Financial Disintermediation and Entrepreneurial Learning: Evidence from the Crowdfunding Market*

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Abstract

Entrepreneurship is characterized by high failure rates and extreme uncertainty. In light of this, entrepreneurs' learning about potential returns at an early stage is essential to their entry and allocation of resources. This paper uses the crowdfunding market to provide direct micro-level evidence on entrepreneurial learning. I find that entrepreneurs update beliefs based on feedbacks from the crowd in ways consistent with a simple Bayesian learning model, placing more weight on information with relatively higher precision. Moreover, entrepreneurs make entry and project choice decisions based on what they learned. Over time, learning improves an entrepreneur's funding outcomes and reduces her likelihood of switching projects. I further establish the learning advantage of crowdfunding using local housing price movements and small business loan supply shocks as changes to the relative cost of crowdfunding vis-à-vis bank borrowing. I find that, as crowdfunding becomes relatively more costly, entrepreneurs choosing crowdfunding face higher uncertainty ex-ante and engage in more learning ex-post. My paper uncovers a new role of crowdfunding: the facilitation of learning. It suggests that feedback from financial markets, traditionally only available to listed firms, can become accessible to entrepreneurs of new ventures as early-stage financing is disintermediated by the involvement of the crowd.

Keywords: entrepreneurship, crowdfunding, financial disintermediation, learning
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1. Introduction

Entrepreneurship stands at the center of creative destruction and drives economic growth (Schumpeter (1934, 1942), Aghion and Howitt (1992)). Yet at the micro-level, being an entrepreneur is not profitable: entrepreneurs on average earn less and bear more risk than salaried workers or investors in public equity (Hamilton (2000), Moskowitz and Vissing-Jørgensen (2002), Hall and Woodward (2010)). One explanation for this is incorrect beliefs about future returns held by entrepreneurs (Cooper, Woo, and Dunkelberg (1988), Landier and Thesmar (2009), Åstebro, Hertz, Nanda, and Weber (2014)). High uncertainty associated with entrepreneurship makes it very hard to form correct beliefs about returns ex ante (Kerr, Nanda, and Rhodes-Kropf (2014)). Specifically, individuals who overestimate their returns are more likely to enter entrepreneurship than those who underestimate them (Camerer and Lovallo (1999), Van den Steen (2004)). This optimism-led overentry will persist if the feedback necessary to correct it is lacking or ignored by entrepreneurs. A result of this is high failure rates among new businesses, while worthy ideas by pessimistic entrepreneurs are not pursued.

In light of this, entrepreneurs' learning from early feedback is critical to their entry decisions and the allocation of resources to new ideas. However, there is little evidence on this process. On the one hand, unlike managers of listed firms who benefit from timely information contained in financial market prices (Bond, Edmans, and Goldstein (2012)), entrepreneurs have little access to feedback. Traditional financiers to entrepreneurs either provide little feedback (banks), or are inaccessible to most entrepreneurs at the entry or pre-entry stage (VCs and angels).[1] On the other hand, even if early feedback becomes available, there is no evidence whether and how entrepreneurs will learn. Can entrepreneurs separate information from noise, or do they simply react to feedback in a naïve, non-Bayesian way? If imperfect feedback is taken at face value, learning can sometimes exacerbate the inaccuracy of beliefs. Resources needed to maintain the quality of feedback under this scenario can also be prohibitively costly. How do entrepreneurs learn? Does it affect their real decisions? Finally, what type of early-stage financing facilitates the learning process?

In this paper, I use the crowdfunding market to answer these questions. Crowdfunding

[1] 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).

is a recent financial innovation that disintermediates entrepreneurial finance by allowing entrepreneurs to directly raise funds online from the general public.[2] This disintermediation unleashes an unprecedented amount of learning opportunities previously unavailable to entrepreneurs, and presents a clear setting to observe and measure entrepreneurs' learning behaviors. Using a unique dataset from the world's largest reward-based crowdfunding market, Kickstarter, I first show that entrepreneurs not only learn from the feedback from the crowd, but also update beliefs in a Bayesian way, underweighting feedback with more noise. Further, learning affects entrepreneurs' entry decisions and project choices, and leads to better fundraising outcomes over time. I then provide evidence consistent with crowdfunding having additional learning value vis-à-vis traditional intermediated financing such as bank borrowing, highlighting the learning benefits of disintermediated early-stage financing.

On Kickstarter, an entrepreneur posts a project pitch online and sets a funding target she wishes to achieve within a funding window. Backers pledge money in small amounts in return for the promises of in-kind rewards. Funding follows an "all-or-nothing" rule. A project is funded if, by the end of the funding window, the total pledged amount equals or exceeds the funding target, in which case the entrepreneur gets all the pledged money;[3] otherwise the project is unfunded and no money is transferred to the entrepreneur. The platform also features various social components for entrepreneurs and backers to communicate and interact. The database contains 137,371 projects, both funded and unfunded, ever launched on the platform between April 2009 and April 2014. To the best of my knowledge, this is the most comprehensive crowdfunding database compiled so far.

Using this data, I first test whether entrepreneurs learn in accordance with a simple Bayesian learning model under imperfect information. Employing a sample of entrepreneurs who have launched multiple projects, I use the initial funding target as a proxy for an entrepreneur's prior expectation about backers' demand. I then use the actual pledged amount as feedback and the funding target of the entrepreneur's next same-type project as a proxy for her posterior.[4] I first find that entrepreneurs' posterior beliefs are positively

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[2] See Section 2.1 for a more detailed introduction of crowdfunding.
[3] Less 5% fee charged by Kickstarter.
[4] Project type is a refined categorization of projects defined by Kickstarter. Each project is classified by Kickstarter into one of 51 project types based on the nature of the project.

associated with both their priors and the feedback from the crowd, suggesting entrepreneurs do react to the crowd's feedback in forming their beliefs. Further, consistent with Bayesian updating under imperfect information, entrepreneurs place more weight on feedback and less weight on their priors when the feedback is more precise or when their priors are less precise. These results are economically significant and are robust to accounting for sample selection. This suggests that entrepreneurs are not just naïve learners, but are able to adjust their learning based on the precision of feedback.

Next, I study whether learning affects entrepreneurs' real decisions. I first examine how feedback from an entrepreneur's previous project affects her subsequent continuation decisions. I find that entrepreneurs who received more positive feedback from the crowd, as measured by higher pledge ratio (i.e. pledged amount divided by funding target) or more comments posted by backers, are more likely to stay on the platform and crowdfund again. Conditional on crowdfunding again, those received better feedbacks are also more likely to launch projects similar to their previous projects. Further, I find that, within a given entrepreneur, the probability of launching a project different from the previous one decreases over time. These results suggest that, at the extensive margin, learning affects entry decisions and project choices, and that experimentation helps resolve entrepreneurs' uncertainty about their comparative advantages and improve their matching with projects.

I then examine the implication of learning on project funding outcomes. If learning improves entrepreneurs' project choices or fundraising strategies, funding outcomes should improve over successive projects for a given entrepreneur. I find that entrepreneurs achieve higher pledge ratio, pledged amount, and number of backers over time. These effects are stronger when restricting to successive projects within the same project type, for which learning should be more effective. Entrepreneurs improve by lowering funding targets, shortening project pitch, using more images and videos, and simplifying the reward structure. These observed entrepreneur behavior changes account for 62% of the improvement in funding outcome, with the remaining 38% being explained by unobserved entrepreneur behavior changes and learning by backers. This suggests that entrepreneurs' learning seems to dominate backers' learning in explaining funding outcome improvements.

So far I have shown that entrepreneurs engage in substantial amounts of learning *ex-post* given the learning opportunities on the crowdfunding market, and their learning appears to be Bayesian rather than naïve. A natural question is how the learning opportunities differ *ex-ante* between crowdfunding and traditional early-stage financing such as bank borrowing.[5] I argue that crowdfunding provides superior learning opportunities to entrepreneurs due to *better* and *earlier* feedbacks generated in the process. Relying on internet technology, crowdfunding leverages collective information production by the crowd at low costs. High diversification and risk-sharing of crowd investing make crowdfunding accessible to entrepreneurs at an earlier stage than traditional financiers, thereby bringing more real option value. To provide evidence consistent with crowdfunding having additional learning value vis-à-vis bank borrowing, I exploit shocks to entrepreneurs' selection into crowdfunding when they choose between the two financing methods. If local borrowing cost decreases so that crowdfunding becomes relatively more costly, entrepreneurs *choosing* crowdfunding should shift to those who derive particularly high learning value from it. In other words, cheaper local borrowing attracts away entrepreneurs who mainly crowdfund for money and helps tease out those who crowdfund for feedback. Using instrumented local housing price variations 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 credit. I then find that, as local borrowing becomes cheaper, new entrepreneurs on Kickstarter on average face higher uncertainty, propose projects with higher fixed costs, and engage in more learning ex-post. This suggests that, consistent with the learning advantage of crowdfunding vis-à-vis bank borrowing, entrepreneurs choosing crowdfunding derive higher value from learning as crowdfunding becomes more costly relative to bank borrowing.

Together, my results suggest that, given entrepreneurs' ability to learn effectively, the provision of early albeit imperfect feedback is likely an important tool to regulate entrepreneurs' entry and to improve their returns. The advent of crowdfunding fulfills such an objective by leveraging the wisdom of the crowd and democratizing learning opportunities for entrepreneurs. It suggests that feedback from financial markets, traditionally only available to listed firms, can become available to entrepreneurs of new ventures as early-

[5] Robb and Robinson (2014) document that bank debt, especially collateralised personal debt, is the predominant financing source for new firms in US. Cosh, Cumming, and Hughes (2009) find that bank debt comprises the highest percentage of outside finance for UK entrepreneurial firms in terms of both the type of finance approached and the type of finance obtained.

stage financing is disintermediated by the involvement of the crowd.

This paper contributes to several strands of literature. First, it contributes to the literature on 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, skewed, and unknowable. Experimentation resolves uncertainty about potential returns and creates real option value for further pursuits. The costs and constraints on the ability to experiment therefore impacts entry into entrepreneurship. Hombert, Schoar, Sraer, and Thesmar (2014) study a large-scale French reform that provides downside insurance for unemployed individuals starting a business. The reform lowers the cost of experimentation by allowing risk-averse individuals to learn about their chances of success as entrepreneurs. The authors find that new entrants are not of worse types than incumbent entrepreneurs, suggesting that entrants were previously prevented from entering not because of low ability but because of high uncertainty. Manso (2014) shows how failing to account for the option value of experimentation can bias the estimates of the mean and variance of returns to entrepreneurship. This paper provides direct evidence on the entrepreneurial learning process on which this literature builds. It shows that entrepreneurs are indeed Bayesian learners and they experiment as they go. My paper also suggests that, by democratizing learning opportunities, crowdfunding lowers the cost of experimentation and improves entrepreneurs' risk-return trade-offs.

This paper also adds to the nascent literature on crowdfunding. A large part of the literature examines mechanisms and incentives on crowdfunding markets, as well as the determinants of funding success.[6] Related to this paper, several studies document the wisdom of the crowd in crowdfunding markets. Looking at peer-to-peer lending, Iyer, Khwaja, Luttmer, and Shue (2015) find that peer lenders predict a borrower's likelihood of default with 45% greater accuracy than the borrower's exact credit score (unobserved by the lenders),

[6] 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), Bernstein, Korteweg, and Laws (2015), and Li and Martin (2014) examine the determinants of funding success on 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.

highlighting peer lenders' advantages in producing soft-information. Mollick and Nanda (2015) compare crowd and expert judgment in funding Kickstarter projects and find a high degree of agreement between their funding decisions. Mollick (2013) finds that entrepreneurial quality is assessed in similar ways by both VCs and crowdfunders, but crowdfunding alleviates geographic and gender biases associated with the way that VCs look for signals of quality. 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 builds upon this literature and studies whether, given the wisdom of the crowd, entrepreneurs take cues from the crowd and make entry and project choice decisions accordingly. This paper also deepens our understanding of crowdfunding by uncovering an important role it plays in entrepreneurship: the facilitation of entrepreneurial learning.

