Platform-provided Disclosure on Investor Base and Entrepreneurial Success: Evidence from Crowdfunding

John (Jianqiu) Bai, Ting Chen, Xiumin Martin, Chi Wan*

Abstract

We employ a sharp regression discontinuity design to identify the causal effects of investor base disclosure on funding outcomes and entrepreneurship success. Starting from February 2016, Kickstarter discloses backer statistics including geographic locations and previous funding experience of the backers once the number of backers for a project reaches 10. Exploiting this discontinuity, we show that the disclosure of investor base information increases the likelihood of funding success by 10% and the amount of funds pledged by 13%. The effect is more pronounced when the project quality is high and for projects with less credible creators, high ex-ante uncertainty, high information asymmetry between creators and backers, and high expected payoff for backers. We also find that investor base disclosure increases the likelihood of product delivery. A policy change analysis with a much larger sample confirms the external validity of our findings.

Keywords: crowdfunding, self-regulation, disclosure, investor base, information asymmetry, discrete RDD, unregulated markets

JEL: M41, G24, L15, O31, D04

* We thank William J. Mayew (The Editor) and two anonymous referees for their insights and advice that significantly improved the paper. We also thank Jeremy Bertomeu, participants and the discussant Philip Wang at the Financial Accounting and Reporting Section Midyear conference 2023, Kathleen Hanley (discussant) at the Western Finance Association conference 2023, and workshop participants at Boston University, Beijing University, University of Oklahoma, New York University, Seoul National University, and Washington University in St. Louis. John (Jianqiu) Bai is from the D'Amore-McKim School of Business at Northeastern University, Boston, MA 02115 and can be reached at j.bai@northeastern.edu; Ting Chen is from the College of Management, University of Massachusetts Boston, Boston, MA 02125 and can be reached at Ting.Chen@umb.edu; Xiumin Martin is from the Olin Business School at Washington University in St. Louis, 1 Brookings Dr, St. Louis, MO 63130 and can be reached at xmartin@wustl.edu; Chi Wan is from the College of Management, University of Massachusetts Boston, Boston, MA 02125 and can be reached at Chi.Wan@umb.edu. All remaining errors are our own.

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Abstract

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1. Introduction

Self-regulation plays a crucial role in overseeing and governing financial markets.[1] Many notable markets such as the foreign exchange market and Over-the-Counter Derivatives Market rely heavily on self-regulation to ensure compliance with laws, protect investors, and maintain market stability.[2] Existing research argues that exchanges are equipped with the essential motivation and expertise to engage in self-regulation for at least two reasons. First, competition among exchanges compels them to adopt policies to sustain their position in the competitive landscape (Easterbrook 1986). Second, self-regulation offers greater adaptability to changing market conditions and allows for a more comprehensive understanding of industry dynamics when formulating rules, in contrast to government regulation (Zingales 2004). However, theoretical research also argues that surplus-extraction does not necessarily imply efficiency (Lizzeri 1999) and self-regulation might not provide sufficient information to the optimal level (Huddart et al. 1999; Bertomeu and Cheynel 2013). This study seeks to evaluate the efficacy of self-regulation in the context of market-maker-provided disclosures in a crowdfunding market.

Kickstarter is a reward-based crowdfunding market maker that facilitates the matching between entrepreneurs (referred to as project creators) and fund providers (commonly known as backers), who receive tangible rewards in exchange for their contributions. Kickstarter derives its primary revenue from the commissions charged on successfully funded projects. Since its inception, Kickstarter has experienced remarkable growth, having successfully funded over 223,300 projects and attracting pledges worth more than $6 billion from a user base of 20 million backers as of July 2022. However, the platform's substantial market presence and rapid expansion have presented challenges in terms of regulatory oversight and

[1] Some self-regulating agencies include: ten national securities exchanges, one national securities association, ten registered clearing agencies and the Municipal Securities Rulemaking Board (MSRB) currently registered under the Securities Exchange Act of 1934. The exchanges and the National Association of Securities Dealers (NASD), the only registered national association, provide and regulate market facilities, promulgate rules governing the conduct of their members, inspect and monitor compliance of those members, and discipline members for violations. Clearing agencies furnish participants with comparison, clearance, and settlement services. The MSRB establishes rules to regulate the activities of broker-dealers and banks that buy, sell and underwrite municipal securities.

[2] Some examples include the National Futures Association (NFA), the Chicago Board Options Exchange (CBOE), and the International Swaps and Derivatives Association (ISDA).

contractual enforcement. This is further complicated by the dual role played by backers, who function as both consumers and investors within the Kickstarter ecosystem, thus adding complexity to regulatory endeavors (Cascino et al. 2019). The challenges in regulatory oversight are exemplified by the regulatory framework established by the Securities and Exchange Commission (SEC) in 2019, which specifically excluded reward-based crowdfunding from securities regulation.[3] Unlike equity-based or lending-based crowdfunding models, reward-based crowdfunding does not entail the offering of securities or financial returns. Moreover, Kickstarter, being perceived as an intermediary, falls outside the purview of consumer regulation and, therefore, does not bear product liability.

Nevertheless, Kickstarter voluntarily adopted various measures to counteract strong market competition. Some of the major competitors include Indiegogo, CrowdFunder (UK), GoFundMe, Patreon, and Seed&Spark.[4] Our study focuses on a policy introduced by Kickstarter in 2016, referred to as investor-base disclosure (IB DISCLOSE hereafter). Under this policy, Kickstarter dynamically releases information regarding a project's investor base. Once a project reaches a minimum threshold of 10 backers, Kickstarter discloses details such as the number of returning and new backers, as well as the top 10 cities where the backers are located (refer to Figure 1 for examples).[5,6] It is important to note that IB DISCLOSE is distinct from the underlying concept of investor base (IB) as it involves the public release of IB-related information. Given that the information provided by the platform is likely to be perceived as more credible and objective than the information provided by project creators, this study postulates that if the disclosed information is

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[3] https://www.sec.gov/files/regulation-crowdfunding-2019_0.pdf

[4] Indiegogo is geared towards tech innovations, creative projects, and community-focused activities, constituting a major contender for Kickstarter. CrowdFunder (UK) is a UK-based crowdfunding platform that is similar to Kickstarter and Indiegogo. GoFundMe specializes in raising funds for medical expenses or disaster relief. Patreon is a membership-based platform supporting creators through regular contributions from their audience. Seed&Spark offers funding opportunities for independent filmmakers and creative artists.

[5] We use investors and backers interchangeably throughout this paper, both of which refer to individuals who pledge money to Kickstarter projects.

[6] In theory, it is possible that the number of investors can go down below 10 after it reached 10 earlier. However, the number of backers rarely declines. We scrape all projects created after May 8, 2022 on a roughly hourly basis. This process ended on June 16, 2022. During this process, 3,597 projects are scraped for the information about their hourly evolvement. We find that backers rarely cancel their pledges. Only 1.03% projects have experienced a backer withdrawal that reduces the number of backers from 10 to 9.

informative about project quality, IB DISCLOSE can reduce information asymmetry and have an impact on market outcomes.

Prior research (e.g., Agrawal et al. 2014) argues backers on the Kickstarter platform face classic information asymmetry problems. Because the contractual agreement between a backer and a creator pertains to a future transaction, where the product is delivered later, backers are naturally concerned about the creator's capacity to deliver the promised products and ensure their quality. Furthermore, unlike venture capital or private equity funding that typically involve only wealthy, sophisticated, and informed individuals, Kickstarter is open to the general public, with many backers having no prior experience with the platform. Consequently, the presence of information asymmetry can result in adverse selection, deterring backers from participating in the Kickstarter market.

We contend that IB DISCLOSE has the potential to address information asymmetry and thus reduce adverse selection in at least two non-mutually exclusive ways. Firstly, the disclosure of backers' past backing experience can provide certification for project quality, as backers' ability to evaluate creators' ability and project quality improves over time through repeated interactions with the platform (Herzenstein et al. 2011). Therefore, the percentage of investors with past backing experience, if revealed, can function as a sorting device that alleviates information asymmetry between potential backers and the creator.

IB disclosure can also reduce information asymmetry by revealing the geographical diversity of backers. The wisdom of crowds suggests that diverse backgrounds, whether cultural or geographic, produce more informative decisions (Hong and Page 2001; Surowiecki 2004). Consistent with this view, a recent study by Chen (2023) finds that investors’ greater geographic dispersion is associated with more efficient stock price response to earnings news. In addition, in the context of crowdfunding, families and friends are considered related parties of the creator. Since their backing decisions are more likely to be driven by moral support for creators rather than project quality, revealing backers’ geographic information consequently allows potential backers to discern the severity of related party transactions and improve their ability to evaluate project quality.

