entering Kickstarter. The analyses at the project level. In Panel A, the dependent variable *Project Novelty* is one minus the cosine similarity score between the word vector of a project's pitch and the combined word vector of all project pitches in the same project type; *Experience Index* is a variable constructed from entrepreneur's biography indicating how experienced an entrepreneur is; *Fixed Costs* is a variable measuring the mentioning of words related to fixed costs in a project's project pitch. See Appendix I for details on the construction of these three variables. The independent variable *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) from the Federal Housing Financing Agency (FHFA). Following Cvijanovic (2014), I instrument *Local housing price index* with the interaction of MSA-level land supply elasticity (Saiz 2010) and national real estate prices (the S&P/Case-Shiller Home Price Index). Panel B follows Panel A and interact *Local housing price index* with *High home ownership*, a dummy variable indicating that the ZIP code in which an entrepreneur resides has above median home ownership rate. In Panel C, the dependent variables are the same as those in Panel A. The independent variable *Local SBL supply shock* is the weighted average shock to banks' supply of small business loans in each county-year (see Appendix III for detailed definition). I also control for MSA-level (county-level) *Unemployment rate*, *Population*, and *Income per capita* in Panels A and B (Panel C). Standard errors are clustered at the MSA level in Panels A and B, and at the county level in Panel C. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Project Novelty		Experience Index		Fixed Costs	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Local housing price index	0.021***	0.045***	-0.127***	-0.362***	0.313***	0.469**
	[0.003]	[0.007]	[0.042]	[0.130]	[0.080]	[0.217]
First stage:						
Land supply elasticity		-0.304***		-0.304***		-0.303***
× national real estate price		[0.043]		[0.043]		[0.043]
Local controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	105,061	105,061	105,061	105,061	105,061	105,061
Adjusted R^2	0.010	0.009	0.044	0.045	0.237	0.236

Panel B

	Project Novelty		Experience Index		Fixed Costs	
	OLS	IV	OLS	IV	OLS	IV
Local housing price index	0.018***	0.034***	-0.122***	-0.329**	0.213***	0.647**
	[0.003]	[0.007]	[0.041]	[0.133]	[0.077]	[0.263]
Local housing price index × High home ownership	0.006**	0.017***	-0.202**	-0.427*	0.195**	0.304***
	[0.003]	[0.007]	[0.100]	[0.234]	[0.097]	[0.115]
High home ownership	0.011**	0.018	-0.005	-0.009	-0.022	-0.017
	[0.006]	[0.014]	[0.010]	[0.010]	[0.019]	[0.019]
Local controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	105,061	105,061	105,061	105,061	105,061	105,061
Adjusted R^2	0.010	0.009	0.044	0.045	0.237	0.230

Panel C

	Project Novelty	Experience Index	Fixed Costs
Local SBL supply shock	0.009***	-0.117***	0.140***
	[0.003]	[0.030]	[0.044]
Local controls	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes
No. of observations	120,719	120,719	120,719
Adjusted R^2	0.002	0.036	0.230

Table 8. Local Borrowing Costs and Ex-Post Learning in Crowdfunding Market

This table examines how local borrowing cost and thus the relative cost of crowdfunding affects entering entrepreneurs' ex-post learning process. The specification is analogous to that in Table 2 Panel A. The samples are based on the sample used in Table 2 Panel A for which I can observe MSA-level housing prices (in column 1) or county-level small business lending supply shocks (in column 2). The dependent variable is the log funding target of an entrepreneur's next same-type project and captures the entrepreneur's posterior expectation. The independent variables are the log funding target of the entrepreneur's current project (capturing prior expectation) and the pledged amount received by the current project (capturing feedback). *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) from the Federal Housing Financing Agency (FHFA). *Local SBL supply shock* is the county-year level weighted average shock to banks' supply of small business loans (see Appendix III for detailed definitions). Both *Local housing price index* and *Local SBL supply shock* are standardized and their main effects are included in regressions but omitted from the table. Other control variables are the same as those in Table 2. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent var: Ln(next target amount)	(1)	(2)
Ln(target amount)	0.423***	0.389***
	[0.012]	[0.011]
Ln(pledged amount)	0.021***	0.080***
	[0.007]	[0.006]
Ln(target amount) × Local housing price index	-0.023***	
	[0.008]	
Ln(pledged amount) × Local housing price index	0.001	
	[0.004]	
Ln(target amount) × Local SBL supply shock		-0.025***
		[0.009]
Ln(pledged amount) × Local SBL supply shock		0.017***
		[0.005]
MSA FEs	Yes	No
Year-quarter FE	Yes	Yes
Project type FE	Yes	Yes
Other controls	Yes	Yes
No. of observations	11,579	12,894
Adjusted R^2	0.520	0.519

Table 9. Addressing the Endogeneity of Feedback: Differential Attention Shocks to Featured Projects

This table exploits the order by which projects are presented in Kickstarter's weekly newsletters to address the endogeneity of funding outcome as a feedback. Panel A compares the projects that are presented first, second, and third in the newsletters. Columns 1 to 3 present the means of various project characteristics as well as funding outcomes for the three groups of projects. Columns 4 and 5 present the p-values of mean difference tests between the first and second, and between the second and third group of projects. Columns 6 and 7 present the p-values of Kolmogorov-Smirnov tests of equality of distributions between the first and second, and between the second and third group of projects. Panel B examines whether project characteristics predict selection into each of the three groups. *Group 1 vs 2* is a dummy equal to 1 if a project is presented first in a newsletter and 0 if presented second. *Group 2 vs 3* and *Group 1 vs 3* are analogously defined. Panel C compares projects in the first and the second group in terms of their subsequent entry decisions, project choices, as well as funding targets. *Launch again* is a dummy equal to one if an entrepreneur has launched another project after the current project. *Project similarity* is the Bigram text similarity score between the pitch of an entrepreneur's current project and that of her next project. *Ln(next target amount)* is the log funding target amount of an entrepreneurs' next project. Panel C also controls for the ln(target amount) of the current project and project type fixed effects. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Comparison of projects presented first, second, and third in newsletters