Finally, this paper is related to the literature on financial (dis)intermediation. The literature compares intermediated and disintermediated financial markets in their matching and screening efficiency as well the surpluses created for investors and borrowers. The wisdom of the crowd literature reviewed above suggests that disintermediated markets have the potential to screen as effectively as intermediaries. Wei and Lin (2015) find that a regime shift on Prosper.com from auction to intermediated pricing leads to loans being funded with higher probability and at higher interest rates. However, all else equal, loans are also more likely to default under intermediated pricing, thereby undermining lenders surplus from trading. Fang, Ivashina, and Lerner (2014) compare the performance of direct (disintermediated) and intermediated investment in private equity, and find limited outperformance by direct investments despite savings on intermediation costs. Morse (2015) discusses the potential of peer-to-peer lending to disintermediate consumer finance. She concludes that lenders and borrowers are able to benefit from the removal of intermediation costs and extra information (especially soft information) production. My paper contributes to this literature by studying an unexplored aspect of financial disintermediation: its impact on agents' learning. I show that, disintermediated early-stage financing can improve entrepreneurial decisions by providing much-needed early feedbacks.

The rest of the paper is organized as follows. Section 2 introduces crowdfunding and Kickstarter and describes the data. Section 3 introduces the theoretical framework, develops hypotheses, and discusses empirical strategies. Section 4 presents the main results. Section

5 discusses robustness and external validity. Section 6 concludes.

2. Setting and Data

2.1. Crowdfunding

Crowdfunding is the practice of openly funding a project or venture by raising many small amounts of money from a large number of people, typically via the Internet. As a new financial phenomenon, it is reshaping the entrepreneurial finance landscape and has attracted great public attention.[7] The global crowdfunding market has grown tremendously from $530 million in 2009 to $16.2 billion in 2014, with now around 1250 platforms in more than 50 countries.[8] 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 usually used to fund personal expenditures or debt consolidation, 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 is currently pending implementation by the Securities and Exchange Commission.

An important distinction of crowdfunding from traditional entrepreneurial financing 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 only provide a market place for investors and entrepreneurs to match, and do not engage in intermediary roles such as

[7] See Figure A1 in Appendix V for a comparison of trends in Google search interests for crowdfunding and venture capital.
[8] 2015 Crowdfunding Industry Report, Massolution.
[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).

screening, pricing, or ex-post monitoring. Information asymmetry in these markets is mitigated by the crowd's collective information production and social learning, while transparency and reputation costs help curtail moral hazards. Further, investors are able to achieve substantial diversification thanks to online search and investment algorithms. This greatly improves risk-sharing. These mechanisms, essentially enabled by internet technologies, sustain the functioning of 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), Ouya (an Android-based gaming console), 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 design, 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.[12] 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 rewards corresponding to different contributing amounts. Funding follows an all-or-nothing rule: the project is funded if, by the end of the funding window, 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 itself plays a fairly passive role, mainly providing a market place for entrepreneurs and backers to meet and match, and does not

[10] Most of the projects come from U.S., with U.K. and Canada come 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] In reward-based crowdfunding, backers can be considered as a type of trade creditor to which an entrepreneurs owes a liability in the form of "goods deliverable".

engage in any screening, pricing, or advising, nor does it guarantee returns or arbitrate disputes between entrepreneurs and backers.[13]

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

2.3. Data

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 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, project-backer network, and projects' daily funding histories. 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 provide further statistics and descriptions of the dataset in Section 4.1.

3. Theoretical Framework, Hypotheses Development, and Empirical Strategies

3.1. A simple Bayesian learning model

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

In this section, I test whether entrepreneurs learn from the feedback from the crowd, and whether learning occurs in a Bayesian way. I first lay out a simple Bayesian learning model with imperfect information to generate testable predictions. I then discuss the empirical implementation.

An entrepreneur comes to the crowdfunding platform with a prior about the potential return to her project, which reflects the value of the unique combination of the project and the entrepreneur. Through crowdfunding, the entrepreneur accumulates information from the feedback from the crowd and uses this information to update her prior. Following earlier work (Javanovic (1979), Harris and Holmstrom (1982), Gibbons et al. (2005)), I assume the entrepreneur's prior belief of the true return μ is normally distributed with expectation μ_0 and precision h_0:

$$\mu \sim N\left(\mu_0,\ \frac{1}{h_0}\right). \tag{1}$$

The crowd provides a feedback f, which represents an imperfect signal of the true return with precision h_c:

$$f|\mu \sim N\left(\mu,\ \frac{1}{h_c}\right). \tag{2}$$ [14]

The entrepreneur then form a posterior by updating her prior in a Bayesian way based on the crowd's feedback. Following DeGroot (1970), the entrepreneur's posterior expectation takes on a simple expression: a weighted average of the prior expectation μ_0 and the feedback f:

$$\mu_f = E(\mu|f) = \frac{h_0}{h_0+h_c} \times \mu_0 + \frac{h_c}{h_0+h_c} \times f. \tag{3}$$

The posterior variance is $Var(\mu|\varepsilon) = \frac{1}{h_0+h_c}$, which is smaller than the prior variance $Var(\mu) = \frac{1}{h_0}$. This means that learning reduces uncertainty faced by the entrepreneur. Equation (3) generates the following hypothesis.

Hypothesis 1: *An entrepreneur's posterior* (μ_f) *is positively associated with her prior* (μ_0) *and the crowd's feedback (f), and will places more weight on the information with relatively*

[14] Here I assume that the entrepreneur's prior has a subjective distribution identical to the objective distribution of the true return, and that the crowd's feedback is a conditionally unbiased estimate of the true return, reflecting wisdom of the crowd documented in the literature. The model can be easily extended to account for the biases of the entrepreneur or of the crowd. It can be shown that, as long as the crowd is less biased than the entrepreneur or the entrepreneur can partially correct for the crowd's bias, Bayesian updating still reduces the bias of and the variance faced by entrepreneur.

higher precision if the entrepreneur updates in a Bayesian way.

To test this hypothesis, I make use of a sample of entrepreneurs that have launched multiple projects on Kickstarter.[15] I use a project's funding target as a measure of an entrepreneur's prior expectation about the amount she and her project can attract from the backers. The all-or-nothing funding rule gives entrepreneurs incentives to estimate the amount an entrepreneur-project expects to attract: a target too high will jeopardize the chance of raising any money, while a target too low will drive away backers due to the risk of implementing undercapitalized project (Cumming et al. (2015)).[16] 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 project as well as their beliefs 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 same-type project.[17] The rationale is that, an entrepreneur's updated belief about backers' interests in 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 positively correlates with her updated posterior.

To measure the precision of entrepreneurs' priors, I make use of a mandated section of project page called Risks and Challenges. Since September 2012, Kickstarter requires all entrepreneurs to include on the project page a section discussing the potential risks of their projects and the challenges in executing them. This disclosure section therefore captures the amount of uncertainty perceived by an entrepreneur with respect to the outcome of her project. I use the inverse of the logarithmic word count of this section to proxy for entrepreneurs' prior precision. I then use the average site age of a project's backer base to proxy for the precision of the crowd's feedback. The idea is that backers will collectively provide more reliable feedback if they are on average more experienced with backing projects

[15] 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 new project.
[16] In addition, backers on all-or-nothing based platforms tend to stop funding a project after seeing 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.
[17] Kickstarter categorizes projects into 51 refined project types based on the contents of the projects. In Table A2 Appendix II, I further restrict to a subsample of projects that are highly similar to the previous projects launched by the same entrepreneurs.

on Kickstarter. To construct this measure, for each project, I obtain the calendar month each of its backers first joined Kickstarter and calculate his/her site age as the number of months between the project launch month and the backer's entry month. I then compute the average site age across backers for each project. Finally I remove project launch month fixed effects from this measure to remove the mechanical relationship between project launch month and backers' site age.

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

$$\widetilde{posterior} = \alpha + \beta \times prior + \gamma \times feedback + \varphi X + \varepsilon, \tag{4}$$

$$\begin{aligned} \widetilde{posterior} = \alpha + \beta \times prior + \gamma \times feedback + \rho \times prior\ precision + \tau \times\ feedback\ precision \\ + \theta_1 \times prior \times prior\ precision + \theta_2 \times feedback \times prior\ precision \\ + \theta_3 \times prior \times feedback\ precision + \theta_4 \times feedback \times feedback\ precision + \varphi X + \varepsilon, \end{aligned} \tag{5}$$

where *prior* is the funding target of an entrepreneur's current project, *prior precision* is the inverse of the log word count of the project's risk disclosure section, *feedback* is the actual pledged amount, *feedback precision* is the average site age of the project's backers, $\widetilde{posterior}$ 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 ρ>0), and X is a vector of control variables that include project 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 (4). Further, if such learning is in a Bayesian way, we should expect $\theta_1 > 0, \theta_2 < 0, \theta_3 < 0$, and $\theta_4 > 0$ in equation (5).

3.2. Learning and the exercise of continuation options

The analysis above 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? Understanding these questions will help shed light on the effect of learning on the extensive margin decisions of entrepreneurs.

If launching crowdfunding campaigns involves fixed costs, then only entrepreneurs with high enough posteriors, i.e., those received very positive feedback, will participate again on the platform. Entrepreneurs that received negative feedback would correct down their beliefs about their projects or their abilities, and, if the correction is large enough, may simply 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 value of her match with the original project type is very low, so that improving upon the original project would not justify a positive return. 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 pledged amount and the funding target, and captures how much of the entrepreneur's initial funding expectation is met by backers' pledge.[18] 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 or 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 project to these two measures of feedback positivity. Finally, in addition to discrete project type change, I also look at the continuous change in project content by algorithmically comparing the pitch texts of an entrepreneur's two consecutive projects.

The above two hypotheses highlight the dynamic nature of learning and experimentation on the crowdfunding market. Over time, entrepreneurs experiment across different projects and learn from the crowdfunding outcomes. This trial-and-error process should gradually resolve an entrepreneur's uncertainty about the quality of her match with the project, i.e., her comparative advantage. Drawing on the labor literature on occupational learning (Gervais et al. (2011), Papageorgiou (2009), Wee (2014)) and theory on trial-and-error search (Callander (2011)), I conjecture that, trial-and-error search (project switching)

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

should occur the most when entrepreneurs are starting off, and then decreases over time as entrepreneurs have better understanding of their comparative advantages.

Hypothesis 3: *Within an entrepreneur over successive projects, the likelihood of switching projects decreases over time.*

3.3. Implications of learning for funding outcomes

In this section, I examine how learning and experimentation affect crowdfunding outcomes. If learning and experimentation improve entrepreneurs' matching with projects, we should observe better projects being proposed over time within a given entrepreneur. Further, holding constant the projects, learning could also lead to entrepreneurs' adoption of better fundraising strategies. Both learning about project and learning about financing will improve funding outcomes over time. Lastly, learning by investors through their repeated interactions with the entrepreneur may also facilitate financing by reducing information asymmetry (Stiglitz and Weiss (1981)). These learning effects and thus the improvement in funding outcomes should be strongest when we restrict to projects of the same type within an entrepreneur. As such, I predict the following:

Hypothesis 4: *Within an entrepreneur over successive projects, funding outcomes improve over time, especially within the same type of projects.*

I use a couple of measures to capture funding outcomes: log pledge ratio, log pledge amount, log pledge amount per backer, and the log number of backer. I then examine what behavior changes by entrepreneurs explain funding outcome changes. Finally, I estimate the proportion of funding outcome changes unexplained by these observable behavioral changes, which serves as an upper bound for the proportion explained by unobserved investor learning.