If IB DISCLOSE improves information precision on project quality, two predictions follow. First, IB DISCLOSE reduces backers' adverse selection, and thus draws more backers to the market. This effect predicts that IB DISCLOSE increases the likelihood of funding success. Second, the more precise information allows backers to sort high quality versus low quality projects, thereby increasing funds flowing to high quality projects and away from low quality projects, which results in more efficient capital allocation. The more efficient capital allocation predicts that IB DISCLOSE increases the likelihood of project success (product delivery) conditioning on projects successfully funded.

To empirically assess the effect of IB DISCLOSE on market outcomes, we employ a discrete regression discontinuity design (RDD) approach, which takes advantage of the unique threshold-based disclosure policy of Kickstarter (Lee and Card 2008). We assume that projects just above the threshold (i.e., with backers just exceeding 10) are comparable to those just below the threshold (i.e., the number of backers just falling below 10), so that any differences in outcomes can thus be attributed to the implementation of IB DISCLOSE. Given the potential bias in the average treatment effect from Lee and Card (2008)'s methodology when the running variable is discrete, we adopt the alternative methods proposed by Kolesár and Rothe (2018) that helps to mitigate this bias in the estimate.

Using a sample spanning the period between February 2016 and December 2021, we find that IB DISCLOSE significantly increases funding success by around 10%. This effect is economically large relative to the average funding success rate of 22.2% in our main sample. Additionally, IB DISCLOSE increases the total amount of funds raised relative to the stated goal by about 13.5%. Importantly, these results are robust to different choices of kernel function (Calonico et al. 2014) or polynomial order, which are critical for assessing the performance of confidence intervals in RDD applications. These results provide evidence that IB DISCLOSE enhances the ability of backers to evaluate the quality of projects and ultimately leads to better market outcomes in terms of funding success and the amount of funds raised.

The threshold-based disclosure policy employed by Kickstarter allows us to use the discrete RDD approach to tackle the endogeneity concern. Another unique feature of Kickstarter enables us to conduct an ideal falsification test to further address the correlated omitted variable issue. Specifically, Kickstarter backfilled the IB information for projects launched before February 17, 2016, providing us with a pre-implementation period to compare our findings. If correlated omitted unobservables are driving our results and remain constant for the pre- and post-implementation periods, we would expect to see similar results in the pre-implementation period. Our falsification analysis shows no evidence of the disclosure effect in the pre-implementation period, suggesting that our results are unlikely to be driven by correlated omitted unobservables. Additionally, we also conduct an extra falsification test using other randomly selected cut-offs of the number of backers (i.e., 5, 6, 14, 15, 20, 30 and 100 backers) for IB DISLCOSE and find that the disclosure effect is not present for these alternative thresholds, suggesting that the effect is unique to the 10-backer threshold.

To further address the concern of correlated omitted variables, we conduct a matched sample analysis using the main sample by matching the projects that are slightly above the disclosure threshold with those that are slightly below the threshold based on pre-existing project, creator characteristics, and project category, using Mahalanobis 1-to-1 matching. Our results continue to hold. We also address the potential concern that agents may be able to manipulate the running variable (e.g., McCrary 2008; Imbens and Wooldridge 2009), which in our case, is the number of backers. We find no evidence that manipulation is the underlying cause of our documented effects.

While our use of the RDD design provides a clean framework for identifying the causal effect of disclosure on project outcomes, we acknowledge the limitation in terms of the external validity of our study's setting. Due to the inherent nature of the RDD, which specifically concentrates on projects with the number of backers around the disclosure threshold, it is difficult to generalize the causal effect of IB DISCLOSE to projects outside this range. We thus urge that caution be exercised when interpreting our estimates. Meanwhile, to further alleviate this concern, we conduct a policy change analysis surrounding 2016 in which Kickstarter instituted the investor-base disclosure policy. This test is in close spirit to difference-in-differences and the sample contains all projects launched after March 2012.[7] Our main finding stays robust and qualitatively unchanged.

To understand the underlying mechanism of our documented effects, we conduct two broad sets of cross-sectional tests. The first set of tests aim to explore the information content of IB disclosure concerning project quality. We investigate whether and how the positive effect of IB DISCLOSE on funding outcomes varies with the proportion of returning backers and the geographical dispersion of backers. If IB DISCLOSE indeed affects both the success likelihood and the amount of fund raised, we would expect the effect to be present mostly for projects with more returning backers and more diverse backers, because investor-base information pertaining to these projects carries a stronger signal. We find results supporting this conjecture: the disclosure effect on funding success and total amount of funding is significantly positive when projects have more experienced and geographically diverse backers. In contrast, the disclosure effect is weaker or indistinguishable from zero for projects having fewer returning backers and a more concentrated backer base.[8]

The second set of cross-sectional tests attempts to explore project characteristics that capture cross-sectional variation in the value of IB disclosure. To this end, we construct four proxies: the ex-ante credibility of creators, the ex-ante uncertainty of project outcomes, the ex-ante information asymmetry between the backer and the creator regarding the project, and the expected payoff to backers. We measure the ex-ante credibility of a creator by his or her track record at Kickstarter, that is, whether a creator has successfully funded a project in the past at Kickstarter. We measure the uncertainty of project outcomes

[7] As discussed in detail in section 4.2.1, Kickstarter disclosed the list of backers that have contributed to a project as well as the timing of their contributions on the project's webpage before March 2012 and removed such information after that.

[8] We expect the IB disclosure effect to be negative for projects with fewer returning backers and a more concentrated backer base, since such investor base signals low product quality. The weaker or insignificant results reported in Table 7 are inconsistent with our expectation. However, when we use the 10th percentile as the cutoff to define projects with fewer returning backers or lower geographical concentration, we do find a generally negative and statistically significant IB disclosure effect (untabulated and available upon request). The evidence suggests the results are sensitive to the choice of cross-sectional cutoffs. In addition, the cross-sectional results might reflect backers' risk aversion. That is, when potential backers do not have investor base information, they can assume the average product quality to be low – comparable to those projects having fewer returning backers and a more concentrated backer base. If so, when IB is revealed, there is either zero or slight upward belief update of project quality. A recent study by Zhou, Cui and Wang (2022) finds evidence of backers' risk aversion using projects at Indiegogo.

based on the proportion of words in the project description that pertain to innovation. The idea is that if a project is innovative and creates a product that is distinctly different from previous projects, it involves a greater amount of uncertainty. We gauge the information asymmetry between the backers and the creators with a commonly used readability measure, namely the Fog index.[9] The higher the Fog index, the more difficult it is to read a document. Finally, we measure the expected payoff to the backers with the average reward size of the project. The higher this value is, the more "stake" backers have in the project. We hypothesize that the value of IB DISCLOSURE is likely the highest when the ex-ante credibility of creators is low, when the uncertainty surrounding project outcomes is high, when backers and creators have a significant information wedge, or when backers' expected payoffs are high. We find evidence consistent with our hypotheses: The positive effect of IB DISCLOSE on funding outcomes is more pronounced for projects with less credible creators, high ex-ante uncertainty, high information asymmetry between creators and backers, and high expected payoff for backers.

Taken together, the evidence of the two sets of cross-sectional tests confirms that our main findings of the IB disclosure effect indeed comes from the information disclosed, and lends further support to our argument that IB disclosure reduces information asymmetry alleviating adverse selection.

In our next set of analyses, we investigate the effect of IB DISCLOSE on the pace of acquiring backers and funding. If IB DISCLOSE reduces information asymmetry, we expect a substantial acceleration in the rate of acquiring additional backers and pledged funds when the number of backers surpasses the disclosure threshold. Our empirical results support this conjecture: By analyzing a sample of projects launched between May 11 to June 15 of 2022, for which we were able to collect backer and funding related information on an *hourly* basis, we observe a significant increase in the speed of gaining additional backers and pledged funds due to IB DISCLOSE,

In our final analysis, we investigate the effect of IB DISCLOSE on the efficiency of capital allocation by focusing on its impact on the probability of product success, measured by the likelihood of a

[9] Fog Index is the number of years of formal education a reader of average intelligence would need to read the text.

product launch. We restrict the sample to successfully funded projects, and find that IB DISCLOSE is associated with an improvement of around 12% in the likelihood of product delivery.