	Group mean			P-value of T-test		P-value of Kolmogorov-Smirnov test	
	First (1)	Second (2)	Third (3)	First – Second (4)	Second – Third (5)	First – Second (6)	Second – Third (7)
Project characteristics							
Ln(target amount)	9.464	9.427	9.334	0.395	0.256	0.579	0.284
Funding window (in days)	35.768	37.373	37.238	0.143	0.464	0.346	0.900
Ln(project pitch length)	6.504	6.472	6.541	0.333	0.177	0.284	0.900
Ln(no. of videos)	0.766	0.741	0.764	0.150	0.160	0.999	0.999
Ln(no. of images)	1.657	1.717	1.620	0.289	0.186	0.021	0.021
Avg. log(reward price threshold)	4.147	4.119	4.001	0.372	0.082	0.146	0.146
Ln(biography length)	6.044	6.030	5.989	0.450	0.359	0.346	0.494
Experience Index	1.644	1.621	1.599	0.392	0.398	0.992	0.955
Funding outcomes							
Ln(pledge ratio)	1.029	0.769	0.753	0.002	0.435	0.015	0.752
Ln(pledged amount)	10.688	10.189	10.081	0.000	0.213	0.001	0.346
Ln(# of backers)	6.660	6.222	6.099	0.000	0.150	0.005	0.284

Panel B. Effect of observables on selection into each of the three groups

	Group 1 vs 2	Group 2 vs 3	Group 1 vs 3
Ln(target amount)	0.009	0.011	0.011
	[0.0263]	[0.0269]	[0.0269]
Funding window (in days)	-0.003	0.000	0.000
	[0.00323]	[0.00302]	[0.00302]
Ln(project pitch length)	0.049	-0.066	-0.066
	[0.0459]	[0.0541]	[0.0541]
Ln(no. of videos)	0.085	-0.118	-0.118
	[0.150]	[0.0949]	[0.0949]
Ln(no. of images)	0.027	-0.040	-0.040
	[0.0398]	[0.0357]	[0.0357]
Average log(reward price threshold)	0.037	0.069	0.069
	[0.0448]	[0.0660]	[0.0660]
Ln(biography length)	-0.025	0.008	0.008
	[0.0473]	[0.0401]	[0.0401]
Experience Index	0.039	-0.020	-0.020
	[0.0516]	[0.0462]	[0.0462]
Project type FEs	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
No. of observations	370	370	370
Adjusted R^2	0.095	0.087	0.087

Panel C. Comparing the first and the second group in subsequent decisions

	Launch again	Project similarity (cond. on launching again)	Ln(next target amount)
Group 1 vs 2	0.0772**	0.0300**	0.574***
	[0.0287]	[0.0146]	[0.161]
Control	Yes	Yes	Yes
Project type FE	Yes	Yes	Yes
No. of observations	370	68	68
Adjusted R^2	0.040	0.223	0.342

Appendix I. Variable Definitions

Variable Name	Definition
Target amount	The funding target amount (in $) set by entrepreneurs for their project. Amount in other currencies are converted to US dollar based on the exchange rate in the month of the project launch.
Pledged amount	Amount (in $) pledged by the backers by the end of the project's funding window.
Pledge ratio	The ratio between *Target amount* and *Pledged amount*. When this ratio is larger than or equal to one, the project is funded and the pledged amount is transferred to the entrepreneurs. When this ratio is less than one, the project is unfunded and the entrepreneur gets no funding and the pledged amount is returned to backers.
Funded	A dummy indicating the project is successfully funded. This happens when the pledged amount reaches or exceeds the target amount, i.e., pledge ratio equal to or larger than one.
Number of backers	The number of backers that pledged the project.
Pledged amount per backer	The average amount pledged by each backer.
Funding window (in days)	The number of days the entrepreneur set for the funding of her project.
Project pitch length	The logarithm of the number of words in project's main pitch
Risk disclosure length	The logarithm of the number of words in project's Risk and Challenges section. This variable is only available for projects launched since September 2012.
Number of videos	The number of videos used in the project pitch.
Number of images	The number of images used in the project pitch.
Has website	A dummy equal to one if there is a dedicated website for the project.
Number of rewards tiers	The number of reward tiers offered to backers. Each reward tier corresponds to a price threshold. Backers backing an amount above the threshold are promised the corresponding reward before an estimated delivery date.
Average log(reward threshold)	The average of the logarithm of price thresholds across all reward tiers offered by a project.
Number of projects created	The number of Kickstarter projects created by the entrepreneur as of the project launch date.
Number of projects backed	The number of Kickstarter projects backed by the entrepreneur as of the project launch date.
Number of Facebook friends	The number of Facebook friends the entrepreneur has. For entrepreneurs that are do not have Facebook, this variable is set to zero.
Has Facebook	A dummy equal to one if the entrepreneur has Facebook.