3.4. The ex-ante learning advantage of crowdfunding

So far I have focused on how entrepreneurs learn given the learning opportunities on the crowdfunding market. In this section, I take a step back and ask how these learning opportunities differ ex-ante between crowdfunding and traditional early-stage financing methods. Does crowdfunding possess additional value from learning besides providing finance? Understanding this is important as it helps shed light on the impact of financial disintermediation on agents' learning.

I argue that crowdfunding provides *better* and *earlier* feedbacks to entrepreneurs than do traditional entrepreneurial financing sources, thereby commanding additional option value of learning.

First, crowdfunding platforms reduces information production costs and leverages the wisdom of the crowd. Relying on internet technology, crowdfunding platforms lower the participation cost of the crowd, each of whom bringing his/her own piece of information. Through online social interactions, different pieces of information can be quickly disseminated, aggregated, and updated. 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 social learning and the collective information production of the crowd ("wisdom of the crowd") (Golub and Jackson (2010), Mollick and Nanda (2015), Mollick (2013)). These feedbacks are especially helpful in reward-based crowdfunding, as backers are also potential consumers who can provide unique product market information unavailable from other traditional financiers.

Feedback from crowdfunding also comes at an earlier stage than traditional financing methods. The removal of fixed intermediation costs on crowdfunding markets lowers the efficient transaction size, so that smaller financings are possible than in intermediated markets.[19] 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 other traditional financing sources.[20] As such, feedbacks from crowdfunding are more likely to arrive before entrepreneurs' key decisions such as manufacturing and commercialization, thereby commanding an option value.

On the other hand, although VCs and angels have advantages in mentoring and

[19] 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.

[20] 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.

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.[21] Bank borrowing is therefore the most common financing alternative for entrepreneurs, as documented in Robb and Robinson (2014) and Cosh, Cumming, Hughes (2009). Banks, however, provide relatively poor feedback on entrepreneurs' projects. Most of the lendings to entrepreneurs are in either personal loans or business loans financed through personal balance sheet with personal wealth as guarantee or collateral (Avery, Bostisc, and Samolyk (1998), Robb and Robinson (2014), Meisenzahl (2014)).[22] These lending decisions are therefore largely based on entrepreneurs' personal credit conditions and collateral availability, rather than the product market potential of their projects. Further, in banks, investment decisions are delegated to a loan officer, while disintermediated markets allow the participation of many investors holding diverse opinions. Markets are therefore more suitable than banks to finance and provide feedback to projects more subject to disagreements (Allen and Gale (1999)). Lastly, because of the binary nature of loan application outcome (approval or decline) and the opacity of banks about the information they produce (Kaplan (2006), Breton (2011), Dang, Gordon, Holmström, and Ordonez (2014)), feedbacks from banks lack the richness and transparency associated with the ones produced from crowdfunding.

If crowdfunding provides better learning opportunities, then coupled with entrepreneurs' ability to learn, it should possess higher learning value compared with traditional early-stage financing such as bank borrowing. To empirically test this, the ideal setting is a direct comparison of crowdfunding and traditional financing methods. However, there is no exogenous geographic expansion of crowdfunding that allows for a clean 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 exogenously,

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

[22] 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)).

crowdfunding becomes relatively more expensive. If crowdfunding has additional learning value compared with bank borrowing, then entrepreneurs that do not derive particularly high learning value from crowdfunding will switch from crowdfunding to bank borrowing, thereby driving up the average learning value derived by those that remain using crowdfunding.

I build on the Bayesian learning model in Section 3.1 to formalize this empirical framework. Entrepreneur i chooses between bank borrowing and crowdfunding. When borrowing from the bank, she makes her commercialization decision without any feedback.[23] Bank borrowing gives the entrepreneur an ex-ante value of

$$V_i^B = Max\left[0,\ E(\mu)\right] - R_i^B, \tag{6}$$

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 crowdfunding cost of R_i^C.[24] Crowdfunding therefore gives her an ex-ante value of

$$V_i^C = E_f\left\{Max\left[0,\ E(\mu|f)\right]\right\} - R_i^C. \tag{7}$$

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

$$\mu = s - I \tag{8}$$

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

$$O_i = E_f\left\{Max\left[0,\ E(s|f) - I\right]\right\} - Max\left[0,\ E(s) - I\right] > R_i^C - R_i^B. \tag{9}$$

It can be shown that

i) $O_i \geq 0$;

[23] 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.

[24] 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 rewards, and the discount of reward price thresholds relative to the true market values of rewards.

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 (9) 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 ($h_c = 0$). As can be seen from its expression, the 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, the option value increases in the precision of crowd's feedback (h_c) and decreases in the precision of entrepreneur's prior (h_0). The option value O_i 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 therefore $E_i[O_i|O_i > R_i^C - R_i^B]$, which increases when R_i^B *weakly* decreases. This means entrepreneurs on crowdfunding platforms on average derive higher option value from learning when local borrowing cost decreases. The intuition is that cheaper local borrowing makes crowdfunding relatively more costly so that 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 5: *When local financing cost decreases so that crowdfunding becomes relatively 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) also 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 lead to more entrepreneurial activities by relieving collateral constraints. A positive local housing price shock should therefore lower the costs of bank borrowing.[25] At the same time, it should not affect financing costs 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 increase and one without—and look at the differential shifts in the composition of entrepreneurs entering Kickstarter. Region that experienced housing price increases should produce crowdfunding entrepreneurs who face higher ex ante uncertainty, propose projects with higher fixed costs, and engage in more learning ex post.

It is worth noting 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 in reaction to housing price changes. However, as long as *some* individuals experience better access to finance and switch from crowdfunding to bank borrowing (i.e., R_i^B *weakly* decreases), we should see a change in the *average* option value derived by the remaining entrepreneurs. Similarly, the inequality inside $E_i[O_i|O_i > R_i^C - R_i^B]$ does not have to be binding for every entrepreneur. Some entrepreneurs may face lower financing costs from crowdfunding than from banks and would choose crowdfunding regardless of learning opportunities. Again, my identification relies on the presence of at least some entrepreneurs whose crowdfunding-bank choices react to changing local housing prices.

One potential concern 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 hence their demand for products or services produced by Kickstarter entrepreneurs.[26] To address this, I exclude projects that face predominantly local demands such as projects in Food and Restaurant, Fashion and Apparel, Dance, and Theatre, and show the robustness of my results. Another

[25] 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.

[26] 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. Similarly, Agrawal et al. (2011) find that the average distance between entrepreneurs and investors in another reward-based crowdfunding platform is about 3,000 miles.

concern is that higher housing prices may relieve financial constraints for entrepreneurs through the wealth effect in addition to the collateral channel (Jensen, Leth-Peterson, and Nanda (2014), Kerr, Kerr, and Nanda (2014)). My identification uses collateralised bank borrowing as one financing alternative to crowdfunding. However, the same identification framework can be easily extended to include both bank borrowing and personal wealth as alternatives to crowdfunding, in which case both the wealth 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 wealth induced by increasing housing prices make them 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 relatively poor 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 wealth shock. This suggests 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 reflects the supply shocks of 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 advantage of this data is that it is reported at the bank-county level as opposed to the bank-level. It therefore 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) and Flannery and Lin (2015), which is an improved variation of the fixed effect estimator used in studies such as Khwaja and Mian (2008), Jimenez, Ongena, Peydro, and Saurina (2012), and Schnabl (2012) to control for credit demand.[27] I construct county-level lending supply shocks as

[27] Amiti and Weinstein (2013) and Flannery and Lin (2015)'s 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.

weighted averages of bank-level shocks based on banks' lending shares in each county. The estimation procedure in 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. Empirical Results

4.1. Descriptive statistics

Before describing my main results, 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 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.

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 and shorter risk disclosure, provide more reward choices, and employ more videos and images in communicating with backers. 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 entrepreneurs seem to be associated with higher success rates. Overall, the statistics suggest that having a reasonable funding target, communicating well in project pitch, and being socially active online is very 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 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 highest. Kickstarter also defines a more refined categorization of projects that contains 51 project types. To better control for unobserved heterogeneities across projects, I use this refined categorization to define project type fixed effects in all my subsequent analyses. I also use this refined categorization to define same-type projects and project type switch in later analyses.

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. Panel C compares the initial projects launched by these repeat entrepreneurs and the projects launched by one-time entrepreneurs. There is no significant difference 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.[28] However, they do seem to be more active online, backing more projects of other entrepreneurs and having more Facebook friends.

4.2. Bayesian learning

As discussed in Section 3.1, my tests of Hypothesis 1 make use of the sample of repeat entrepreneurs who have launched multiple projects of the same type in order to track their belief changes. Table 1 presents the results. Column 1 tests the specification in equation (4) in Section 3.1. I regress funding target of each entrepreneur's next same-type project (posterior) on the funding target of her current project (prior) 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, with both coefficients significant at the 1% level. Columns 2 through 4 test Hypothesis 1 under the specification in equation (5). In column 2, I first interact the prior and the feedback with the precision of entrepreneur's prior, measured as the inverse of the log word count of the risk disclosure of the current project. In column 3, I do the same interaction using the precision of the crowd's feedback, measured as the average site age of the current project's backers. Column 4 presents the full-blown specification combining both sets of interactions from columns 2 and 3.[29] 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 the crowd's feedback is more precise, or when their priors are less precise. In terms of magnitude, a one standard deviation increase in prior precision increases the weight on prior by 8.3% and decreases the weight on feedback by 48%, while a one standard deviation increase in feedback precision decreases the weight on prior by 3.7% and increases the weight on feedback by 12%.

I then explore how learning differs between male and female entrepreneurs. The overconfidence 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 associated with high uncertainty (Lundeberg, Fox and Puncochar (1994), Barber and Odean (2001), Levi, Li and Zhang (2014)). In activities such as entrepreneurship,

[28] See Appendix I and footnote 36 for details on the construction of the experience index.

[29] The prior precision measure is only available for projects launched after September 2012 when Kickstarter starts to mandate risk disclosure, so the sample size is smaller in columns 2 and 4.

men may therefore overweight the importance of their priors and be less responsive to feedback than do female entrepreneurs. This is what I found in Panel B of Table 1. In Panel B, I condition the sample on individual entrepreneurs that are not registered as firms on Kickstarter. Following Greenberg and Mollick (2014), I algorithmically identify the gender of entrepreneurs by their first names.[30] I then interact both prior and feedback with the gender indicator of the entrepreneur. The result shows that, in updating beliefs, compared with female entrepreneurs, male entrepreneurs on average place 8% more weight on their priors and 28% less weight on the feedback from the crowd. This is consistent with the above conjecture.

4.3. Learning and the exercise of continuation options

In this section, I examine how learning affects entrepreneurs' continuation decisions after their current projects. Before formally testing Hypothesis 2, I first explore the non-parametric relationship between feedback positivity and entrepreneurs' continuation decisions. My main measure of feedback positivity is the log ratio of pledged amount to funding target, capturing how much of an entrepreneur's initial funding expectation is met by backers' pledge.[31]

In Figure 4A, I use kernel regression to estimate the relation between the probability an entrepreneur launches a second project after the current one (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 very skewed to the right tail. We see that within both funded and unfunded projects, there is a general positive relation between pledge ratio and the probability of launching another project. However, there is a discrete drop in comeback probability around the funding success threshold where pledge ratio is equal to one (indicated by the dashed line). As discussed in Section 3.2, this is because entrepreneurs are much less likely to crowdfund again once funded and if they do

[30] Following Greenberg and Mollick (2014), I use the *genderize.io* tool to match the first names of entrepreneurs with a database of 208,631 first names across 79 countries and 89 languages. For each name, the database also 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%. In 94.6% of the matched cases, the probability exceeded 95%, suggesting a high degree of accuracy.