Our study makes three primary contributions. First, we offer evidence on the efficacy of the market-maker-provided disclosures in reducing information asymmetry in an unregulated market where cheap talks can be rampant. Our evidence suggests such disclosures are highly effective in reducing adverse selection and improving the efficiency of capital allocation. Our paper relates to recent empirical studies by Michels (2012), Cascino et al. (2019), Madsen and McMullin (2020), Donovan (2021), and Kim et al. (2022), who have primarily focused on voluntarily disclosed information provided by project *creators*. In contrast, our study places emphasis on backers' information released by the crowdfunding *platform* itself. Compared to creators' voluntary disclosure, platform-provided information is not only verifiable and credible due to the lack of discretion, but also comparable across projects, and thus has the greater potential to alleviate information asymmetry and facilitate capital formation. Therefore, our study complements prior research and highlights an important and effective policy tool for self-regulation. Our study also offers important insights into how crowding platforms can take effective measures to mitigate information frictions and facilitate market transactions, given the industry's significant economic potential and recent growth.

Second, our study contributes to the debate on self-regulation and in particular the regulatory role of platforms. On one hand, prior research (Fischel and Grossman 1984; Easterbrook 1986), argues that exchanges adopt efficient rules, and Farrell and Katz (2000) speculate that platforms can play a social planner role as they capture part of benefits from the efficiency improvement of their ecosystem. Our study offers evidence supporting this argument; on the other hand, prior research (Pirrong 1993;1995; Huddart et al. 1999; Bertomeu and Cheynel 2013) also casts doubt on the efficacy of self-regulation. While our study does not allow to evaluate this argument as we do not observe the counterfactual outcomes of full disclosure, we do observe that, as the crowdfunding market becomes more competitive, Kickstarter replaced the non-disclosure policy with a threshold-based policy. Their policy evolution appears to be consistent with Easterbrook's insight that competitive market improves the efficiency of self-regulation.

Last, our paper relates to prior studies that have explored the impact of disclosure policies on market outcomes in various contexts. For instance, Jiang et al. (2016) demonstrate that the implementation of a disclosure tier system by Pink Sheets LLC enhances the market liquidity of transparent firms. In another study, Gerakos et al. (2013) present evidence indicating that firms listed on AIM, a privately regulated exchange relying on Nominated Advisers for regulatory oversight, exhibit underperformance and engage in earnings management compared to similar firms listed on traditionally regulated exchanges. Their findings suggest that private regulation and enforcement may not be as effective as their public counterparts. Our research highlights that private institutions design policies that promote market efficiency, capital formation, and effective capital allocation.

2. Research setting, literature review and hypothesis development

2.1 Research setting

Crowdfunding has risen in recent years as an increasingly popular way for new entrepreneurs to raise startup capital. Reward-based crowdfunding is a type of crowdfunding where the creators of a new product or service organize campaigns on the online crowdfunding platform to solicit a large group of individuals to contribute to their campaign in exchange for non-financial reward in return (Kuppuswamy and Bayus 2018). The reward systems for this type of crowdfunding are often tiered,[10] with the main rewards being the product or service that the campaign was created to fund. Reward-based crowdfunding is attractive to new entrepreneurs for several reasons: First, it allows them to raise capital without incurring additional debt or giving up ownership or equity in their venture; Second, it allows an entrepreneur to attract a group of funders (customer-investors) who essentially pre-purchase the product and help reduce demand uncertainty (Belleflamme et al. 2015; Strausz 2017; Chemla and Tinn 2020); Third, it allows entrepreneurs

[10] For example, the "Ben's Bread Co." project (https://www.kickstarter.com/projects/bensbread/bens-bread-co/description) offers "Sourdough loaf + hand-written Thank You" for pledges of $15 or more; "Baker's Dozen Sourdough English Muffins" for pledges of $50 or more; "Pre-Opening Party" for pledges of $150 or more; and "Private Bread Class with Ben" for pledges of $1,000 or more.

to harvest the wisdom of crowd by engaging backers in the design of a product (Agarwal et al. 2014; Belleflamme et al. 2015; Cornelius and Gokpinar 2020).

Based in the U.S., Kickstarter is one of the world's largest and most prominent reward-based crowdfunding platforms (Mollick and Nanda 2016). Since its launch in 2009, Kickstarter has helped over 223,300 projects in categories like arts, music, film, games, publishing, food and crafts, design, and technology, and successfully raised over 6.1 billion as of July 2022. Kickstarter campaigns are all-or-nothing. If the campaign reaches its funding goal, the creator will receive the pledged funds (minus a flat 5% platform fee and 3-5% payment processing fee) and will be expected to deliver the promised rewards. On the other hand, for campaigns that do not reach their funding goals, the creators will not receive any of the pledged funds and the backers will have their contributions back. Rewards are typically products that the campaign was created to fund (i.e., copy of an album) or more experiential rewards (i.e., visits to a private cooking class). Rewards can be set for any pledge amount up to the maximum pledge value.[11] In addition, Kickstarter has a policy that backers can only pledge to a project once and backers can only choose one reward tier per pledge. However, backers can modify their pledge amount or reward selection before a project ends.

Compared to traditional funding methods, crowdfunding makes funders and their actions more visible to the public (Belleflamme et al. 2015). One important decision that crowdfunding platforms face is to what extent they should make information regarding funding transactions, funders' identity, and contribution history public. When Kickstarter was founded in 2009, a potential funder could observe a list of the other backers that had contributed to a project as well as the timing of their contributions on the project's webpage. However, Kickstarter removed this information from their website design shortly after March 2012, presumably due to privacy concerns of the backers. In February 2016, Kickstarter introduced a Community Tab, under which it discloses the top ten cities and countries of backers and the numbers of new and returning/experienced backers when projects reach **ten or more backers during the campaign**

[11] See https://help.kickstarter.com/hc/en-us/articles/115005128334-Is-there-a-maximum-reward-tier-value-

process, regardless of the dollar amount invested by these backers and the outcome of the projects (i.e., successfully reaching the funding goal or not).[12] For instance, "Fox Designs/illustrations with Fashion Fit Apparel" is an unsuccessful project ($193 in pledges vs. funding goal of $3,663) with only 9 backers for which no "Community" tab is available and no information about backer is revealed (See Figure 1, Project A).[13] On the other hand, "Step Outside" is also an unsuccessful project ($462 in pledges vs. funding goal of $6,000), but because it has 10 backers, the information on the top 10 cities where backers come from and the number of new vs. returning backers becomes observable under "Community" tab (See Figure 1, Project B).[14] The reason for the policy change is not explicitly stated.[15] However, it is reasonable to believe that this is out of Kickstarter's incentive to design the two-sided markets (creators and backers) to maximize a creator's funding success. That is, given that the platform's revenue hinges critically on whether a project creator can successfully raise funds (i.e., 5% of the total funds raised), if the disclosure of investor base can improve funding success as we postulate, Kickstarter's revenue will thus be maximized.

2.2 Literature review and hypothesis development

Information asymmetries between creators and crowd funders are inherent to the crowd funding market (Belleflamme et al. 2015; Hildebrand et al. 2017; Wessel et al. 2021). Backers in reward-based crowd funding platforms are informationally disadvantaged as they have to rely on the information provided by project creators to evaluate the project quality and creator ability (hidden information) (Akerlof 1970; Grossman 1981).

Reducing the information asymmetry between creators and funders through disclosure help mitigate adverse selection in reward-based crowdfunding markets (Grossman and Hart 1980; Grossman 1981; Milgrom 1981). Previous studies have focused on voluntary disclosures provided by creators to the funders. For instance, using data from Kickstarter, Cascino et al. (2019) find that the amount of disclosure,

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[12] See: https://www.kickstarter.com/blog/introducing-the-community-tab
[13] https://www.kickstarter.com/projects/grandnineofficial/fox-designs-illustrations-with-fashion-fit-apparel
[14] https://www.kickstarter.com/projects/stepoutside/step-outside/community
[15] We have engaged in conversations with multiple employees at Kickstarter but the rationale for the choice of 10 backers as a threshold is regarded as a business secret.

measured as either the length of a project's campaign pitch or the length of its "risks and challenges" section in the campaign page, is positively associated with the amount pledged and the probability of a project being funded. They further document that, subsequent to a rule change on Kickstarter that increases the threat of consumer litigation, the association between project funding and disclosure increases, and the increase is more pronounced in states with stricter consumer protection regulations. Their findings suggest that consumer protection regulation enhances the perceived credibility of disclosure. Madsen and McMullin (2020) and Kim et al. (2022) examine how a policy change at Kickstarter to increase the salience of project risks affects backers' funding decisions. Both studies find that backer support for high-risk projects decreases after the mandatory introduction of a "risks and challenges" section, but that lengthier risk disclosures (Madsen and McMullin 2020), risk disclosures with relevant information, authentic language, and balanced tones (Kim et al. 2022) mitigate this decrease in backer support.