Biography length	The logarithm of the number of words in the entrepreneur's biography
Number of Q&As	The number of questions posted on a project's page.
Number of updates	The number of updates provided by the entrepreneur on the project's page.
Number of comments	The number of comments posted by backers on a project's wall.
Number of comments per backer	The number of comments posted divided by the number of backers.
Prior precision	The cosine similarity score between the word vector of a project's pitch and the combined word vector of all project pitches in that project type. To construct this variable, I first clean all project pitch texts by removing numbers, non-text symbols, and some frequently-appeared prepositions, articles, pronouns, auxiliaries, and conjunctions. I then create a word vector for each project pitch by breaking the text into unique words with corresponding frequencies. I do the same for each project type based on the pooled text of all projects' pitches in that project type. I then compute the cosine similarly score between the word vector of each project and the aggregate word vector of the project's associated project type.
Feedback precision	The average number of projects a project's backers have backed on Kickstarter prior to backing this project.
Prior precision_alt	The inverse of the logarithmic word count of the Risk and Challenges section. This variable is available for projects launched since September 2012.
Feedback precision_alt	The average number of months of a project's backers have been on the platform.
Male	A dummy indicating the gender of the entrepreneur. Following Greenberg and Mollick (2014), gender is algorithmically coded using the *genderize.io* tool by comparing entrepreneurs' first names with a database of 208,631 distinct names across 79 countries and 89 languages. For each name, the database assigns a probability that a specific name-gender attribution (male or female) is correct in the population of a country. An entrepreneur is identified to be of a specific gender if the associated probability exceeds 70%. This variable is only defined for non-firm individual entrepreneurs.
Education	A dummy indicating the entrepreneur has a bachelor or above bachelor degree. This is identified by searching for key words "Bachelor", "Master", "Ph.D.", "Doctor", "University", "College", "Graudate School", "Graduate Degree", "M.B.A.", "MBA" from the entrepreneurs' biographies. This variable is only defined for non-firm individual entrepreneurs.
Jockey	Following Marom and Sade (2013), I construct *Jockey* as the number of times the entrepreneur's name (entrepreneurs' names) or pronouns and possessive adjectives ("I", "my", "we", "our", "he", "his", "she", "her", etc.) are mentioned in the project pitch.
Project similarity	The Bigram similarity score between the pitch texts of two projects. The Bigram algorithm compares two strings using all combinations of two consecutive characters within each string. The score, valued between 0 and 1, is computed as the ratio of the total number of bigrams that are in common between the two strings divided by the average number of bigrams in the strings.
Project dissimilarity	One minus *Project similarity*.

Local housing price index	The MSA-quarter level Housing Price Index (HPI) published by the Federal Housing Finance Agency (FHFA), scaled by 1/100. The index is based on transactions involving conforming, conventional mortgages purchased or securitized by Fannie Mae or Freddie Mac.
Land supply elasticity × national real estate price	The instrument for the *Local housing price index*. Following Cvijanovic (2014), it is constructed as the interaction between Saiz (2010) land supply elasticity and the S&P/Case-Shiller nation home price index. This variable varies at the MSA-quarter level.
Local SBL supply shock	The county-year level weighted average shocks of bank supply of small business loans with origination amount less than $100k. See Appendix III for details on the construction of this variable.
MSA-level demand for finance on KS	The logarithm of quarterly aggregate funding target amount on Kickstarter at the Metro/Micropolitan Statistical Area (MSA) level.
County-level demand for finance on KS	The logarithm of quarterly aggregate funding target amount on Kickstarter at the county-level.
Unemployment rate	Annual MSA- and county-level unemployment rate. Obtained from the Local Area Uemployment Statistics (LAUS) database of the Bureau of Labor Statistics.
Population	Annual MSA- and county-level population (in logarithm) obtained from the Beaurea of Economic Analysis (BEA) Regional Economic Accounts.
Income per capita	Annual MSA- and county-level income per capital (in logarithm) obtained from the Beaurea of Economic Analysis (BEA) Regional Economic Accounts.
High home ownership	A dummy variable indicating that the ZIP code in which an entrepreneur resides has above median home ownership rate. ZIP code level home ownership rates are obtained from American Community Survey 2009-2013 5-year Data Release.
Project Novelty	One minus the cosine similarity score between the word vector of a project's pitch and the combined word vector of all project pitches in that project type. This variable is equal to 1−*Prior precision*.
Experience Index	The log number of times experience-related keywords appear in an entrepreneur's biography. To create this index, I first construct a text bank combining the biography texts of all entrepreneurs. This text bank is then transformed into a dictionary of words with associated frequency scores. From this dictionary, I manually identify 85 keywords most commonly associated with professional or entrepreneurial experience. I then compute the frequencies these keywords appear in each entrepreneur's biography and define the log of this frequency number as the *Experience Index*.
Fixed Costs	A variable that counts the mentioning of words related to fixed costs in a project's project pitch. Word list related to fixed costs is based on Cumming et al. (2015) and includes: acquire, building, construct-, develop-, equipment, fixed cost(s), legal fees, license, machine, manufactur-, mold, overhead cost(s), patent, permit, produced, production, prototype, purchas-, rent, R&D, research and development, tool.
Peer propensity	The proportion of repeat entrepreneurs (excluding the focal entrepreneur) on Kickstarter in the local ZIP code.

Appendix II: Additional Tables

Table A1. This table compares projects launched by one-time entrepreneurs (104,597 projects) and repeat entrepreneurs (32,774 projects) along various project and entrepreneur characteristics.

	Projects by one-time entrepreneurs	Initial projects by repeat entrepreneurs
	No. of projects	
	104,597	13,582
	Project characteristics (means)	
Target amount	24,040.61	22,406.26
Pledged amount	7,121.81	6,791.61
Pledge ratio	1.36	1.41
Funded	0.43	0.37
Number of backers	93.97	98.63
Pledged amount per backer	74.15	68.19
Funding window (in days)	35.68	37.61
No. of words in project pitch	551.08	530.81
No. of words in risk disclosure	69.04	41.44
No. of videos	0.99	0.93
No. of images	3.56	3.74
Has website	0.81	0.86
No. of reward tiers	8.68	8.44
Average log(reward threshold)	3.64	3.56
No. of Q&As	0.56	0.69
No. of updates	3.96	5.88
No. of comments	23.69	29.72
No. of comments per backer	0.08	0.12
Project Novelty	0.66	0.67
Fixed Costs	2.00	1.95
	Entrepreneur characteristics (means)	
No. of projects created	1.00	2.49
No. of projects backed	1.94	3.75
No. of Facebook friends	438.28	537.19
Has Facebook	0.56	0.62
No. of words in biography	122.09	114.91
Male	0.69	0.75
Experience Index	1.58	1.58