[31] I use the log ratio because the empirical distribution of the raw ratio is very skewed and is bounded below at zero: many successful projects achieved very high pledge ratios and failed projects have ratios strictly less than one.

not have further supply of projects. To deal with this discontinuous drop 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. Another interesting observation is that the relation between pledge ratio and comeback probability is strongest among the most successful projects: change in pledge ratio from the 90th to the 100th percentile raises the comeback probability by about 23 percentage points from 20% to 43%. This suggests that a big success on Kickstarter gives an entrepreneur a very strong signal about her project or her ability as an entrepreneur and greatly increases the probability that she will continue her pursuit.

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 the feedback level and the probability of continuing with the same project type. Because previously unfunded entrepreneurs are more likely to try again with the same project (with improvement) than 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 generally a positive relation between backer interests and the two continuation probabilities.

Table 3 presents OLS regression results including more controls and fixed effects. Panel A measures feedback positivity with log pledge ratio and Panel B with log 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.[32]

[32] 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.

The regression results are similar to those obtained from the non-parametric analysis.

It is worth discussing the type of learning underlying the two continuation decisions. The decision of whether to participate in crowdfunding again can reflect an entrepreneur's learning both about her ability and about the project. However, conditional on participating again, i.e., conditional on believing in one's general ability as an entrepreneur, the decision of whether to switch project reflects learning about project, or the entrepreneur's comparative advantage in different projects.

I then proceed to test Hypothesis 3. Table 4 examines within-entrepreneur changes in the likelihood of switching projects. In Table 4 Panel A, the first dependent variable *Project type switch* is a dummy variable indicating an entrepreneur's next project being of a type different from the current project. The second dependent variable, *Project dissimilarity* (one minus *Project similarity*), is a continuous variable between zero and one capturing the project pitch difference between an entrepreneur's current and her next project. The independent variable is the *Project sequence number* within a given entrepreneur, with her first project labeled 1, second labeled 2, and so forth. I control for entrepreneur fixed effects, year-quarter fixed-effects, project type fixed effects, and the time distance between the current and the next project. The sample is restricted to entrepreneurs who have launched more than two projects in order to observe within-entrepreneur changes in switching probability. As shown in Table 4 Panel A, the coefficient on *Project sequence number* is significantly negative for both dependent variables, supporting the hypothesis that, within an entrepreneur, the likelihood of trial and error search (switching projects) decreases over time. It suggests that entrepreneurs start off uncertain about their comparative advantages (their match qualities with different projects) and gradually learn about them through experimentation.

It is worth noting that, apart from learning about match quality, an alternative explanation for the above pattern is learning by doing. As an entrepreneur spends more time on a specific type of project, she accumulates more job-specific skills in that field (learning by doing), and faces greater costs to switch to other project types. To distinguish learning about match quality from learning-by-doing, in Table 4 Panel B I decompose each entrepreneur's prior projects on Kickstarter into experimenting ones and non-experimenting ones. For each crowdfunding round, I count the number of times an entrepreneur has switched project (*Prior no. of switches*) versus continued with the prior project (*Prior no. of continuations*). As an alternative, I also count the number of past projects in a different type than the current project (*Prior no. of different-type projects*) versus those in the same type as the current project (*Prior no. of same-type projects*). If learning about match quality primarily drives my results, I should observe switching probability decreasing with the accumulation of prior experimenting projects, but not with the accumulation of non-experimenting projects. This is what I find. In Table 4 Panel B, the likelihood of project change decreases only with *Prior no. of switches* and *Prior no. of different-type projects*, but increases with or is unrelated to *Prior no. of continuations* and *Prior no. of same-type projects*. This suggests that the accumulation of job-specific skills (learning by doing) does not drive my results in Panel A.

Lastly, I explore potential non-linearity in the evolvement of project type switch probability. If learning is fast or uncertainty is small so that entrepreneurs can quickly pin down what they are best at, the switch probability should drop the most in the first few trials and gradually stabilize. This would imply a convex relationship between the switch probability and the project sequence number. To investigate this, I factorize *Project sequence number* into dummies and estimate the probability of project type switch at each project sequence number. Figure 5 plots the estimated probabilities. There is a largely steady decrease in the switch probability over time. However, the decrease is not convex, and if anything, is close to linear. This may suggest that there is enough uncertainty about comparative advantage so that learning is not occurring fast enough to completely resolve it over a few trials.

Overall, the results in this section show that entrepreneurs' learning has real effects on their entry and project choices. Entrepreneurs are ex ante uncertain about the return to their projects or their comparative advantages, and learn about them over time through experimentation.

4.4. Learning and funding outcomes

I now examine the implications of learning on funding outcomes. In Hypothesis 4, I predict that learning will lead to better funding outcomes over time within an entrepreneur, especially for the same type of projects. Table 5 presents the test of this hypothesis. Similar to Table 4, I look at within-entrepreneur changes in various funding outcomes by regressing these outcomes on project sequence number. Panel A shows that entrepreneurs achieve higher pledge ratio, higher absolute pledged amount, and attract more backers over time.

This happens despite that entrepreneurs tend to lower their funding target amounts over time, as indicated in the last column of Panel A. In Panel B, I examine learning within the same project type. I redefine project sequence number as the sequence number within the same project type launched by the same entrepreneur and replace entrepreneur fixed effects with entrepreneur-project type fixed effects. As hypothesized, improvements in funding outcomes are much stronger than in Panel A. This is consistent with learning being more effective within the same type of projects.

In Table 6, I further explore what observed behavior changes by entrepreneurs contribute to better funding outcomes over time. In Panel A, I find that, in addition to lowering funding targets, entrepreneurs improve by providing more frequent updates, shortening their project pitch, using more images and videos, simplifying the reward structure, and lowering the reward thresholds. Including these observed behavior changes explain about 62% of the improvements in funding outcomes (Panel B), with the remaining 38% being explained by other unobserved entrepreneur behavior changes as well as learning by backers. Although I cannot pin down the exact proportion of funding outcome improvement explained by backers' learning, 38% should serve as an upper bound. This suggests that, at least in explaining funding outcome improvements, learning by entrepreneurs dominates learning by investors.

4.5. The ex-ante learning advantage of crowdfunding

In this section, I focus on the ex-ante learning value of crowdfunding. As discussed in Section 3.4, I establish the learning advantage of crowdfunding using shocks to the choice between crowdfunding and bank borrowing. Entrepreneurs traditionally rely on collateralized borrowing to finance their new businesses (Robb and Robinson (2014), Meisenzahl (2014)), whereas crowdfunding does not require any collateral. A positive shock to local housing prices therefore increases the relative cost of crowdfunding vis-à-vis bank borrowing. Likewise, a positive supply shock to local small business lending would also push down the borrowing cost for entrepreneurs and make crowdfunding relatively more costly. This triggers some entrepreneurs to switch from crowdfunding to bank borrowing. If crowdfunding has additional learning value, then entrepreneurs who remain using crowdfunding should be those that benefit particularly from learning, i.e., those facing high uncertainty and deriving high option value from learning.

I first validate my assumption that crowdfunding and bank borrowing are substitutes in providing finance. I look at changes in demand on Kickstarter in response to local housing price variations as well as small business loan supply shocks. If bank borrowing is a viable alternative to financing projects on Kickstarter, 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 7 confirms this. In Panel A, the dependent variable *MSA-level demand for finance on KS* is the logarithm of aggregate quarterly funding target amount on Kickstarter at the Metro/Micropolitan Statistical Area (MSA) level.[33] The independent variable *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) compiled by the Federal Housing Financing Agency (FHFA). I also follow Cvijanovic (2014) to 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-quarterly 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 aggregate quarterly funding target amount on Kickstarter at the county level. The independent variable *Local SBL supply shock* is the county-year level weighted average shocks of bank supply of small business loans (see Appendix III for detailed definition). The sample covers 2,144 counties and 20 quarters from April 2009 to March 2014. In both Panels A and B, I also employ a Tobit (instrumented Tobit) specification to account for the fact that demand on Kickstarter is bounded below at zero.

Across all specifications in Panels A and B, I find a significantly negative relationship between access to local credit and demand 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 there is indeed a substitution between bank borrowing and crowdfunding, and cheaper access to local credit increases the relative cost of crowdfunding.

I then test how the relative cost of crowdfunding affects the option value and therefore the uncertainty and fixed costs faced by entrepreneurs choosing crowdfunding. I use two

[33] My dataset contains the latitudes and longitudes of entrepreneurs' addresses that allow me to map to ZIP codes via Google Maps Geocoding. I then 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 to FIPS (Federal Information Processing Standard) county codes.

measures to proxy for uncertainty.[34] 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.[35] 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.[36] 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 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 variables can be found in Appendix I.

Table 8 presents the results. I find that, as local borrowing cost drops, as proxied by

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[34] I do not use the risk disclosure measure in Section 4.2 as a proxy for uncertainty due to its short time span. Kickstarter only starts to mandate risk disclosure in September 2012, leaving me only one and half years of data to relate to housing price changes and local lending supply shocks.

[35] 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. The *Project Novelty* measure is one minus the cosine similarity score.

[36] 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*.

[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.

higher local housing prices (Panel A) and positive small business loan supply shocks (Panel B), entrepreneurs entering Kickstarter are less experienced, choose riskier projects and projects involve higher fixed costs. This is consistent with the theoretical prediction that, in equilibrium, higher relative costs of crowdfunding leads to higher uncertainty and option value faced by entrepreneurs that choose crowdfunding over bank borrowing.

To further ensure that the relation between housing prices and entrepreneurial activities on Kickstarter is not driven by shifts in local demands, in Panel A of Table A3 in Appendix II, I replicate regressions in Table 8 excluding projects in Food and Restaurant, Fashion and Apparel, Dance, and Theatre, which likely face predominantly local demands. The results remain very similar. In addition, I show in Panel B of Table A3 that my results are robust when focusing on projects in more traditional sectors such as Hardware and Design, Fashion and Apparel, Food and Restaurant, Games, Publishing, and Technology.

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 with proxies of local borrowing costs with entrepreneur's prior and feedback measures. Lower local borrowing costs and therefore higher relative cost of crowdfunding should in equilibrium drive entrepreneurs to engage in more learning in crowdfunding market, i.e., placing more weight on feedback and less weight on prior in updating beliefs. Table 9 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 those remaining using crowdfunding despite cheaper local credit do engage in more learning ex-post.

Overall, the results from Table 8 and 9 are consistent with the presence of additional learning value for crowdfunding vis-à-vis bank borrowing when entrepreneurs choose between the two financing sources.

5. Robustness and further discussion

5.1. Sample selection

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., those repeat entrepreneurs may have unobserved characteristics that also correlate with their subsequent funding targets so that my estimates are not representative of what happens to the full sample of entrepreneurs. To address this, I employ a two-stage Heckman selection model where the inverse Mills ratio from the first stage is included as a regressor in the second stage 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 local 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 effect in participation in 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 interactions and therefore peers effects are most likely to takes place. The idea is that 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 conditioning on her previous funding target.

Table A1 in Appendix II presents the results using this two-stage model. The results are very similar to those in Table 2. 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 that there is in a positive (albeit sometimes insignificant) selection. This means 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 impact on my estimates of the learning coefficients.

5.2 Bayesian learning: alterative samples

In this section, I show that the Bayesian learning results are robust to the use of alternative samples. Table A2 in Appendix II reproduces Table 2 under three subsamples. In Panel A, I restrict the sample to projects in more traditional sectors, i.e. 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 B, I remove very small projects and focus on projects with funding targets of at least $10,000. In Panel C, I focus on entrepreneurs' next projects that are not just in the same type as the current projects but also "almost the same" in terms of contents, i.e. those with a project pitch similarity score of at least 0.95 (on a scale of 0-1 with 1 being exactly the same) compared with the current projects. Across all three samples, the results remain quantitatively the same as those reported in Table 2.