Our setting differs from these existing studies in two important aspects. First, previous studies focus on voluntarily disclosed, unverifiable project information, whereas we focus on objective, verifiable project information provided by the platform. Such distinction is important to isolate the disclosure effect, while holding constant the decision usefulness of the information. In contrast, prior research tests the effect of changes in information usefulness holding disclosure decision constant. Second, an important empirical issue in many studies of the antecedents and consequences of crowdfunding is the endogeneity of project quality. In voluntary disclosure setting, for instance, the underlying project quality can increase both the amount of disclosure provided by creators and the likelihood of funding/product success, thus making it difficult to draw causal interpretations of the results. The 10-backer disclosure threshold in our setting is exogenous to the creators as well as backers, which allows us to apply discrete RDD for a causal interpretation of any identified relationship between disclosure and funding/ project outcomes.

We argue that IB DISCLOSE provides information on product-quality, and therefore reduces information asymmetry between the creator and potential backers in two non-mutually exclusive ways. First, backers' past backing experience can certify project quality. This is because experienced backers tend to have greater ability to evaluate the project quality. Sorensen (2007) makes a similar argument in the context of venture capital. He finds that entrepreneurial companies backed by more experienced venture capitalists are more likely to go public and the result is partially due to sorting−more experienced VCs invest in better companies. Consistent with these arguments, Kim and Viswanathan (2019) use a data set on individual investments in an online crowdfunding platform for mobile applications and find that early investors with experience—particularly investors with app development or app investment experience—have a disproportionate influence on later investors in the crowds, leading to rational herding. In short, investors' past backing experience serves as a signal for product quality and thus reduces information asymmetry between potential backers and the creator.

Second, one of the key benefits of crowdfunding to creators is to harvest the wisdom of crowds (Agrawal et al. 2014; Belleflamme et al. 2015). Prior research suggests wisdom of crowds produces more informative decisions when the crowds come from a diverse background, be it cultural or geographic (Hong and Page 2001; Surowiecki 2004). A recent study by Chen (2023) shows that, in the context of the U.S. equity market, investors' greater geographic dispersion is associated with more efficient price responses to earnings news. Consequently, the disclosure of backers' geographic information can enhance potential backers' ability to evaluate the project quality.

Based on the above two aspects, if IB DISCLOSE reduces information asymmetry and thus mitigates adverse selection, drawing *more* backers to the crowdfunding market, we hypothesize (stated in alternative form):

H1: Disclosing IB information on average increases the likelihood of funding success.

As a corollary to H1, if indeed a higher proportion of returning backers and more geographical diversification indicate higher project quality, we expect the positive effect of investor-base disclosure to be stronger for the projects with these attributes.

H2a: Disclosing investor-base information has a more pronounced effect on the funding success for those projects with a larger proportion of returning backers.

H2b: Disclosing investor-base information has a more pronounced effect on the funding success for those projects with more geographically diverse backers.

If a lower proportion of returning backers and less geographical diversification indicate poor project quality, we expect disclosing IB information will have a negative effect on funding outcomes for projects with these attributes. However, such negative effect can vary with backers' risk aversion. As backers become more risk averse, the negative effect tends to decline or even becomes positive (Brown, Harlow and Tinic 1988).

3. Research Design, Data and Summary Statistics

3.1 Research design

We exploit Kickstarter policy that the geography and previous experience of investors is only revealed upon the number of backers reaching ***ten*** by applying a sharp regression discontinuity design (RDD) for identifying the effect of IB DISCLOSE on funding outcomes. Recent research has made significant progress in the application of RDD when the running variable is discrete (rather than continuous). For example, Lee and Card (2008) (hereafter LC) note that if the running variable takes on only a modest number of distinct values, and the gaps between the values close to the threshold are sufficiently large, which is true in our case, there may be few or no observations close to the threshold. This raises the concern of a large bias in the average-treatment-effect estimator. To address the concern, LC propose using standard errors which are clustered by the running variable. Despite of the popularity (e.g., Oreopoulos 2006; Card, et al. 2008), subsequent research by Kolesár and Rothe (2018) (hereafter KR) theoretically and empirically demonstrate that LC's methodology cannot solve bias problems in discrete RDD settings, and furthermore, the usual cluster-robust standard error formula can yield confidence intervals with worse coverage properties than Eicker-Huber-While heteroscedasticity-robust standard error. To address these issues, KR propose two alternative methods for calculating the confidence intervals with guaranteed statistical properties.[16] KR's methodology has been gaining popularity in recent research in economics and finance (Clark et al. 2020; Machin et al. 2020; Goodman et al. 2021; Chaurey and Le 2022). We therefore follow

[16] We thank KR for providing the software package RDHonest (available at https://github.com/kolesarm/RDHonest).

KR's methodology closely, as it not only achieves asymptotically correct confidence intervals, but also yields the least biased estimate of the average treatment effect for RDD with a discrete running variable.

The running variable in our setting is the number of backers (*Backers*), and the treatment threshold is 11.[17] The running variable has limited support below the threshold with 10 support points (*Backers*∈ {0,1,2,…,9}). Our regression specification is as follows (Lee and Card 2008; Imbens and Lemieux 2008; Lee and Lemieux 2010):

$$\begin{aligned} Funding\ outcome_i &= \alpha_h + \beta_h \cdot IB\_DISCL_i + \sum_{j=1}^{p} \gamma_{h,j} \cdot (Backers_i - 11)^p \\ &+ \sum_{j=1}^{p} \tau_{h,j} \cdot IB\_DISCL_i \cdot (Backers_i - 11)^p + \varepsilon_i \end{aligned} \tag{1}$$

where *i* indexes projects. IB_DISCL is an indicator variable that takes the value of one if the statement, $Backers_i \geq 11$, is true, and zero otherwise. Equation (1) is a linear model with different intercept and slope on each side of the threshold for $p = 1$, and a quadratic specification when $p = 2$.

We use two measures of project funding outcomes. Given the "all or nothing" nature of Kickstarter's fund-raising structure, the first outcome variable is an indicator variable *Success*, which equals to one if a project has reached its funding target, and zero otherwise. The second outcome variable *Pledges* is equal to the total amount of dollars pledged to the project, scaled by the project's stated goal. This measure can exceed a value of one, as projects can be oversubscribed, and some creators leave the projects open to continued outreach and effective sales.

The coefficient β_h is the empirical estimate of the causal effect of the treatment (i.e., IB DISCLOSE) for funding outcomes at the threshold. The parameter h is the bandwidth that determines the range of the running variable over which the specification approximates the true conditional expectation function of

[17] As discussed in section 3.2, we only have the snapshot IB information at the end of funding campaigns, therefore, we cannot separate projects for which the number of backers reached 10 upon funding closure from those before the closure. As our focus is to identify the IB disclosure effect on funding outcomes, the disclosed information of the former should not have any impact on funding outcomes, and thus should be excluded from our analysis. Due to inability to distinguish the two, to be conservative, we exclude all projects with exactly 10 backers to obtain a cleaner sample for clear statistical inference.

funding outcome given the number of backers, and the choice of h affects all coefficient estimates. Given the discrete nature of the running variable, h can only assume the value of natural numbers (i.e., h∈ {1, 2…}). As a result, the discrete RDD specified in Equation (1) cannot be estimated using conventional local linear or kernel regression approaches. In particular, the optimal bandwidth suggested by Imbens & Kalyanaraman (2012) for a continuous running variable is proportional to $N^{-1/5}$ ($h \propto N^{-1/5}$ where N is the sample size), which clearly converges to zero as the sample size tends to infinity. The smallest possible value of h in our setting, however, is 1, regardless of the sample size. Therefore, we closely follow KR to estimate the coefficients in model (1) for our main empirical tests. Furthermore, from a technical standpoint, adopting the KR approach ensures that our inference of a discreet RDD is based on the bounded second derivative, which accounts for the exact finite-sample bias of the estimator and enjoys excellent coverage properties of confidence intervals.