Table A2. Adjustment of Beliefs by Entrepreneurs: Correcting for Sample Selection

This table presents the results of entrepreneurs' belief adjustment after correcting for sample selection. Samples and variable definitions are the same as those in Table 2 Panel A. The empirical specification is a two-stage Heckman selection model. The first stage estimates the selection into the second stage sample, i.e., entrepreneurs that launched at least two projects of the same type. The independent variables in the first stage include all control variables and fixed effects used in the second stage as well as the excluded instrument, *Peer propensity*, which is defined as the proportion of repeat entrepreneurs (excluding the focal entrepreneur) on Kickstarter in the local ZIP code. In all columns, I report the coefficient of *Peer propensity* in the first stage, the coefficient of the inverse Mills ratio (lambda) in the second stage, as well as the χ^2 statistics for the log likelihood comparison test testing the presence of sample selection. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent var: Ln(next target amount)	(1)	(2)	(3)	(4)
Ln(target amount)	0.393***	0.392***	0.388***	0.386***
	[0.0125]	[0.0126]	[0.0121]	[0.0121]
Ln(pledged amount)	0.0750***	0.0756***	0.0677***	0.0680***
	[0.0076]	[0.0076]	[0.0083]	[0.0084]
Ln(target amount) × Prior precision		0.0161**		0.0162**
		[0.0070]		[0.0068]
Ln(pledged amount) × Prior precision		-0.0161***		-0.0156***
		[0.0044]		[0.0045]
Ln(target amount) × Feedback precision			-0.0276***	-0.0270***
			[0.0082]	[0.0082]
Ln(pledged amount) × Feedback precision			0.0216***	0.0217***
			[0.0063]	[0.0064]
Prior precision		-0.002		0.001
		[0.0601]		[0.0574]
Feedback precision			0.218***	0.215***
			[0.0662]	[0.0665]
1st stage: Peer propensity	0.726***	0.726***	0.726***	0.726***
	[0.0346]	[0.0346]	[0.0346]	[0.0346]
Inverse Mills ratio (lambda)	0.157**	0.157**	0.150**	0.149**
	[0.074]	[0.073]	[0.074]	[0.074]
$\chi 2$ of log likelihood comparison test	4.581**	4.626**	4.113**	4.135**
Project type FEs	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
No. of observations	13,038	13,038	13,038	13,038

Table A3. Adjustment of Beliefs by Entrepreneurs: Alternative Samples

This table reproduces Table 2 Panel A under alternative subsamples. Panel A imposes the sample restriction that an entrepreneur's current project being almost the same as her next same-type project, i.e. with project pitch similarity score of at least 0.95 (1 being exactly the same). Panel B restricts to projects in more traditional sectors—projects in "Hardware and design", "Fashion and apparel", "Food and restaurant", "Games", "Publishing", and "Technology". Panel C focuses on larger projects with funding target amounts of at least $10,000 USD. All specifications follow those used in Table 2 Panel A. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Alternative definition of similar projects

Dependent var: Ln(next target amount)	(1)	(4)	(5)	(6)
Ln(target amount)	0.431***	0.416***	0.425***	0.411***
	[0.0132]	[0.0128]	[0.0133]	[0.0126]
Ln(pledged amount)	0.0894***	0.0856***	0.0807***	0.0763***
	[0.0076]	[0.0078]	[0.0087]	[0.0088]
Ln(target amount) × Prior precision		0.0196**		0.0192**
		[0.0080]		[0.0077]
Ln(pledged amount) × Prior precision		-0.0120**		-0.0112*
		[0.0056]		[0.0057]
Ln(target amount) × Feedback precision			-0.0231**	-0.0241**
			[0.0099]	[0.0093]
Ln(pledged amount) × Feedback precision			0.0270***	0.0245***
			[0.0065]	[0.0065]
Prior precision		-0.069		-0.0648
		[0.0647]		[0.0615]
Feedback precision			0.154*	0.183**
			[0.0814]	[0.0771]
Project type FEs	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
No. of observations	8,781	8,781	8,781	8,781
Adjusted R^2	0.556	0.545	0.561	0.551

Panel B: Projects in traditional sectors

Dependent var: Ln(next target amount)	(1)	(4)	(5)	(6)
Ln(target amount)	0.438***	0.438***	0.436***	0.436***
	[0.0181]	[0.0185]	[0.0175]	[0.0179]
Ln(pledged amount)	0.0793***	0.0790***	0.0683***	0.0677***
	[0.0105]	[0.0111]	[0.0122]	[0.0129]
Ln(target amount) × Prior precision		0.0240***		0.0238***
		[0.0076]		[0.0075]
Ln(pledged amount) × Prior precision		-0.0240***		-0.0227***
		[0.0058]		[0.0057]
Ln(target amount) × Feedback precision			-0.0273***	-0.0257**
			[0.0103]	[0.0109]
Ln(pledged amount) × Feedback precision			0.0266***	0.0262***
			[0.0065]	[0.0064]
Prior precision		-0.0312		-0.00208
		[0.1010]		[0.0758]
Feedback precision			0.176*	0.167*
			[0.0912]	[0.0926]
Project type FEs	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
No. of observations	4,891	4,891	4,891	4,891
Adjusted R^2	0.529	0.522	0.534	0.540

Panel C. Larger projects

Dependent var: Ln(next target amount)	(1)	(4)	(5)	(6)
Ln(target amount)	0.436***	0.429***	0.441***	0.434***
	[0.0303]	[0.0302]	[0.0298]	[0.0301]
Ln(pledged amount)	0.0639***	0.0643***	0.0561***	0.0561***
	[0.0010]	[0.0097]	[0.0111]	[0.0108]
Ln(target amount) × Prior precision		0.0476***		0.0258***
		[0.0172]		[0.0091]
Ln(pledged amount) × Prior precision		-0.0165**		-0.0178***
		[0.0065]		[0.0048]
Ln(target amount) × Feedback precision			-0.0280**	-0.0277**
			[0.0122]	[0.0123]
Ln(pledged amount) × Feedback precision			0.0225***	0.0223***
			[0.0068]	[0.0069]
Prior precision		-0.328*		-0.078
		[0.185]		[0.0829]
Feedback precision			0.231**	0.233**
			[0.102]	[0.103]
Project type FEs	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
No. of observations	3,992	3,992	3,992	3,992
Adjusted R^2	0.373	0.376	0.378	0.378