5.3. External validity of results

The use of platform data in this paper naturally 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 are crucial to the formation rich learning opportunities. These features include the involvement of the crowd, online social interactions, and accessibility to early-stage entrepreneurs. 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 the type of things entrepreneurs can learn about. However, the basic learning mechanisms and the general distinctions of crowdfunding from traditional financing sources remain the same across different crowdfunding types. Therefore, the results in this paper can speak to crowdfunding as a new financing method in general.

6. Conclusion

Entrepreneurship is characterized by high failure rates and extreme uncertainty. In light of this, entrepreneurs' ability to learn about potential returns at an early stage is critical to the entry process, and has important implications for the entrepreneurial risk-return trade-off. In this paper, I use the crowdfunding market to answer three questions: How do entrepreneurs learn given the learning opportunities? Does learning affect entrepreneur's real decisions? What type of early-stage financing facilitates the learning process? Using a comprehensive dataset from the world's largest reward-based crowdfunding platform Kickstarter, I find that entrepreneurs are Bayesian learners: they update beliefs based on feedback from the crowd and place more weight on information with relatively higher precision. Moreover, entrepreneurs make their continuation decisions based on what they learned. Within an entrepreneur over time, learning improves funding outcomes and reduces the likelihood of switching projects. This suggests that entrepreneurs are ex ante uncertain about their projects or their comparative advantages and they learn as they go. I further establish the learning advantage of crowdfunding using local housing price variations and small business loan supply shocks as shifters of the relative cost of crowdfunding vis-à-vis bank borrowing. I find that, as crowdfunding becomes relatively more costly, entrepreneurs remaining using crowdfunding face higher uncertainty ex ante and engage in more learning ex post. Overall, my results highlight the facilitation of learning as an important non-financial role of crowdfunding. It 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 on Kickstarter. All amounts are in U.S. dollars.

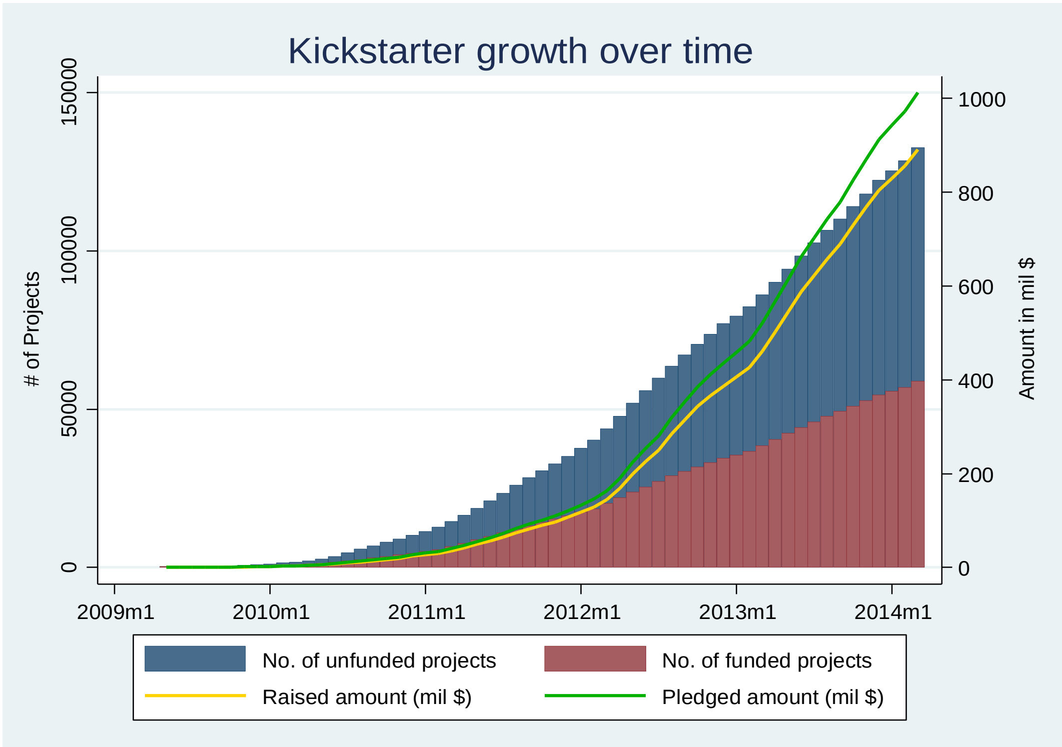

Figure 2. A Sample Kickstarter Page

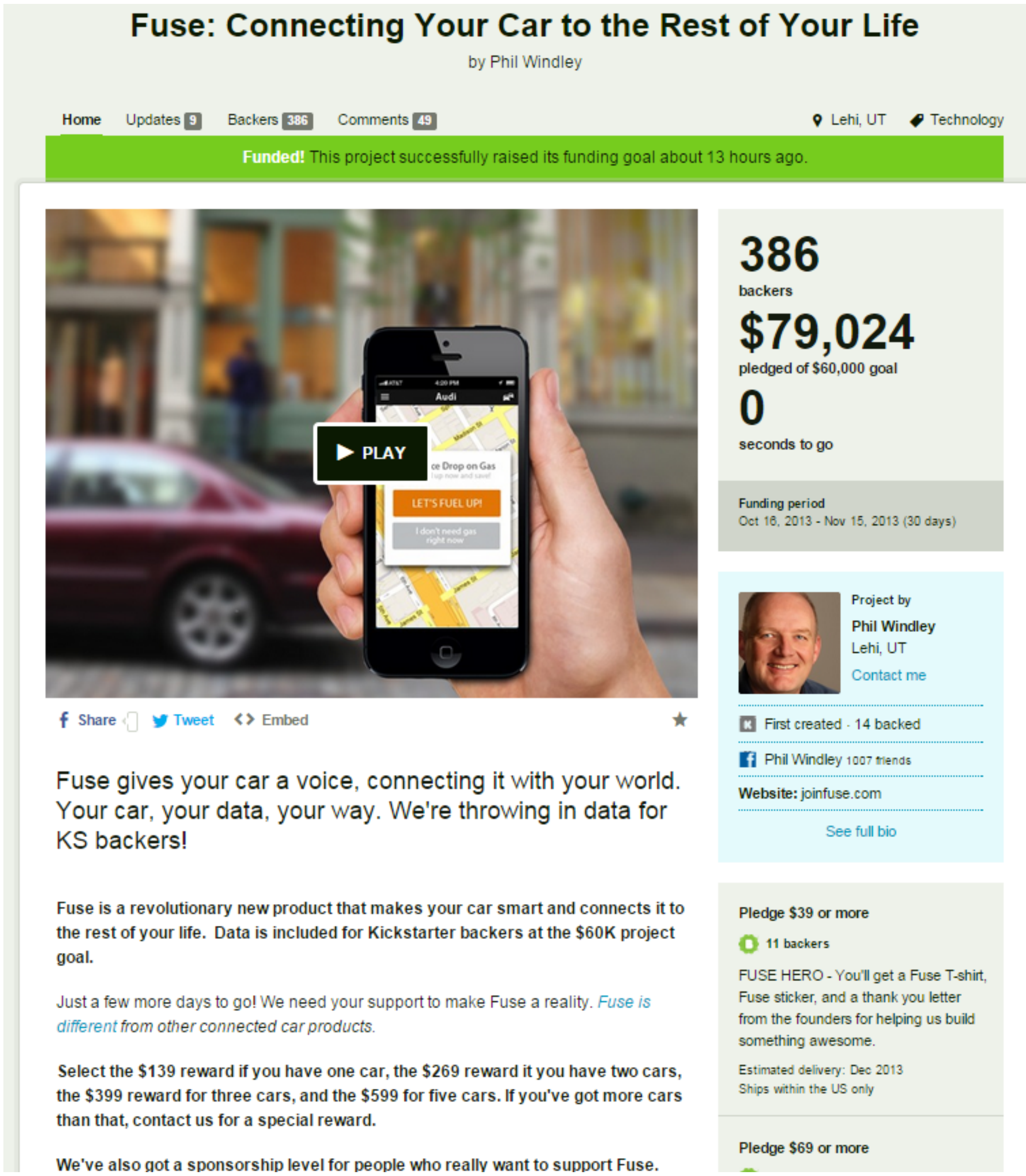

Figure 3. Geographic Distribution of Funding Demands on Kickstarter in U.S.

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.

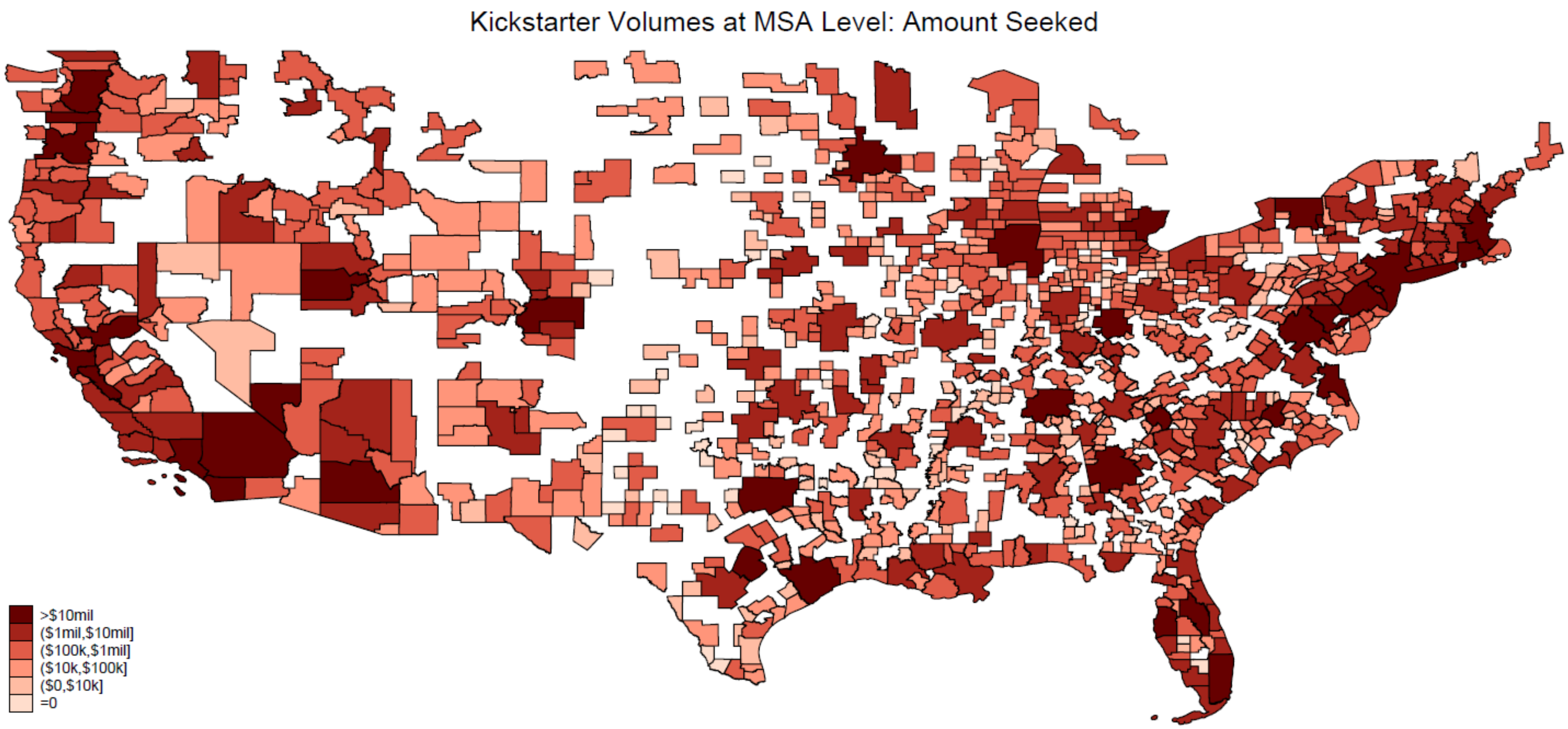

Figure 4. Non-parametric Relation between Feedback Level and Continuation Probability

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 Figure 4A and Figure 4C is the probability an entrepreneur launches another project on Kickstarter after the current project. The vertical axis in Figure 4B and Figure 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 Panel A and B, 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 Panel C and D, feedback positivity is measures as log(1+number of comments per backer). The sample in Panel A and C includes all projects launched before May 2013 (to allow for one year to observe entrepreneurs' comeback decisions). The sample in Panel B and D includes all projects launched after entrepreneurs' initial projects. All kernel regressions use a local linear specification with 50 bins.