3.2 Sample collection and summary statistics

To examine the effect of IB DISCLOSE in reward crowdfunding, we scrape Kickstarter.com for all 215,741 projects launched between February 16, 2016 (i.e., the date when Kickstarter introduced the community tab) and December 31, 2021.

Because coefficient estimates in RDD are often sensitive to the choice of bandwidth (h), it is important to select the bandwidth in a data-driven automated way to avoid specification searching and ad hoc decisions (Cattaneo et al. 2019). The most popular approach in practice seeks to minimize the finite-sample mean-squared error (MSE) of the local polynomial RDD point estimator (Imbens and Lemieux 2008; Cattaneo et al. 2019). We follow this approach and determine that the optimal bandwidth based on our data is 3. Therefore, we limit our main sample to the projects with the number of backers that fall within this optimal bandwidth window around the 10-backer disclosure threshold. Because we only have the snapshot IB information at the end of funding campaigns (though this information is released and updated continuously after reaching the release threshold), we cannot separate projects for which the number of backers reached 10 upon funding closure from those before the closure. As our focus is to identify the IB disclosure effect on funding outcomes, the disclosed information of the former should not have any impact on funding outcomes, and thus should be excluded from our analysis. Due to inability to distinguish the two, to be conservative, we exclude all projects with exactly 10 backers to obtain a cleaner sample for clear statistical inference. Our final sample consists of 19,407 projects, of which 10,623 projects have 7-9 backers and thus do not provide any disclosure regarding their investor base, while the remaining 8,784 projects have 11-13 backers and thus disclose the top 10 countries/cities of their backers and the number of new vs. returning backers under the "community" tab of the project main webpage. Table 1 provides more details about variable construction. Table 2, Panel A, provides the summary statistics on the analytical sample.

Two observations are noteworthy: First, it is quite difficult to run a successful campaign, as only 22% projects are funded. The total amount pledged for a project is $1,251.0 on average and 35.7% when scaled by its funding goal. The percentage of projects that eventually delivered products is only 7.9. Condition on successful funding, this figure rises to 35.5. While the 35.5% product delivery rate is much lower than 60.4% reported in Mollick (2015), it is likely due to the higher representation of projects with lower amount of funds raised in our sample.[18] Second, funding goals – the amount of money creators look for in their campaign – exhibit large heterogeneity and a highly right-skewed distribution. The average (median) funding goal (*Goa*l) of the projects is $39,811 ($5,000), but the standard deviation is $503,041.

When we examine creator and project characteristics, a few facts also stand out: First, Kickstarter is a rather democratic platform, as creators experience varies widely. This is reflected by the fact that each creator on average has 0.26 successfully funded projects (*Previous Success*).[19] On the other hand, most backers have some experience funding other projects. In our sample, 59.3% backers have previously supported other projects on Kickstarter. When we look at project characteristics, we find that the average

[18] For example, Mollick (2015) focuses his survey on projects raising more than $1,000, whereas in our sample over 50% of projects raised less than $461.

[19] Note that the descriptive statistics for most of the variables in our sample such as the average (median) number of backers, the percentage of successfully funded projects (Funding success), and the average (median) funding goal are lower compared to other studies that use Kickstarter data (e.g., Mollick 2015: Kuppuswamy and Bayus 2018). This is expected given that we limit our sample to the projects with the number of backers that fall within the optimal bandwidth window (3) around the 10-backer disclosure threshold.

length of the project blurb (i.e., the short project summary underneath the project title) (*Blurb Length*) is 15.9 words. The average funding period of a project (*Horizon*) is 34 days.

In Panel B of Table 2, we present the correlation matrix of the key variables used in our analyses. It is worth noting that funding success is positively correlated with product delivery, but the correlation is 0.54 instead of 1, which implies that not all projects that are successfully funded eventually deliver their final products. More importantly, projects with higher proportion of returning backers and lower geographical concentration of backers do seem to have higher funding success and product delivery, which validates our maintained assumption that these two investor-base attributes can signal product quality.[20]

4. Empirical Results

4.1 Baseline results: the effect of investor base disclosure on funding outcomes

We begin by presenting the baseline results on the relationship between IB DISCLOSE and funding outcomes. Table 3 contains the results of estimating Equation (1). In Panel A, we use an indicator variable *Success* to measure project funding success. *Success* is coded one if a campaign reaches its funding goal, and zero otherwise. We choose a polynomial of order 1 for the estimation[21] and present the results using three alternative Kernel functions: triangular, uniform and Epanechnikov Kernels. The coefficient estimate in Column (1) is based on the MSE-optimal bandwidth, 3, as discussed in section 3.2. We also report the coefficient estimates based on two alternative bandwidths, 2 and 4, respectively, in Column (2) and Column (3) as robustness tests.

As is shown in column (1) of Panel A, IB DISCLOSE, which is triggered by the 10-backer threshold, increases the average success rate by about 10.3% (triangular Kernel). Z statistics for this estimate based on KR is around 7 and significant at 1% level. Given the average funding success rate for the projects in

[20] To gain a better understanding of the geographical distribution of Kickstarter projects, we also plot the total number of projects in our sample and their funding outcomes at city level. The untabulated plots suggest that although the projects are highly concentrated in metropolitan areas such as New York, Chicago and Los Angeles, funding outcomes are less geography dependent and more evenly distributed. Therefore, creators from metropolitan areas are more competitive for funding.

[21] All our results hold if we use a polynomial of order 2 (i.e., quadratic specification) instead of order 1. The choice of the order 1 is motivated by Figure 3, which shows that the linear functional form provides a good fit of the outcome variable on both sides of the treatment threshold.

our sample is 22.2%, the IB DISCLOSE effect represents an increase of 46.4% (=10.3%/22.2%). Using alternative bandwidths leads to qualitatively similar results (Columns (2) and (3)).

In Panel B, we re-estimate Equation (1) but replace the binary outcome variable *Success* with a continuous variable, *Pledges*, which is the ratio of the total amount of dollars pledged to the project scaled by the project's stated goal. As shown in column 1, IB DISCLOSE increases the pledges as a percentage of stated funding goal by roughly 13.5% (Z=7.087, P<0.001; triangular kernel). In terms of economic magnitude, the IB disclosure effect represents a 37.8% (=13.5%/35.7%) increase relative to the average project in our sample, for which pledges make up roughly 35.7% of its funding goal.

Figure 2 presents a graphical view of our baseline results. Figures 2.1 and 2.2 display the unconditional means of funding success rate and total dollar amount pledged relative to the project's stated goal for projects with [7,9] and [11,13] backers. Fitted values from nonparametric kernel regressions (i.e., triangular Kernel and local polynomial of order 1), from the right and left of the threshold, are superimposed over these averages. It is evident that both funding success rate and dollar share pledged exhibit a sharp discontinuous increase around the threshold.[22]

In Panel C of Table 3, we augment Equation (1) by including other covariates that are likely to be associated with backer support. Note the RDD with a discrete running variable developed by KR does not allow for further inclusion of covariates. Therefore, as a robustness check, we report the estimated coefficients obtained by a continuous RDD developed by Calonico et al. (2014), Calonico et al. (2018, 2020), and Calonico et al. (2019) with a full set of additional control variables.

The dependent variables are *Success* and *Pledges* in columns (1) to (3) and (4) to (6), respectively. We include as control variables characteristics of the projects themselves as well as of the creators. Specifically, for project characteristics, we first include the length of the project blurb (*Blurb Length*),

[22] As discussed previously, we exclude projects with 10 backers from the empirical analyses. An underlying assumption is that disclosure of investor base does not affect the ability of raising funds for these projects, which implies that their funding success and pledged funds are closer to the ones under no disclosure regime (i.e., # of backers<10) as to the ones under disclosure regime (i.e., # of backers>10). This is indeed what we observe – both the likelihood of funding success and the ratio of pledged funding are closer to the amount as predicted under no disclosure than disclosure (Untabulated).

which is measured as the logarithm of the number of words in the project blurb. Several previous studies have documented that projects with longer descriptions are more likely to achieve funding success and on average obtain more funding (Cascino et al. 2019; Kuppuswamy and Bayus 2018). We also include serval other project characteristics including the project's stated goal (*Goal*), the duration of the funding period (*Horizon*) and whether the project is picked by Kickstarter Staff (*Staff-picked*). Prior studies find that successful projects tend to have a more modest funding goal and a shorter funding period and are more likely to be picked by Kickstarter staff as "project we love" (Kuppuswamy and Bayus 2018).