Table A4. Local Borrowing Costs and the Learning Value of Crowdfunding: Alternative Subsamples

Panel A reproduces Table 7 dropping projects that likely face local demands, i.e. projects in "Food and restaurant", "Fashion and apparel", "Dance", and "Theatre". Panel B reproduces Table 7 focusing on projects in more traditional sectors such as "Hardware and design", "Fashion and apparel", "Food and restaurant", "Games", "Publishing", and "Technology". All specifications are the same as those used in Table 7. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Excluding projects with local demand

	Project Novelty		Experience Index		Fixed Costs	
	OLS	IV	OLS	IV	OLS	IV
Local housing price index	0.017***	0.034***	-0.084**	-0.359***	0.296***	0.453**
	[0.003]	[0.007]	[0.036]	[0.124]	[0.075]	[0.205]
First stage:						
Land supply elasticity		-0.332***		-0.332***		-0.332***
×national real estate price		[0.054]		[0.054]		[0.054]
Local controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	89,075	89,075	89,075	89,075	89,075	89,075
Adjusted R^2	0.016	0.016	0.036	0.036	0.257	0.257

	Project Novelty	Experience Index	Fixed Costs
Local SBL supply shock	0.013***	-0.128***	0.137***
	[0.004]	[0.032]	[0.047]
Local controls	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes
No. of observations	102,557	102,557	102,557
Adjusted R^2	0.001	0.026	0.250

Panel B. Projects in more traditional sectors

	Project Novelty		Experience Index		Fixed Costs	
	OLS	IV	OLS	IV	OLS	IV
Local housing price index	0.023***	0.042***	-0.100**	-0.232*	0.269**	0.382*
	[0.004]	[0.011]	[0.048]	[0.130]	[0.136]	[0.218]
First stage:						
Land supply elasticity		-0.374***		-0.374***		-0.374***
×national real estate price		[0.048]		[0.048]		[0.048]
Local controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	35,968	35,968	35,968	35,968	35,968	35,968
Adjusted R^2	0.018	0.018	0.040	0.040	0.278	0.278

	Project Novelty	Experience Index	Fixed Costs
Local SBL supply shock	0.014***	-0.130***	0.232**
	[0.005]	[0.050]	[0.093]
Local controls	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Project type FEs	Yes	Yes	Yes
No. of observations	40,744	40,744	40,744
Adjusted R^2	0.002	0.027	0.269

Table A4. Validation of key measures

In Panel A, projects are sorted into quintiles based on the value of *Project Novelty* (which is equal to 1–*Prior precision*), *Risk Disclosure* (which is equal to 1/*Prior precision_alt*), and *Experience Index*, respectively. Higher quintile numbers correspond to higher values in these measures. I then tabulate the mean and the standard deviation of funding outcome *ln(pledge ratio)* in each quintile for each sorting variable. Panel B sorts project top categories by the average of the *Jockey* measure.

Panel A. Validating uncertainty measures

	Sorting variable: *Project Novelty* (or 1–*Prior precision*)		Sorting variable: *Risk Disclosure* (or 1/*Prior precision_alt*)		Sorting variable: *Experience Index*	
Quintiles	Mean of ln(pledge ratio)	Mean of ln(pledge ratio)	Mean of ln(pledge ratio)	Mean of ln(pledge ratio)	Mean of ln(pledge ratio)	Std. dev. of ln(pledge ratio)
1	-1.390	-1.188	-1.683	-1.683	-1.683	1.997
2	-1.449	-1.345	-1.516	-1.516	-1.516	1.966
3	-1.523	-1.482	-1.532	-1.532	-1.532	1.936
4	-1.639	-1.701	-1.497	-1.497	-1.497	1.906
5	-1.725	-1.978	-1.441	-1.441	-1.441	1.859

Panel B. Mean of *Jockey* by project top categories

Top project category	Mean of *Jockey*
Music	1.949
Dance	0.573
Theater	0.206
Fashion and apparel	0.094
Food and restaurant	-0.021
Film and video	-0.140
Publishing	-0.270
Art	-0.286
Photography	-0.494
Comics	-0.588
Hardware and design	-1.473
Technology	-2.292
Games	-2.315

Appendix III. Estimating Local Small Business Loan Supply Shocks

As an alternative measure of shocks to local borrowing costs of entrepreneurs, I use detailed bank-county level small business lending data to estimate local lending supply shocks that are separate from local demand shocks. I employ a decomposition method developed by Amiti and Weinstein (2013) (see Flannery and Lin (2015) and Greenstone, Mas, and Nguyen (2015) for recent applications).

The small business loan data come from the Federal Financial Institutions Examination Council (FFIEC).[41] Under the Community Reinvestment Act (CRA), all financial institutions regulated by the Office of the Comptroller of the Currency, Federal Reserve System, Federal Deposit Insurance Corporation, and the Office of Thrift Supervision that meet the asset size threshold are subject to data collection and reporting requirements. Each bank reports its small business lending data in each county it operates. The loan data is further decomposed into four categories based on the loan amount at origination: \$250K to \$1 million, \$100K to \$250K, and below \$100K. I focus on loans smaller than \$100K as 97% Kickstarter projects have funding targets lower than this amount.