Figure 4A

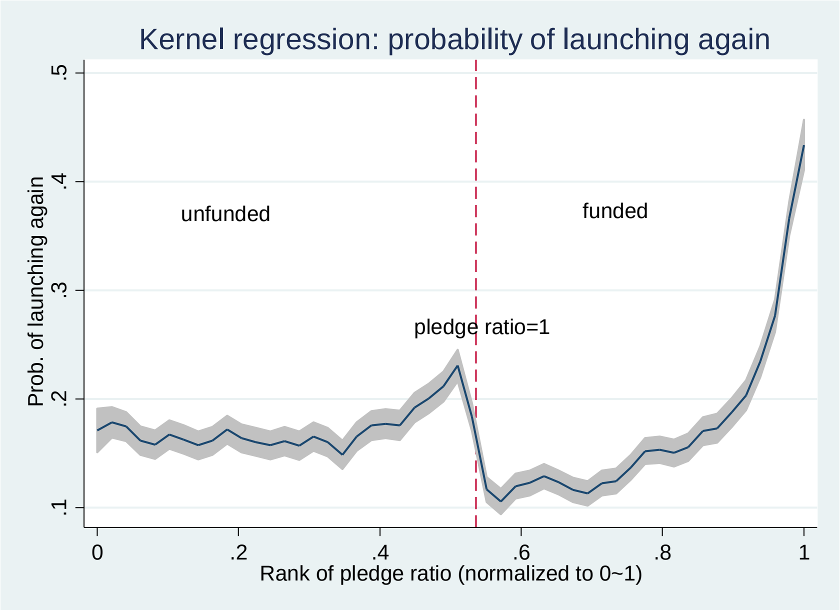

Figure 4B

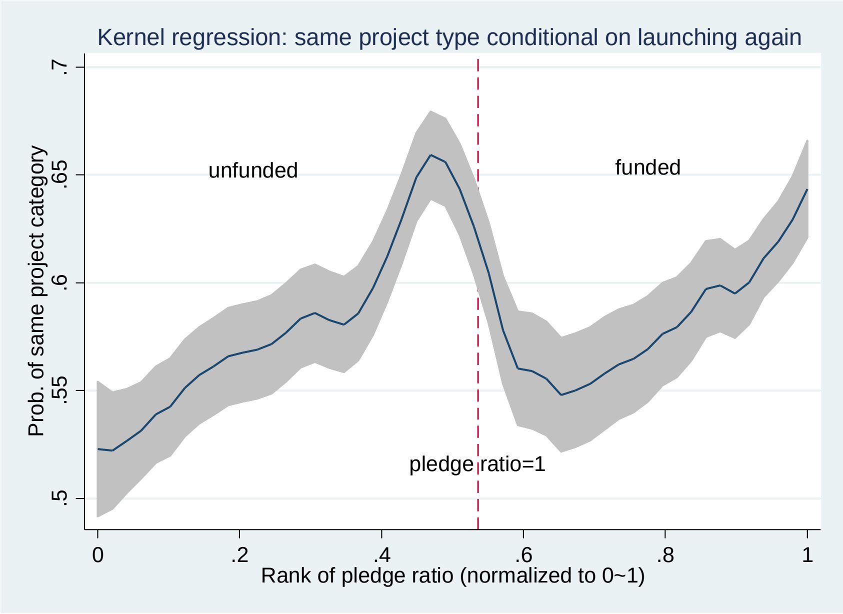

Figure 4C

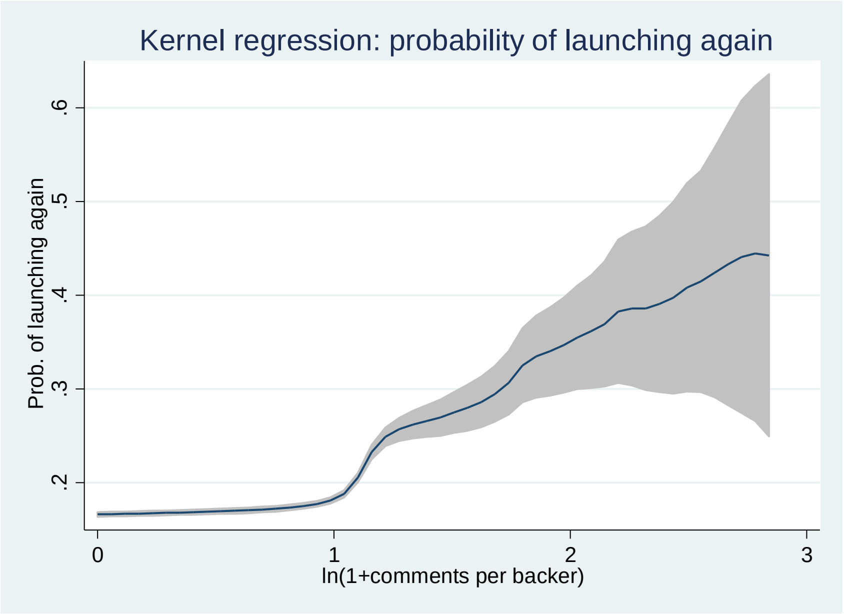

Figure 4D

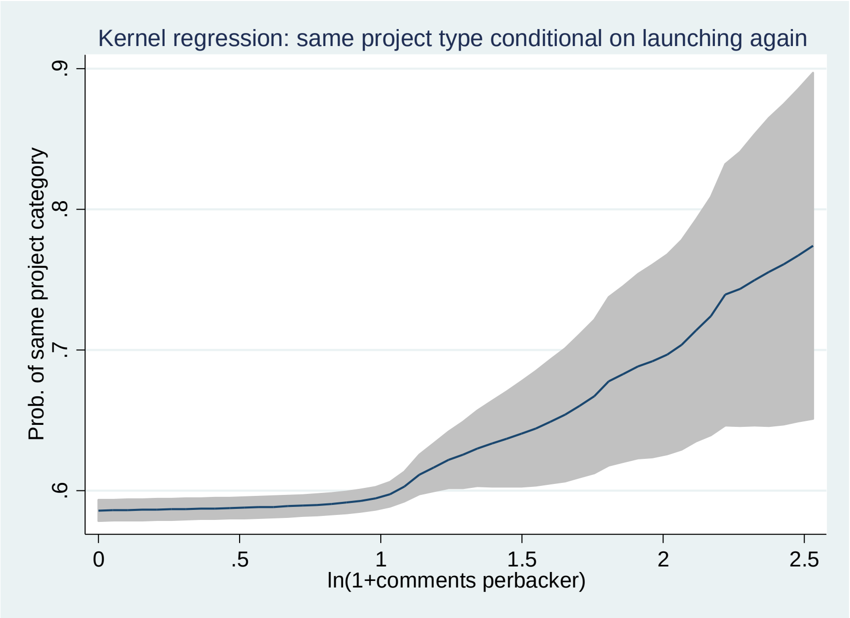

Figure 5. Estimated probabilities of project type switch

This figure plots the estimated probability of project type switch for each project sequence number within an entrepreneur. I follow the sample and specification used in column 1 of Table 4 Panel A, except that the *Project sequence number* is factorized into dummies. The estimated coefficients on these dummies are then plotted out to indicate, for each project sequence number, the average probability that an entrepreneur's next project is of a different type than the current project.

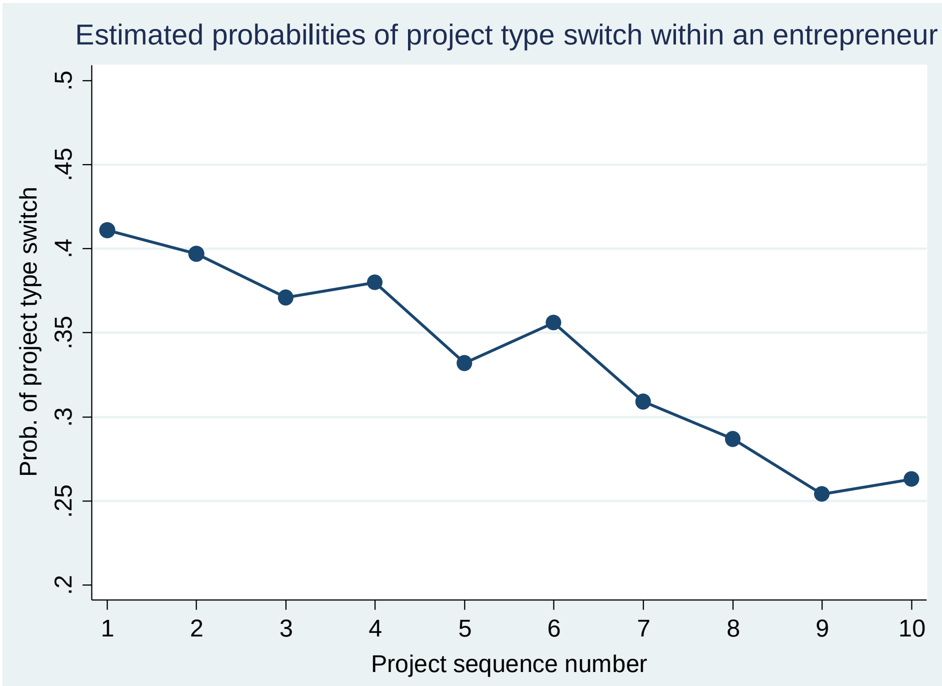

Table 1. Summary Statistics

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, average funding target amount, and average success rate for each top category. Panel C compares projects launched by one-time entrepreneurs (104,597 projects) and repeat entrepreneurs (32,774 projects) along various project and entrepreneur characteristics.