In terms of creators' characteristics, we control for race (*Minority*), gender (*Female*) and the total number of successfully funded projects that they created before *(Previous success)* (Pope and Sydnor 2011; Gorbatai and Nelson 2015). It is important to control for these creator characteristics as they have been found to impact funding success (e.g., Gafni et al. 2021). We cluster standard errors in Columns (2) and (5) at the product category level. Consistent with the RDD literature, the inclusion of more covariates increases the size of the MSE-optimal bandwidth (Column (1) and (2); Column (4) and (5)). For the purpose of comparison, we also present the results based on the optimal bandwidth size of 3 that we used in the baseline analysis (Column (3) and (6)).

The estimated effect of investor base disclosure on the likelihood of funding success is comparable to the baseline results in both the direction and the magnitude: the IB disclosure at the threshold increases the average success rate by about 5.3%-10% (Columns (1) to (3)). The disclosure effect on the total amount pledged relative to the project's goal is similar in magnitude when compared to the baseline results (11.5%-14.7% vs. 13.5%), and highly significant (Columns (4) to (6)).

Overall, our results are consistent with our main hypothesis (H1) that disclosing IB increases the likelihood of funding success. Because our results are robust to various estimators, we employ the sharp RDD with discrete running variables as our primary specification, due to its clear advantage for analyzing our data.

4.2. Robustness tests

Although the discrete RDD approach facilitates causal identification of the effect of IB DISCLOSE on funding outcomes, we need to ensure the documented effects are indeed due to the platform-imposed threshold-based disclosure. In this section, we conduct several robustness tests to rule out potential alternative explanations.

4.2.1 Falsification tests

As discussed in Section 3.1, when Kickstarter was founded in 2009, a potential backer could see a listing of the other backers that have contributed to a project as well as the timing of their contributions on the project's webpage. However, Kickstarter removed this information from their website design shortly after March 2012. When Kickstarter introduced the community tab and started disclosing investor base information for projects with 10 backers or above in February 2016, they backfilled the investor base information for projects with 10 backers or above that were launched before the community tab was introduced. These variations in Kickstarter disclosure practice presents us two perfect counterfactuals: no project is treated (between March 2012 and January 2016), and all projects are treated (before March 2012). Therefore, we can perform two falsification tests to strengthen the inference that our findings are attributable to IB disclosure, rather than other alternative explanations. We expect no discontinuity in funding outcomes for projects with below 10 backers and above 10 backers.

For the first test, we collect information on Kickstarter projects launched and completed between March 2012 and January 2016 (*non IB-disclosure regime*) and estimate Equation (1) for these projects using the same bandwidth windows as baseline estimates. Table 4 Panel A and Panel B report the estimated results based on the triangular Kernel and the local polynomial of order 1 for the likelihood of funding success and dollar share pledged, respectively. Regardless of the choice of the bandwidth size, the local point estimate of IB disclosure effect around the threshold is statistically indistinguishable from zero for both funding outcome variables. A graphical representation of the estimation results for the falsification test is presented in Figures 3.1 and 3.2. Looking at the figures, we observe a continuous increasing trend in the funding success rate and dollar share pledged over the number of backers surrounding 10, suggesting that there is no discontinuity around the cut-off value in the absence of the investor base disclosure, which is in stark contrast to Figure 2. To address the concern that the results of the falsification test only hold for the period of 2012-2016, we conduct a similar test for projects launched and completed before March 2012 (*full IB-disclosure regime*) as the second falsification test. Consistent with our expectation, Table 4 Panel C and Panel D show no evidence of discontinuity in funding outcomes around the disclosure-threshold cut-off of 10 backers. A graphical representation of the estimation results for the second falsification test is presented in Figures 3.3 and 3.4. Taken together, the evidence from the two falsification tests further assures the causal effect of IB disclosure on funding outcomes.

We conduct additional falsification test by assuming other randomly selected cut-offs for IB DISCLOSE based on projects launched in the same sample period as our main analysis. This test complements the above analysis to address the concern that the above analysis uses the projects that launched in an earlier period and period-specific confounding factors rather than the IB disclosure drive the difference of results between the falsification test and the main test. In untabulated results, we show that the discontinuity of funding success around 10-backer threshold is unique and does not exist for alternative cut-off values such as 5, 6, 14, 15, 20, 30 and 100 backers. Overall, the two sets of falsification tests further assure us that the IB disclosure effect we document is unlikely to be driven by correlated omitted variables, and rule out alternative explanations such as heuristics or different funding dynamics when there are fewer backers vs. more backers.

4.2.2 Matched sample analysis

To alleviate the concern that unbalanced covariates might partially drive our baseline results, we construct a matched sample using Mahalanobis 1-to-1 matching based on pre-existing project, creator characteristics, and project category (Table 5 Panel A) with a caliper of 0.1. The matching process minimizes the Mahalanobis distance of a set of project and creator characteristics between a treated project (the number of backers>10) and a matched control project (the number of backers<10). Intuitively, the Mahalanobis distance can be viewed as a generalization of the Euclidean distance that further considers the correlation structure of the data. Panel A of Table 5 shows that our matching procedure results in a completely balanced treated and control group of projects with respect to all project and creator characteristics. Importantly, Hotelling's T-squared test cannot reject the null hypothesis that covariates examined are balanced between treated (projects with 11-13 backers) and control (projects with 7-9 backers) group (Cattaneo et al. 2019; Sales and Hansen 2014).

We then re-estimate Equation (1) using this matched sample and reports the results in Table 5, Panel B and Panel C. The IB disclosure effect, although a little smaller compared to the baseline, is still significant both statistically and economically: the disclosure of investor base information increases the probability of funding success by 6.67% and the dollar share pledged by 8.28% (column (1), triangular kernel).

4.2.3 A test of the disclosure policy change to address external validity concerns

In order to establish causality, we have so far relied on the RDD design to estimate the impact of IB disclosure and focused on the projects that have their number of backers around the disclosure threshold. However, it is important to acknowledge that the RDD design does not allow us to estimate the causal effect of IB DISCLOSE for projects that fall outside the disclosure threshold. As a result, one might be concerned about the external validity.

To alleviate the concern, we conduct a policy change analysis using *all* projects launched after March 2012. The reason we start from 2012 is that Kickstarter changed the disclosure policy from full disclosure to no disclosure in 2012 as discussed in section 4.2.1. This test focuses on the 2016 disclosure policy change and is in a similar spirit to difference-in-differences. To ensure the comparability between projects under the two regimes (before and after February 2016), we match projects launched after February 2016 (post-IB disclosure period, i.e., the treated group) with those launched between March 2012 and January 2016 (pre-IB disclosure period, i.e., the control group). The matching is based on minimizing Mahalanobis distance (with a caliper width of 0.1) of all covariates listed in Table 5, Panel A as well as the number of backers.

We then estimate the following equation to evaluate the IB disclosure effect:

$$Funding\ outcome_i = \beta_0 + \beta_1 IB\ DISCLOSE_i + \beta_2 \log(1 + \#\ of\ backers_i) + \gamma Controls_i + \varepsilon_i, \quad (2)$$

where *IB DISCLOSE* = 1 if Kickstarter discloses investor base for the project, and 0 otherwise. Therefore, the control group (*IB DISCLOSE* = 0) consists of all projects in the pre-IB disclosure period between March 2012 and January 2016, as well as projects with fewer than 10 backers in the post-IB disclosure period. We include the same set of control variables that account for projects and creators' characteristics as discussed in Section 4.1. The results reported in Table 6 show the coefficient on *IB DISCLOSE* is positive and significant in both column (1) and (2), indicating that investor base disclosure increases the average funding success rate as well as the dollar share of pledges. This evidence provides additional support for the validity of our main analyses, alleviating the concern about external validity of our main findings using the RDD design and a limited sample around the disclosure threshold.

4.3 Mechanism: heterogeneity in investor base effects

In this section, we explore the cross-sectional heterogeneity in the effect of disclosure of investor base on funding outcomes, shedding light on the mechanisms for our findings. We focus on two broad categories of factors, with the first category capturing variation in the information content of IB disclosure about project quality (i.e., high vs. low), and the second one partitioning projects based on ex ante creator or project characteristics associated with the value of information to be high vs. low.

4.3.1 Project quality revealed by the disclosed information

4.3.1.1 Share of returning backers

One of the potential channels through which IB disclosure may mitigate information frictions is the certification effect of returning backers. Based on Hypothesis 2a, the disclosure of investor-base information should have a more pronounced effect on the funding success for projects with a larger share of returning backers.