I start by writing the growth in bank-county level lending as the following.

$$g_{c,b,t} = \alpha_{c,t} + \beta_{b,t} + \varepsilon_{c,b,t} \tag{1}$$

, where $g_{c,b,t}$ is the growth rate of small business loans extend by bank b to county c from year $t-1$ to year t, $\alpha_{c,t}$ captures credit demand shocks in county c, and $\beta_{b,t}$ captures credit supply shocks for bank b. $\varepsilon_{c,b,t}$ is the error term and $E(\varepsilon_{c,b,t}) = 0$.

Aggregating equation (1) to county level by weighted-averaging across banks yields

$$GC_{c,b,t} = \alpha_{c,t} + \sum_b \theta_{c,b,t-1}\beta_{b,t} \ . \tag{2}$$

Aggregating equation (1) to bank level by weighted-averaging across counties yields

$$GB_{c,b,t} = \beta_{b,t} + \sum_c \varphi_{c,b,t-1}\alpha_{c,t} \ . \tag{3}$$

$GC_{c,b,t}$ is the growth rate of borrowing of county c from all of its banks from year $t-1$ to year t, $GB_{c,b,t}$ is the growth rate of lending of bank b to all of its counties from year $t-1$ to year t, $\theta_{c,b,t-1}$ is the share of bank b's loans obtained by county c in year $t-1$, and $\varphi_{c,b,t-1}$ is the share of county c's loans

[41] CRA defines a small business loan as any loan to a business in an original amount of \$1 million or less, excluding loans to farms or secured by farm or any residential properties.

obtained from bank b in year $t-1$.[42]

Equations (2) and (3) provide a system of $C+B$ equations and $C+B$ unknowns in each time period that enables solving for a unique set of county ($\alpha_{c,t}$) and bank shocks ($\beta_{b,t}$) (up to a numéraire) in each period, where C is the total number of counties and B is the total number of banks.[43] The estimated bank shocks ($\beta_{b,t}$) can then be aggregated to the county-level based on banks' lending shares in each county to form an estimate of county-level local small business loan supply shocks:

$$\textit{Local SBL supply shock}_{c,t} = \sum_b \theta_{c,b,t-1}\beta_{b,t} \tag{4}$$

In solving the system of equations in (2) and (3), I follow Flannery and Lin (2015) and drop, for each year, banks and counties whose total growth in small business loans are above the 99th percentile to minimize the influence of extreme values. To efficiently solve the system, I also ignore, for each bank, the counties whose loans account for less than 1% of lending by this bank, and for each county the banks whose lending account for less than 1% of the loans to that county. Eventually, I end up with estimates of local demand shocks for 3,054 counties and estimates of credit supply shocks for 2,328 banks from 2002 to 2013. The correlation between estimated loan supply shocks and the actual growth rate in lending in my sample is 0.56, which is close to the correlation of 0.62 reported in Flannery and Lin (2015). To put the local supply shock measure in perspective, Figure A2 in Appendix V plots the median, 5th percentile, and 95th percentile of *Local SBL supply shock* over 2002-2013. Figure A3 in Appendix V shows the geographic distribution of average *Local SBL supply shock* over financial crisis years 2008-2010. The temporal and spatial distributions of *Local SBL supply shock* are largely consistent with our knowledge of bank lending during the financial crisis.

[42] Since $\theta_{c,b,t-1}$ and $\varphi_{c,b,t-1}$ are predetermined variables, we can impose the following moment conditions on the data. $E\left[\sum_b \theta_{c,b,t-1}\, \varepsilon_{c,b,t}\right] = \sum_b \theta_{c,b,t-1} E\left[\varepsilon_{c,b,t}\right] = 0$, and $E\left[\sum_c \varphi_{c,b,t-1}\, \varepsilon_{c,b,t}\right] = \sum_c \varphi_{c,b,t-1} E\left[\varepsilon_{c,b,t}\right] = 0$.

[43] For detailed illustration of the decomposition and the estimation method, see Appendix 1.1 of Amiti and Weinstein (2013).

Appendix IV. Identifying the Learning Advantage of Crowdfunding: Allowing both Bank and Crowdfunding to Provide Feedback.

In this appendix, I extend my identification framework in Section 3.4 to allow both bank and crowdfunding to provide feedback. I show my empirical predictions are unchanged.

Similar to the model in Section 3.4, entrepreneur i chooses between bank borrowing and crowdfunding. However, both bank and crowdfunding provide feedbacks. Feedback from the crowd f_c has a precision h_c, and feedback from the bank f_b has a precision h_b. After receiving feedback from the bank or crowdfunding, the entrepreneur update her belief and make her commercialization decision. Bank borrowing gives the entrepreneur an ex-ante value of

$$V_i^B = E\{Max[0,\ E(\mu|f_b)]\} - R_i^B, \tag{1}$$

and crowdfunding gives her an ex-ante value of

$$V_i^C = E\{Max[0,\ E(\mu|f_c)]\} - R_i^C. \tag{2}$$

Again, I assume that the return to the project is equal to an uncertain gross profit s minus a constant fixed cost I:

$$\mu = s - I, \tag{3}$$

where $s \sim N\left(\mu_s,\ \frac{1}{h_0}\right)$ and $\mu_s = \mu_0 + I$. The entrepreneur chooses crowdfunding if $V_i^C > V_i^B$, i.e.,

$$O_i = E\{Max[0,\ E(\mu|f_c)]\} - E\{Max[0,\ E(\mu|f_b)]\} > R_i^C - R_i^B, \tag{4}$$

or

$$O_i = E\{Max[0,\ E(s|f_c) - I]\} - E\{Max[0,\ E(s|f_b) - I]\} > R_i^C - R_i^B. \tag{5}$$

It can be shown that

i) O_i is positive if and only if $h_c > h_b$;

ii) O_i decreases in h_0 if and only if $h_c > h_b$;

iii) When $\mu_0 > 0$, O_i increases in I if and only if $h_c > h_b$;

iv) Let $E_i(.)$ denotes the average across individuals. A decrease in R_i^B for a non-empty set of individuals $\{i\}$ will increase $E_i[O_i|O_i > R_i^C - R_i^B]$ and be associated with a decrease in $E_i(h_0)$ and an increase in $E_i(I)$ (when $\mu_0 > 0$) if and only if $h_c > h_b$.