Panel A

	All projects		Unfunded projects		Funded projects	
Variable	Mean	Median	Mean	Median	Mean	Median
			Funding 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
Success	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
			Project characteristics			
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
			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
			Social aspects			
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
			Other variables			
Prior precision	0.22	0.21	0.22	0.21	0.22	0.21
Feedback precision	0.00	-0.49	-0.05	-0.66	0.05	-0.32
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
Housing price index	193.63	195.74	191.17	190.49	196.75	200.57
Local SBL supply shock	-0.07	-0.17	-0.08	-0.17	-0.06	-0.16

Panel B

Top category	No. of projects	% of projects	Avg. funding target	Success rate
Art	12,265	8.93	24,803	47%
Comics	3,802	2.77	8,720	48%
Dance	1,802	1.31	6,142	69%
Hardware and design	7,158	5.21	25,266	37%
Fashion and apparel	5,560	4.05	13,103	29%
Film and video	33,546	24.42	35,818	40%
Food and restaurant	5,666	4.12	18,071	39%
Games	9,071	6.60	43,521	34%
Music	27,956	20.35	9,115	55%
Photography	4,184	3.05	10,447	36%
Publishing	16,588	12.08	11,373	32%
Technology	4,006	2.92	63,590	33%
Theater	5,767	4.20	12,365	64%

Panel C

	Projects by one-time entrepreneurs	Initial projects by repeat entrepreneurs
No. of projects launched	104,597	13,582
	Project characteristics	
Target amount	24,040.61	22,406.26
Pledged amount	7,121.81	6791.61
Pledge ratio	1.36	1.41
Success	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	
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 2. Bayesian Learning by Entrepreneurs

This table presents results from tests on entrepreneurs' Bayesian learning. The dependent variable is the log funding target of the same entrepreneur's next same-type project and captures entrepreneur's posterior. The independent variables are the log funding target of the entrepreneur's current project (capturing prior) and the current project's actual pledged amount the project received (capturing feedback). In Panel A, *Prior precision* is the reciprocal of the logarithmic word count of the risk disclosure section and is only available for projects launched since September 2012. *Feedback precision* is the average site age of the project's backers. Both *Prior precision* and *Feedback precision* are standardized (removing sample mean and divided by sample standard deviation) in the regressions. In Panel B, *Male* indicates the gender of individual entrepreneurs and is defined only for projects launched by individual (unincorporated) entrepreneurs. The main effects of *Prior precision*, *Feedback precision*, and *Male* are included in regressions but are omitted from the table. Across all specifications I control for 51 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 controls for entrepreneur characteristics (number of Facebook friends, entrepreneur's biography length, and entrepreneur's Experience Index (defined 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)
Ln(target amount)	0.393***	0.436***	0.483***	0.438***
	[0.013]	[0.014]	[0.012]	[0.011]
Ln(pledged amount)	0.075***	0.067***	0.091***	0.063***
	[0.008]	[0.009]	[0.008]	[0.008]
Ln(target amount) × Prior precision		0.026**		0.033***
		[0.011]		[0.010]
Ln(pledged amount) × Prior precision		-0.026***		-0.028***
		[0.007]		[0.007]
Ln(target amount) × Feedback precision			-0.018**	-0.021**
			[0.008]	[0.010]
Ln(pledged amount) × Feedback precision			0.011**	0.039***
			[0.005]	[0.006]
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	4,549	13,038	4,549
Adjusted R^2	0.529	0.578	0.530	0.594

Panel B

	Ln(next target amount)
Ln(target amount)	0.381***
	[0.013]
Ln(pledged amount)	0.079***
	[0.009]
Ln(target amount) × Male	0.031**
	[0.015]
Ln(pledged amount) × Male	-0.022***
	[0.008]
Project type FEs	Yes
Year-quarter FEs	Yes
Other controls	Yes
No. of observations	12,325
Adjusted R^2	0.524

Table 3. Learning and Continuation Decisions

This table presents the effect of feedback positivity on entrepreneurs' continuation decisions: the decision to launch a next project after the current one, and conditional on launching again, launching 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 (allow one year before sample period end to observe entrepreneurs' comeback decisions) after the current project. The dependent variable *Same-type project* is a dummy equal to one if the entrepreneur's next project type is of the same type as the current project. The dependent variable *Project similarity* is the Bigram string similarity score between the project pitch of an entrepreneur's next project and the pitch of the 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(funding target), 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) × (1−Success)	0.0025**	0.0354***	0.0107***
	[0.0013]	[0.0046]	[0.0005]
Ln(pledge ratio) × Success	0.1230***	0.0293**	0.0076***
	[0.00367]	[0.0104]	[0.0016]
success	-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 4. Learning and Trial and Error Search

This table examines within-entrepreneur changes in the likelihood of switching projects. The dependent variable *Project type switch* is a dummy indicating an entrepreneur's next project being of a type different from the current project. The dependent variable *Project dissimilarity* is one minus the *Project dissimilarity* used in Table 3, capturing the difference in the project pitch between an entrepreneur's current and her next project. In Panel A, the independent variable is the *Project sequence number* within an entrepreneur (1 for her first project, 2 for her second project, and so forth). In Panel B, the independent variable *Prior no. of switches* (*Prior no. of continuations*) is the number of times an entrepreneur has switched project type (continued with the previous project type). The independent variable *Prior no. of different-type projects* (*Prior no. of same-type projects*) is an entrepreneur's past number of projects that are in a different type than (in a same type as) her current project. In all regressions I control for entrepreneur fixed effects, year-quarter fixed-effects, project type fixed effects, the number of months between an entrepreneur's next and current project, and controls for current project characteristics (Ln(funding target), funding window (in days), web site dummy, number of reward tiers, average log reward threshold, project pitch length, number of images, number of videos). The sample includes all entrepreneurs who have launched more than two projects in order to observe changes in switch probability. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Project type switch	Project dissimilarity
Project sequence number	-0.0149***	-0.0022***
	[0.0044]	[0.0008]
Months since previous project	0.0071***	0.0008***
	[0.0010]	[0.0002]
Entrepreneur FEs	Yes	Yes
Year-quarter FEs	Yes	Yes
Last project type FEs	Yes	Yes
Other controls	Yes	Yes
No. of observations	8,306	8,306
Adjusted R^2	0.609	0.662

Panel B

	Project type switch	Project dissimilarity	Project type switch	Project dissimilarity
Prior no. of switches	-0.1501***	-0.0029**		
	[0.0181]	[0.0012]		
Prior no. of continuations	0.0853***	-0.0018		
	[0.0241]	[0.0010]		
Prior no. of different-type projects			-0.0638***	-0.0027***
			[0.0161]	[0.0007]
Prior no. of same-type projects			0.0248**	-0.0017
			[0.010]	[0.0015]
Months since previous project	0.0078***	0.0008***	0.0074***	0.0008***
	[0.0012]	[0.0002]	[0.0011]	[0.0002]
Entrepreneur FEs	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Last project type FEs	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
No. of observations	8,306	8,306	8,306	8,306
Adjusted R^2	0.654	0.620	0.619	0.662

Table 5. Within-Entrepreneur Changes in Funding Outcomes

This table examines within-entrepreneur changes in funding outcomes over time. In Panel A the independent variable is the project sequence number within a given entrepreneur (1 for her first project, 2 for her second project, and so forth). In Panel B the independent variable is the project sequence number within an entrepreneur-project type pair. In all regressions I control for project type fixed effects, year-quarter fixed-effects, and other controls included in Table 3. I also control for entrepreneur fixed effects in Panel A and entrepreneur-project type fixed effects in Panel B. The sample is based on entrepreneurs that launched at least two projects. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Ln(pledge ratio)	Ln(pledged amount)	Ln(pledged amount per backer)	Ln(number of backers)	Ln(target amount)
Project sequence number	0.278***	0.068***	0.003	0.063***	-0.325***
	[0.013]	[0.017]	[0.007]	[0.009]	[0.010]
Project type FEs	Yes	Yes	Yes	Yes	Yes
Entrepreneur FEs	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes
No. of observations	31,931	31,931	31,931	31,931	31,931
Adjusted R^2	0.762	0.804	0.728	0.844	0.744

Panel B

	Ln(pledge ratio)	Ln(pledged amount)	Ln(pledged amount per backer)	Ln(number of backers)	Ln(target amount)
Project sequence number	0.407***	0.125***	0.017**	0.104***	-0.416***
_within type	[0.017]	[0.022]	[0.008]	[0.013]	[0.013]
Entrepreneur × project type FEs	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes
No. of observations	31,931	31,931	31,931	31,931	31,931
Adjusted R^2	0.867	0.895	0.85	0.913	0.866

Table 6. Explaining Within-Entrepreneur Changes in Funding Outcomes

Panel A examines within-entrepreneur behavior changes over successive projects. The sample is based on entrepreneurs who have launched at least two projects. The dependent variables in Panel A are defined in detail in Appendix I. The independent variable is the *Project sequence number* within a given entrepreneur (first project labeled 1, second labeled 2, and so forth). In all regressions I control for entrepreneur fixed effects, project type fixed effects, year-quarter fixed-effects, and other controls included in Table 3. Panel B examines how much of the within-entrepreneur change in *Ln(pledge ratio)* is explained by entrepreneur's behavior changes examined in Panel A. The sample is the same as that used in Panel A. In column 2 of Panel B, in additional to controls used in Panel A, I control for all entrepreneur behavior variables from Panel A. Standard errors are clustered at the project type level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	Ln(number of updates)	Funding window (in days)	Ln (pitch length)	Ln(risk disclosure)	Ln(number of images)	Ln(number of videos)	Number of rewards tiers	Average reward threshold
Project sequence number	0.0128*	0.130	-0.0091*	-0.0084*	0.0292***	0.0001	-0.1930***	-0.0880***
	[0.0072]	[0.121]	[0.0050]	[0.0047]	[0.0057]	[0.0026]	[0.0378]	[0.0062]
Project type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entrepreneur FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	31,931	31,931	31,919	31,881	31,919	31,931	31,931	31,931
Adjusted R^2	0.751	0.642	0.769	0.977	0.849	0.705	0.733	0.746

Panel B

	Ln(pledge ratio)	Ln(pledge ratio)
Project sequence number	0.278***	0.107***
	[0.013]	[0.009]
Observed entrepreneur behaviors	No	Yes
Project type FEs	Yes	Yes
Entrepreneur FEs	Yes	Yes
Year-quarter FEs	Yes	Yes
No. of observations	31,931	31,881
Adjusted R^2	0.762	0.882

Table 7. Substitution between Bank Borrowing and Crowdfunding

This table validates the substitution between crowdfunding and bank borrowing in providing financing. 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. It is set to zero for MSA-quarters with no funding demand on Kickstarter. The independent variable *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) compiled by 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). The first two columns present OLS and IV regression results. The third and fourth columns present results under the Tobit and instrumented Tobit model to account for the zero lower bound of the dependent variable. 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 one plus quarterly aggregate funding target amount on Kickstarter at the county level. It is set to zero for county-quarters with no funding demand on Kickstarter. The independent variable *Local SBL supply shock* is the county-year level weighted average shocks of bank supply of small business loans (see Appendix III for detailed definition). The second column presents results under the Tobit model to account for the zero lower bound of the dependent variable. 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

	MSA-level demand for finance on KS			
	OLS	IV	Tobit	IV Tobit
Local housing price index	-0.0307***	-0.0627**	-0.0214***	-0.0568*
	[0.00803]	[0.0286]	[0.00771]	[0.0331]
First stage:				
Land supply elasticity		-0.137***		-0.137***
×national real estate price		[0.0287]		[0.0279]
MSA FEs	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
No. of observations	5,740	5,740	5,740	5,740
Adjusted/Pseudo R^2	0.723	0.722	0.224	-

Panel B

	County-level demand for finance on KS	
	OLS	Tobit
Local SBL supply shock	-0.335***	-0.896**
	[0.124]	[0.449]
Year-quarter FEs	Yes	Yes
No. of observations	42,880	42,880
Adjusted/Pseudo R^2	0.118	0.048

Table 8. 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. In Panel A, there are two dependent variables. *Project Novelty* is one minus the cosine similarity score between the text of a project's pitch and the pooled text of all project pitches within 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) compiled by 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 dependent variables are the same as in Panel A. The independent variable *Local SBL supply shock* is the county-year level weighted average shocks of bank supply of small business loans (see Appendix III for detailed definition). All samples are at the project level. 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

	Project Novelty		Experience Index		Fixed Costs	
	OLS	IV	OLS	IV	OLS	IV
Local housing price index	0.00011***	0.00019*	-0.000836**	-0.00321***	0.00244***	0.00486**
	[0.00004]	[0.00011]	[0.000349]	[0.00118]	[0.000663]	[0.00192]
First stage:						
Land supply elasticity		-0.328***		-0.328***		-0.328***
×national real estate price		[0.0555]		[0.0555]		[0.0555]
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	0.165	0.165	0.045	0.045	0.236	0.236

Panel B

	Project Novelty	Experience Index	Fixed Costs
Local SBL supply shock	0.009***	-0.117***	0.140***
	[0.003]	[0.030]	[0.044]
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 9. 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 Bayesian updating process. The specification is analogous to that in Table 2. The samples are based on the sample used in Table 2 column 1 for which I can observe MSA-level housing prices (in column 1) or county-level small business lending supply shock (in column 2). The dependent variable is the log funding target of the same entrepreneur's next same-type project and captures entrepreneur's posterior. The independent variables are the log funding target of the entrepreneur's current project (capturing prior) and the current project's actual pledged amount the project received (capturing feedback). *Local housing price index* is the quarterly MSA-level Housing Price Index (HPI) compiled by the Federal Housing Financing Agency (FHFA). *Local SBL supply shock* is the county-year level weighted average shocks of bank supply of small business loans (see Appendix III for detailed definition). Both *Local housing price index* and *Local SBL supply shock* are standardized and their main effects 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