To test this hypothesis, we calculate the median share of returning backers in the subsample of projects with backers $\in$ [11, 10+bandwidth]. The sample of 'more returning backers' combines the two subsamples of projects with backers$\in$ [10–bandwidth, 9] and with backers $\in$ [11, 10+bandwidth] that have the share of returning backers equal to or greater than the median. Similarly, the sample of 'fewer returning backers' joins the two subsamples of projects with backers∈ [10–bandwidth, 9] and with backers∈ [11, 10+bandwidth] that have the share of returning backers smaller than the median.

We re-estimate Equation (1) for both subsamples with a triangular kernel and the local polynomial of order 1 and report the results in Table 7, Panel A. Consistent with our baseline estimates, we present the results based on three alternative bandwidth windows: the MSE-optimal bandwidth of 3 (Column (1)) and the alternative bandwidth window of 2 and 4 (Columns (2) and (3), respectively).The results in Panel A1, Column (1) suggest that the IB disclosure effect is more pronounced for the sample of "more returning backers": IB disclosure increases the average funding success rate by about 10.91% for the subsample of projects that disclose more returning backers, and by about 9.6% for the subsample of projects with fewer returning backers. The paired t-test resampling statistics (with 100 bootstrap runs) is 10.29 and rejects the null hypothesis of the IB coefficient equality between two samples (Konietschke and Pauly, 2014; Eq. 2.5).

Turning to the total dollar amount pledged scaled by the project's goal in Panel A2, the contrast of the IB disclosure effect between two samples is even more striking. For projects with more returning backers, the disclosure of investor base increases the dollar share of pledges by roughly 36.9%, while it increases the dollar share of pledge by 8.38% for the projects with fewer returning backers. The difference in the point estimates is highly significant (the bootstrap t-statistic = 62.61, $P<0.001$). Taken together, these results provide strong evidence that the disclosure of investors' past backing experience mitigates information asymmetry, which in turn affects project funding outcomes.

4.3.1.2 Backers' geographic dispersion

A geographically diverse backer base implies more diverse perspectives of the backers and fewer related party transactions between the creator and her families and friends. Hypothesis 2b predicts that the disclosure of investor-base information has a more pronounced effect on the funding success for projects with a more geographically dispersed backer group. To test this hypothesis, we calculate the backer geographic concentration (*HHI_backer*) by squaring the percentage of backers in each top 10 city and then summing the resulting numbers. The sample of 'diverse backers' combines the two subsamples of projects with backers∈ [10–bandwidth, 9] and with backers∈ [11, 10+bandwidth] that have the *HHI_backer* equal to or smaller than the median. Similarly, the sample of 'concentrated backers' joins the two subsamples of projects with backers∈ [10–bandwidth, 9] and with backers∈ [11, 10+bandwidth] that have the *HHI_backer* greater than the median. We re-estimate model (1) for both samples and report the estimated results in Table 7, Panel B (Panel B1 and Panel B2). The estimates are based on a triangular kernel, the local polynomial of order 1, and three alternative bandwidth windows as in baseline estimates.

The results in Table 7, Panel B suggest that the IB disclosure effect is more pronounced for the subsample of projects with more geographically diverse backers: the IB disclosure increases the funding success rate by about 13.81% (Panel B1, col. 1) and the dollar share pledged by about 56.24% (Panel B2, col. 1) for the subsample of projects that disclose more diverse backers, whereas it only increases the funding success by around 5.12% and the dollar shared pledged by 9.56% for projects with less diverse backers. The paired t-test resampling statistics (with 100 bootstrap runs) suggest that the difference in the IB disclosure effect between the two groups are statistically significant at 1% level in terms of both funding success and the dollar share pledged.

Overall, the first set of cross-sectional tests provide further evidence supporting the argument that IB disclosure mitigates information frictions between creators and backers since the information regarding backers' geographical location and previous experience is valuable to potential backers in assessing the project quality and its likelihood of success. [23] Furthermore, the positive coefficient on IB disclosure for projects with fewer returning backers and less geographical diversification suggests backers might be risk averse. The evidence from a recent study by Zhou, Cui and Wang (2022) suggests this is the case, as they

[23] Using the Mahalanobis-metric matched sample in section 4.2.3, we also estimate the following equation to provide robustness checks for H2 using OLS:

$$Funding\ outcome_i = \beta_0 + \beta_1\ Post_{2016} + \beta_2 Geo_{dummy} + \ \beta_3 Returningbackers_{dummy} + \beta_4 Post_{2016} * Geo_{dummy} + \ \beta_5 Post_{2016} * Returningbackers_{dummy} + \beta_6 Log(1 +\ \#\ of\ backers_i\ ) + \gamma Controls_i\ + \varepsilon_i \qquad (3)$$

For equation (3), we assume that a project launched in the pre-IB disclosure period takes the same value of geographical diversity dummy (experienced backers dummy) as its matched project launched in the post-IB disclosure period. For projects with under 10 backers, the geographical diversity dummy and experienced backers dummy take value of 0 for both pre and post IB disclosure period. We expect the interaction terms in equation (3) (i.e., β_4 and β_5) to be positive based on H2. The untabulated results are consistent with our conjecture.

show backers at Indiegogo exhibit preference for pre-order items over crowdfunding projects, since the former are less risky.

4.3.2 Cross-sectional variation in ex ante creator or project characteristics

In this section, we conduct the second set of cross-sectional tests to investigate the heterogeneity of IB disclosure effect among four creator or project characteristics: the ex-ante credibility of the creator, the ex-ante uncertainty of project outcomes, the ex-ante information asymmetry between the backer and the creator regarding the project, and the expected payoff to backers. We present the results of these additional cross-sectional tests in Table 8.

4.3.2.1 Ex-ante credibility of creators

The first factor we focus on is the ex-ante credibility of creators. When creators have already established a truthful disclosure record, their communication with potential backers is unravelling (Stocken 2000), and as a result, platform-provided disclosures are expected to play a less important role. To proxy for creator reputation, we define *Previous Success* as the total number of previously successfully funded projects belonging to the project creator. We then partition our sample based on whether *Previous Success* is greater than zero or not, and re-estimate our baseline regression in each subsample.

The results of this exercise are presented in Column (1) of Table 8, Panel A and B. Consistent with our expectation, we find that IB DISLCOSE increases the average funding success rate (the dollar share of pledges) by about 16.77% (17.06%) for the subsample where creators have no prior established credibility (i.e., Previous Success = 0), compared to 6.48% (7.22%) for projects with more credible creators (i.e., Previous Success >0), respectively.

4.3.2.2 Ex-ante uncertainty of project outcomes

The second factor we focus on is the degree of ex-ante uncertainty of project outcomes (Column (2) of Table 8, Panel A and B), which is proxied by the percentage of innovation-related words in the project description (e.g., Cascino et al 2019). The idea is that information disclosure is presumably more valuable when the level of uncertainty is high (Levin 2001). We then partition the sample based on the measures of ex-ante uncertainty.[24] We re-estimate equation (1) for both subsamples with a triangular kernel and the local polynomial of order 1. The results in Column (2) suggest that IB DISCLOSE increases the average funding success rate (the dollar share of pledges) by about for 13.64% (22.91%) for this subsample as compared to 8.8% (16.34%) for projects with low ex-ante uncertainty. The paired t-test resampling statistics is 26.12 (21.51) and rejects the null hypothesis of the *IB_DISCL* coefficient equality between two subsamples. Thus, the results are consistent with our expectation that IB disclosure matter more for projects with higher ex-ante uncertainty of outcomes.

4.3.2.3 Ex-ante information asymmetry between backers and creators

The next factor we examine is the degree of ex-ante information asymmetry between the backer and the creator (Column (3) of Table 8, Panel A and B). The rationale is that the value of information disclosure is likely high when information asymmetry is high to begin with (Eleswarapu et al. 2004). We use the FOG index of project description to proxy for information asymmetry. The lower the readability (i.e., high Fog index), the higher is the information asymmetry. We construct the two subsamples (Low readability vs High readability) and re-estimate Equation (1) for both subsamples in a similar way as other cross-sectional tests and with the partitioning variable replaced by Fog index of the project descriptions. Consistent with our conjecture, we find that the positive effect of IB DISCLOSE on funding outcomes is stronger for the subsample of projects with lower readability.