Proof:

i) First, recall that h_0 is the precision of an entrepreneur's prior and $\frac{1}{h_0+h_c}$ is the conditional variance of her posterior. By variance decomposition equation, the variance of her posterior expectation is

$$Var[E(\mu|f_c)] = Var[\mu] - E[Var(\mu|f_c)] = \frac{1}{h_0} - \frac{1}{h_0+h_c} = \frac{h_c}{(h_0+h_c)h_0} \quad (6)$$

Therefore we have $E(\mu|f_c) \sim N(\mu_0, \sigma_c^2)$ and $E(\mu|f_b) \sim N(\mu_0, \sigma_b^2)$, where $\sigma_c^2 = \frac{h_c}{(h_0+h_c)h_0}$, and $\sigma_b^2 = \frac{h_b}{(h_0+h_b)h_0}$. Writing σ_c as $\sigma_c = [(\frac{h_0}{h_c}+1)h_0]^{-\frac{1}{2}}$, it can be shown that

$$\frac{\partial\, \sigma_c}{\partial h_0} < 0, \frac{\partial\, \sigma_c}{\partial h_c} > 0. \quad (7)$$

Using the equation for the expectation of a truncated normal distribution from Greene (2008), it can be shown that

$$E\{Max[0,\ E(\mu|f_c)]\} = F(\mu_0, \sigma_c) = \mu_0 + \sigma_c \lambda\left(\frac{\mu_0}{\sigma_c}\right), \quad (8)$$

where $\lambda\left(\frac{\mu_0}{\sigma_c}\right) = \phi(\frac{\mu_0}{\sigma_c})/\Phi(\frac{\mu_0}{\sigma_c})$ is the inverse Mill's ratio, $\phi(.)$ is the probability density function of standard normal distribution, and $\Phi(.)$ is the cumulative density function of standard normal distribution.

Taking the first order derivative of $F(\mu_0, \sigma_c)$ w.r.t. σ_c, we have

$$\frac{\partial F(\mu_0,\sigma_c)}{\partial \sigma_c} = \lambda(\frac{\mu_0}{\sigma_c})[1 + \frac{\mu_0}{\sigma_c}\left(\frac{\mu_0}{\sigma_c} + \lambda\left(\frac{\mu_0}{\sigma_c}\right)\right)]. \quad (9)$$

Applying the Mill's ratio inequality from Gordon (1941): $\frac{x}{x^2+1}\frac{1}{\sqrt{2\pi}}e^{\frac{-x^2}{2}} \leq \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{\frac{-t^2}{2}} \leq \frac{1}{x}\frac{1}{\sqrt{2\pi}}e^{\frac{-x^2}{2}}$ for $x > 0$, it is immediate that $1 + \frac{\mu_0}{\sigma_c}\left(\frac{\mu_0}{\sigma_c} + \lambda\left(\frac{\mu_0}{\sigma_c}\right)\right) > 0$. Since $\lambda\left(\frac{\mu_0}{\sigma_c}\right) > 0$, $\frac{\partial F(\mu_0,\sigma_c)}{\partial \sigma_c} > 0$. Given $\frac{\partial\, \sigma_c}{\partial h_c} > 0$, we also have $\frac{\partial F(\mu_0,\sigma_c)}{\partial h_c} > 0$. I therefore proved that $O_i = F(\mu_0, \sigma_c) - F(\mu_0, \sigma_b) > 0$ if and only if $h_c > h_b$.

ii) Writing O_i as

$$O_i = F(\mu_0, \sigma_c) - F(\mu_0, \sigma_b) \approx [\sigma_c - \sigma_b]\frac{\partial F(\mu_0,\sigma_c)}{\partial \sigma_c} \quad (10)$$

Since $\frac{\partial\, \sigma_c}{\partial h_0} < 0$, and $\sigma_c - \sigma_b > 0$ if and only if $h_c > h_b$, to prove that O_i decreases in h_0 if and only if $h_c > h_b$, I only need to prove $\frac{\partial^2 F(\mu_0,\sigma_c)}{\partial {\sigma_c}^2}$ >0.

It can be shown that

$$\frac{\partial^2 F(\mu_0,\sigma_c)}{\partial {\sigma_c}^2} = \left(\frac{\mu_0}{\sigma_c}\right)^2 \frac{1}{\sigma_c}\lambda\left(\frac{\mu_0}{\sigma_c}\right)[\left(\lambda\left(\frac{\mu_0}{\sigma_c}\right) + \frac{\mu_0}{\sigma_c}\right)\left(2 * \lambda\left(\frac{\mu_0}{\sigma_c}\right) + \frac{\mu_0}{\sigma_c}\right) - 1] \quad (11)$$

Using the Mill's ratio inequality from Sampford (1953): $\lambda(x)[(\lambda(x)+x)(2\lambda(x)+x)-1]>0$ for all finite x, it immediately follows that $\frac{\partial^2 F(\mu_0,\sigma_c)}{\partial {\sigma_c}^2}>0$.

iii) Since $\mu_0=\mu_s-I$, and $\sigma_c-\sigma_b>0$ if and only if $h_c>h_b$, to prove that when $\mu_0>0$, O_i increase in I if and only if $h_c>h_b$, I only need to prove $\frac{\partial^2 F(\mu_0,\sigma_c)}{\partial\sigma_c\,\partial\mu_0}<0$ when $\mu_0>0$.