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.
Success	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	The number of Facebook friends the entrepreneur has. For entrepreneurs

friends	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
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.
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 reciprocal of the logarithmic word count of the Risk and Challenges section. This variable is available for projects launched since September 2012.
Feedback precision	The average site age (in months) of a project's backers removed of project launch month fixed effects.
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 Housing Price Index (HPI) published by the Federal Housing Finance Agency (FHFA) using data provided by Fannie Mae and Freddie Mac. It is based on transactions involving conforming, conventional mortgages purchased or securitized by Fannie Mae or Freddie Mac. This variable varies the Metro/Micropolitan Statistical Area (MSA)-quarter level.
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 one plus 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 one plus quarterly aggregate funding target amount on Kickstarter at the county-level.
Project Novelty	One minus the cosine similarity score between the text of a project's pitch and the pooled text of all projects' pitches within the same 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. The *Project Novelty* measure is one minus the cosine similarity score.
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. Bayesian Learning by Entrepreneurs: Correcting for Sample Selection

This table presents the results of entrepreneurs' Bayesian learning 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*, 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***	0.436***	0.483***	0.439***
	[0.013]	[0.014]	[0.012]	[0.011]
Ln(pledged amount)	0.075***	0.067***	0.091***	0.063***
	[0.008]	[0.009]	[0.007]	[0.008]
Ln(target amount) × Prior precision		0.026**		0.025***
		[0.011]		[0.010]
Ln(pledged amount) × Prior precision		-0.026***		-0.025***
		[0.007]		[0.007]
Ln(target amount) × Feedback precision			-0.0171**	-0.0182*
			[0.008]	[0.010]
Ln(pledged amount) × Feedback precision			0.011**	0.039***
			[0.005]	[0.006]
1st stage: Peer propensity	0.727***	0.778***	0.737***	0.696***
	[0.035]	[0.046]	[0.034]	[0.043]
Inverse Mills ratio (lambda)	0.157***	0.181	0.230***	0.167
	[0.074]	[0.111]	[0.098]	[0.120]
χ^2 of log likelihood comparison test	4.581**	2.682	5.608**	1.885
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	4,549	13,038	4,549

Table A2. Bayesian Learning by Entrepreneurs: Alternative Samples

This table reproduces Table 2 under alternative subsamples. Panel A restricts to projects in more traditional sectors—projects in Hardware and Design, Fashion and Apparel, Food and Restaurant, Games, Publishing, and Technology. Panel B focuses on larger projects with funding target amounts of at least $10,000 USD. Panel 3 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 on a scale of 0-1 (1 being exactly the same). All specifications follow those used 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: Projects in traditional sectors

Dependent var: Ln(next target amount)	(1)	(2)	(3)	(4)
Ln(target amount)	0.438***	0.436***	0.449***	0.445***
	[0.018]	[0.018]	[0.017]	[0.015]
Ln(pledged amount)	0.079***	0.088***	0.0764***	0.0788***
	[0.011]	[0.012]	[0.010]	[0.011]
Ln(target amount) × Prior precision		0.029*		0.026*
		[0.016]		[0.014]
Ln(pledged amount) × Prior precision		-0.032***		-0.032***
		[0.010]		[0.010]
Ln(target amount) × Feedback precision			-0.024**	-0.030**
			[0.012]	[0.014]
Ln(pledge amount) × Feedback precision			0.023***	0.037***
			[0.007]	[0.009]
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	2,520	4,891	2,520
Adjusted R^2	0.529	0.553	0.531	0.557

Panel B. Larger projects

Dependent var: Ln(next target amount)	(1)	(2)	(3)	(4)
Ln(target amount)	0.436***	0.445***	0.437***	0.459***
	[0.030]	[0.030]	[0.029]	[0.032]
Ln(pledged amount)	0.064***	0.054***	0.063***	0.038***
	[0.010]	[0.012]	[0.009]	[0.013]
Ln(target amount) × Prior precision		0.053**		0.056**
		[0.026]		[0.027]
Ln(pledged amount) × Prior precision		-0.043***		-0.044***
		[0.010]		[0.011]
Ln(target amount) × Feedback precision			-0.050**	-0.046*
			[0.022]	[0.027]
Ln(pledge amount) × Feedback precision			0.018***	0.037***
			[0.005]	[0.010]
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	2,520	4,891	2,520
Adjusted R^2	0.529	0.553	0.531	0.557

Panel C. "Almost the same" projects

Dependent var: Ln(next target amount)	(1)	(2)	(3)	(4)
Ln(target amount)	0.431***	0.458***	0.434***	0.466***
	[0.013]	[0.013]	[0.014]	[0.013]
Ln(pledged amount)	0.089***	0.077***	0.088***	0.069***
	[0.008]	[0.009]	[0.007]	[0.009]
Ln(target amount) × Prior precision		0.033***		0.035***
		[0.011]		[0.01]
Ln(pledged amount) × Prior precision		-0.020***		-0.023***
		[0.008]		[0.008]
Ln(target amount) × Feedback precision			-0.022**	-0.020*
			[0.009]	[0.011]
Ln(pledged amount) × Feedback precision			0.014***	0.037***
			[0.004]	[0.007]
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	3,468	8,781	3,468
Adjusted R^2	0.556	0.596	0.557	0.601

Table A3. Local Borrowing Costs and the Learning Value of Crowdfunding: Alternative Subsamples

Panel A reproduces Table 8 dropping projects that likely face local demands, i.e. projects in Food and Restaurant, Fashion and Apparel, Dance, and Theatre. Panel B reproduces Table 8 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 8. *, **, 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	0.00016***	0.00034***	-0.00084**	-0.0036***	0.0030***	0.0045**
	[0.00003]	[0.00007]	[0.00036]	[0.0012]	[0.0007]	[0.0021]
First stage:						
Land supply elasticity		-0.332***		-0.332***		-0.332***
×national real estate price		[0.0543]		[0.0543]		[0.0543]
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	0.164	0.164	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]
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	0.00023***	0.00042***	-0.0010**	-0.0023*	0.00269**	0.00382*
	[0.00004]	[0.00011]	[0.0005]	[0.0013]	[0.00136]	[0.00218]
First stage:						
Land supply elasticity		-0.374***		-0.374***		-0.374***
×national real estate price		[0.0481]		[0.0481]		[0.0481]
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	0.179	0.179	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]
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. Validating Project Novelty and Experience Index as Measures of Project Uncertainty

Projects are sorted into quintiles based on the value of *Project Novelty* and the value of *Experience Index* respectively, with higher quintile number meaning higher values. I then tabulate the mean and the standard deviation of funding outcome *Ln(pledge ratio)* for each quintile for each sorting variable.

	Sorting variable: Project Novelty		Sorting variable: Experience Index	
Quintiles	Mean of ln(pledge ratio)	Std. dev. of ln(pledge ratio)	Mean of ln(pledge ratio)	Std. dev. of ln(pledge ratio)
1	-1.390	1.880	-1.683	1.997
2	-1.449	1.900	-1.516	1.966
3	-1.523	1.921	-1.532	1.936
4	-1.639	1.963	-1.497	1.906
5	-1.725	2.020	-1.441	1.859

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) for a recent application).

The small business loan data come from the Federal Financial Institutions Examination Council (FFIEC).[40] 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 $\mathrm{E}(\varepsilon_{c,b,t}) = 0$.

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

[40] 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 $t-1$.[41]

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.[42] 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.

[41] 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 $E\left[\sum_c \varphi_{c,b,t-1}\, \varepsilon_{c,b,t}\right] = \sum_c \varphi_{c,b,t-1} E\left[\varepsilon_{c,b,t}\right] = 0$.

[42] 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

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

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:

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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.

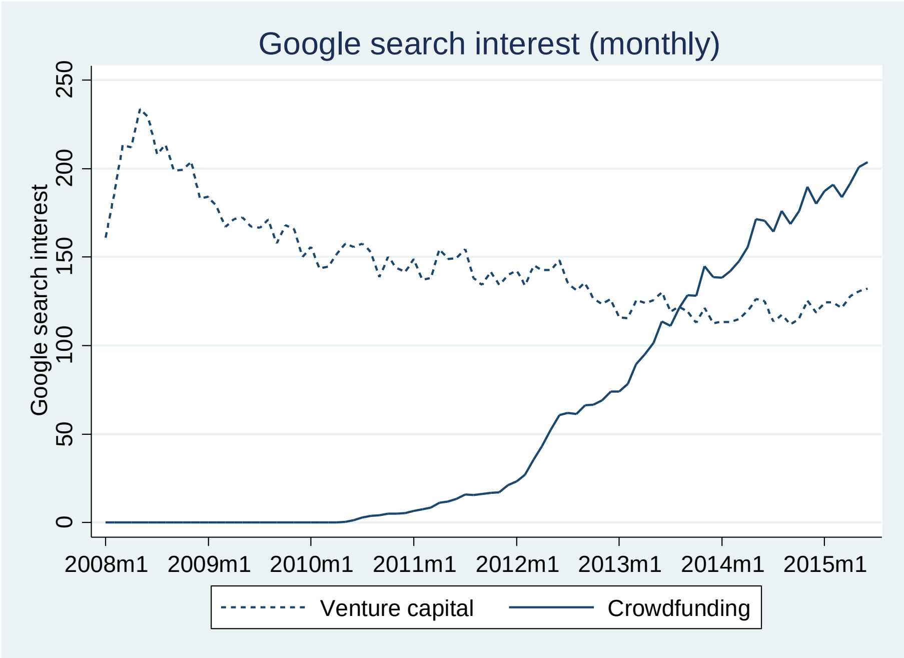

Figure A2. Temporal distribution of local small business loan supply shocks

This graph plots the yearly medians as well as the 5th and 95th percentiles of county-level small business loan supply shocks for the period 2002-2013.

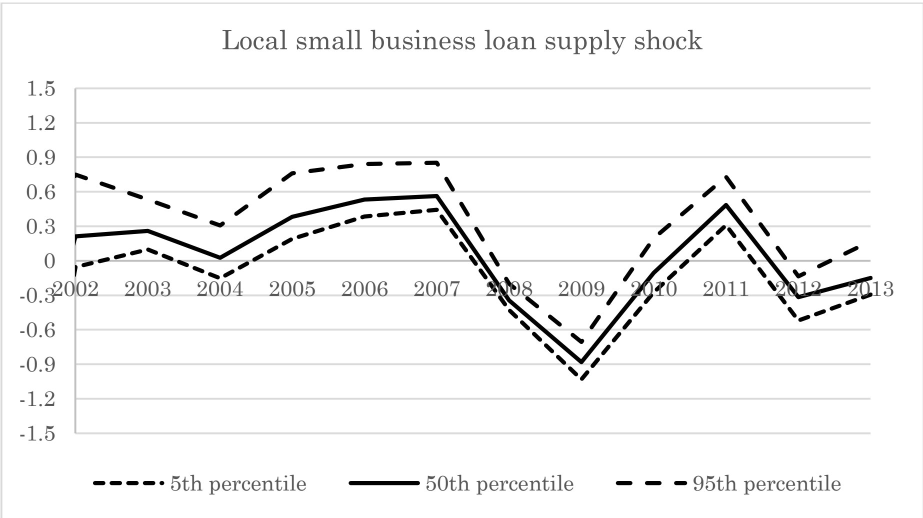

Figure A3. Geographic distribution of small business loan supply shocks during financial crisis years (2008-2010)

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.