It can be shown that

$$\frac{\partial^2 F(\mu_0,\sigma_c)}{\partial\sigma_c\,\partial\mu_0}=-\frac{\mu_0}{{\sigma_c}^2}\lambda\left(\frac{\mu_0}{\sigma_c}\right)\left[\left(\lambda\left(\frac{\mu_0}{\sigma_c}\right)+\frac{\mu_0}{\sigma_c}\right)\left(2*\lambda\left(\frac{\mu_0}{\sigma_c}\right)+\frac{\mu_0}{\sigma_c}\right)-1\right] \qquad (12)$$

Applying the Mill's ratio inequality from Sampford (1953) again, it follows that $\frac{\partial^2 V(\mu_0,\sigma_c)}{\partial\sigma_c\,\partial\mu_0}<0$, when $\mu_0>0$.

iv) A decrease in R_i^B for a non-empty set of $\{i\}$ increases the lower bound in the conditional expectation $E_i[O_i|O_i>R_i^C-R_i^B]$, and therefore increases its value. Given (ii) and (iii), a decrease in $E_i(h_0)$ will be observed if and only if $h_c>h_b$, and when $\mu_0>0$, an increase in $E_i(I)$ will be observed if and only if $h_c>h_b$.

References:

Gordon, Robert D., 1941, Values of Mills' Ratio of Area to Bounding Ordinate and of the Normal Probability Integral for Large Values of the Argument, *The Annals of Mathematical Statistics* Vol. 12, No. 3, 364-366.

Greene, William H., 2008, *Econometric Analysis*, 6th Edition, Prentice Hall.

Sampford, M. R., 1953, Some Inequalities on Mill's Ratio and Related Functions, *The Annals of Mathematical Statistics* Vol. 24, No. 1, 130-132.

Appendix V. Additional Figures

Figure A1. Google search interest for "Crowdfunding" and "Venture capital"

This graph plots monthly worldwide Google search interests for the keywords "Crowdfunding" and "Venture capital" from 2008 January to 2015 June. Data are retrieved from Google Trends.

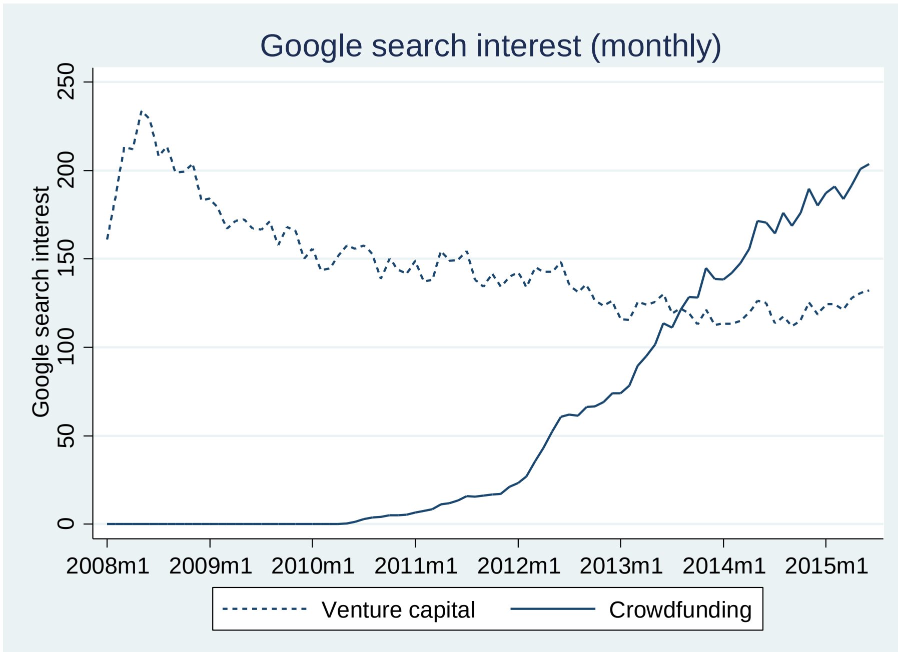

Figure A2. Temporal distribution of local small business loan supply shocks

This graph plots the median and the 5th and 95th percentile of county-level small business loan supply shocks for each year over the period 2002-2013.

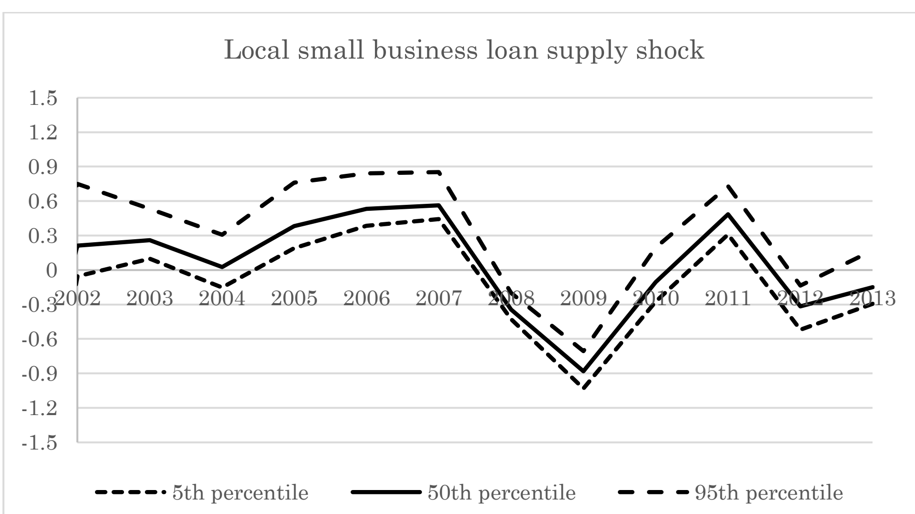

Figure A3. Geographic distribution of small business loan supply shocks during financial crisis years (2008-2010)

This map plots the county-level distribution of small business loan supply shocks over the financial crisis years 2008 to 2010. For each county, I compute the average small business loan supply shock over 2008-2010. Counties are then divided into five quintiles, with darker-colored counties associated with more positive supply shocks and lighter-colored counties associated with more negative supply shocks.