4.3.2.4 Expected payoff to backers

The final factor we focus on is the expected payoff to backers, as measured by the project's reward size. We expect IB DISCLSOURE to be more important for projects with a larger reward size, because the incentive to use value-relevant information increase in payoffs. Consistent with our expectation, we find that the positive effect of IB DISCLOSURE on funding success and the dollar share of pledges is mainly

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[24] The sample of "High ex-ante uncertainty" combines the subsample of projects without IB disclosure and the subsample of projects with IB disclosure that have the percentage of innovation-related words in the project description greater than the median; the sample of "Low ex-ante uncertainty" join the two subsamples of projects without IB disclosure and with IB disclosure that have the percentage of innovation-related words smaller than the median.

driven by the sample of projects with larger reward size (Column (4) of Table 8, Panel A and B): For projects with larger reward size, the IB DISCLOSE increases the average funding success rate and the dollar share of pledges by 18.63% and 25.18% respectively, whereas it has little effect for projects with smaller reward size.

Overall, these additional cross-sectional tests provide further support to our hypothesized relation between IB disclosure and funding outcomes and suggest that IB disclosure reduces information asymmetry between the creator and potential backers and improves the funding outcomes.

5. Additional analyses and discussion

In this section, we conduct additional analyses to further strengthen the causal inferences, test the additional implications of IB disclosure, and rule out alternative explanations.

5.1 IB disclosure on the speed of gaining additional backers and funds

Our results so far convincingly show the positive impact of IB disclosure on funding success. One related and important question is whether the newly released IB information changes the speed at which the project attracts backers and funds around the threshold of 10 backers. Answering this question is technically challenging, because it requires researchers to periodically monitor active projects and collect information on backers and funding status.

To this end, we dynamically scrape active projects between May 11 to June 15 of 2022 for information on backers and funding information.[25] Because of this short period of data collection, about 80% of projects that we scraped were still ongoing as of June 15, 2022. Specifically, for each project, we collect backer and funding related information on an *hourly basis* to ensure that our procedure captures the fast-moving changes in project funding. Overall, we successfully scraped information for 3,597 projects.

To the extent that IB disclosure reduces the information asymmetry between backers and investors, we conjecture that projects that have just reached 10 backers and have IB disclosure made public to prospective investors will accelerate the speed of accumulating backers and funding. Figure 4 presents the

[25] After June 15, 2022, Kickstarter has essentially made it technically impossible to continue to scrape additional information in a dynamic and timely way. Therefore, we had to end our collection efforts then.

results of this dynamic analysis. Figures 4.1 and 4.2 plot the average daily addition in backers and average daily growth rates in pledges, respectively. In both figures, we see a clear "kink" beyond the backer threshold of 10, after which the growth in both the number of backers and pledges increases to a higher level. Take for example the growth in the number of backers, the average daily increase in the number of backers is 0.523 when the number of backers is 9. When the number of backers reaches 11, the daily addition in backers almost triples and reaches 1.439. The difference is statically significant at around 5% level (t=2.426). The percentage growth in pledges also exhibit a similar pattern, but statistically insignificant (t=1.308).

Overall, these results provide additional evidence on the causal impact of IB disclosure on funding success. In particular, by accelerating the speed of gaining backers, IB disclosure contributes to the ultimate higher funding success and total pledged funds.

5.2 IB disclosure on product deliveries

Our next set of analysis examines the effect of IB DISCLOSE on product deliveries. These analyses are motivated by the notion that better information could lead to better resource allocation. If the disclosed information on investor base helps backers to evaluate product quality, we would expect investors to be able to channel funding to high-quality projects and away from low-quality projects. This more effective screening because of IB disclosure will in turn translate into a higher likelihood of product launch.

To test these conjectures, we focus on the successfully funded projects and estimate Equation (1) with the dependent variable- funding outcomes- replaced by Product Delivery. To measure Product Delivery, we first parse all updates issued in the year after the end of funding raising.[26] We then code Product Delivery as 1 if one or more sentences in those subsequent updates does not contain negation ("not" or "n't") and has one of the following word stems, "ship", "sent", "send", "mail", and "receive", and 0 otherwise. The results of this exercise are contained in Table 9. Irrespective of the bandwidth and the sample used, IB DISCLOSE has a strong and positive impact on the probability of product delivery. Take column

[26] For Product delivery, we limit our sample to projects with fund-raising campaign ending before 12/31/2020 to avoid the truncation bias (i.e., projects created more recently have had enough time to accumulate updates).

(1) for example, IB DISCLOSE increases the product delivery likelihood by 12.08%. The evidence underscores that the IB disclosure not only affects funding success, but also improves the efficiency of funds allocation via selecting of high quality projects.

5.3 Strategic Behavior by Backers

While we document a set of robust results on the causal effects of IB Disclosure on funding success, one potential concern is that agents may be able to manipulate the running variable (e.g., McCrary 2008; Imbens and Wooldridge 2009), which in our case, is the number of backers. In particular, to the extent that information on investor base increases funding success, one concern is that backers might strategically wait for a project to reach 10 backers before making her investment (strategic bunching) and/or stage pledge. The idea of staging pledge is that when the number of backers is below 10, backers pledge a smaller amount first; once the number of backers reaches 10, backers' information uncertainty is reduced based on our argument, they will modify the originally pledged amount to a larger amount for high quality projects (i.e., more returning & diverse backers). However, such a strategy would entail constant monitoring of the project webpage, which results in an opportunity cost that can significantly outweigh the benefit of the strategy. Given the small nominal value of a typical pledge and given that backers receive full refunds of their pledges if the project fails to achieve the funding goal, such a strategy does not appear to be plausible.[27]

To further examine the possibility of strategic bunching and/or stage pledge, we decompose our sample period into the earlier period (i.e., 02/17/2016 - 12/31/2017) and later period (i.e., 01/01/2018 - 12/31/2021) and re-estimate our baseline regressions in Equation (1) for two sample periods respectively. We argue that, if there is any strategic behavior of backers in response to the threshold based IB disclosure, it likely occurs in the latter part of the sample period, due to their learning and adjusting the backing strategy gradually. To the extent that strategic manipulation by the backers would reduce the information content of IB disclosure, the effect of IB disclosure on funding success should be weaker in the latter part of our

[27] The mean value of individual pledges in our sample is around \$129.7 and the 25^{th}, $50t^{h}$, and 75^{th} percentiles are \$26.7, \$48.1, and \$98.1, respectively.

sample period. Table A1 shows the results of this exercise. Regardless of the kernel functions employed, we consistently find a positive and significant impact of IB Disclosure on funding success (Panel A) and scaled pledges (Panel B) in both the earlier and latter part of our sample period. More importantly, the coefficient estimates are stable and comparable in magnitude across the two sample periods. Taken together, our results do not indicate any sign of strategic behavior on the part of backers, which mitigates any concerns that the running variable is manipulated.

6. Conclusion

In this paper, we study whether and how one specific form of self-regulation – market-maker-provided disclosure of investor base – influences economic outcomes on an otherwise unregulated platform. Using Kickstarter as a testing laboratory and exploiting a discrete regression discontinuity design, we find robust evidence that investor base disclosure has a strong and positive effect on funding success and the dollar share pledged. Falsification tests suggest that our findings are unlikely to be driven by correlated omitted variables.

In the cross section, we find that the disclosure effect is more pronounced when the quality of information is high (i.e., more returning backers and more geographically diverse backers) and when ex ante creator or project characteristics indicating that the value of information is significant (i.e., less reputable creators, high ex-ante uncertainty about projects, high information asymmetry between creators and backers, and high expected payoff for backers). These results collectively support the notion that IB disclosure affects funding outcomes likely through mitigating information asymmetries between creators and backers. An additional dynamic analysis based on a different sample provides corroborative evidence: Investor-base disclosure accelerates the speed of accumulating both backers and pledged funds. Finally, the disclosure of investor base increases the likelihood of product delivery and capital allocation efficiency.

While the overall positive impact of investor base disclosure on various economic outcomes suggest that platform-provided disclosure is highly effective in improving market outcomes, we also observe significant heterogeneity in investor base disclosures across different platforms. For example, the four major crowdfunding platforms, Indiegogo, CrowdFunder, and GoFundMe all provide information about the total number of backers, Indiegogo and GoFundMe do not provide any information related to backer experience or their geographic location. CrowdFunder does provide the number of projects each backer has funded previously but has no geographic information. Even within Kickstarter, it does not provide full transparency. It only releases the investor base information upon a threshold reached. Therefore, it still remains an important unresolved question as to how platforms set their disclosure requirements, and the answer has implications for marketplace regulation.

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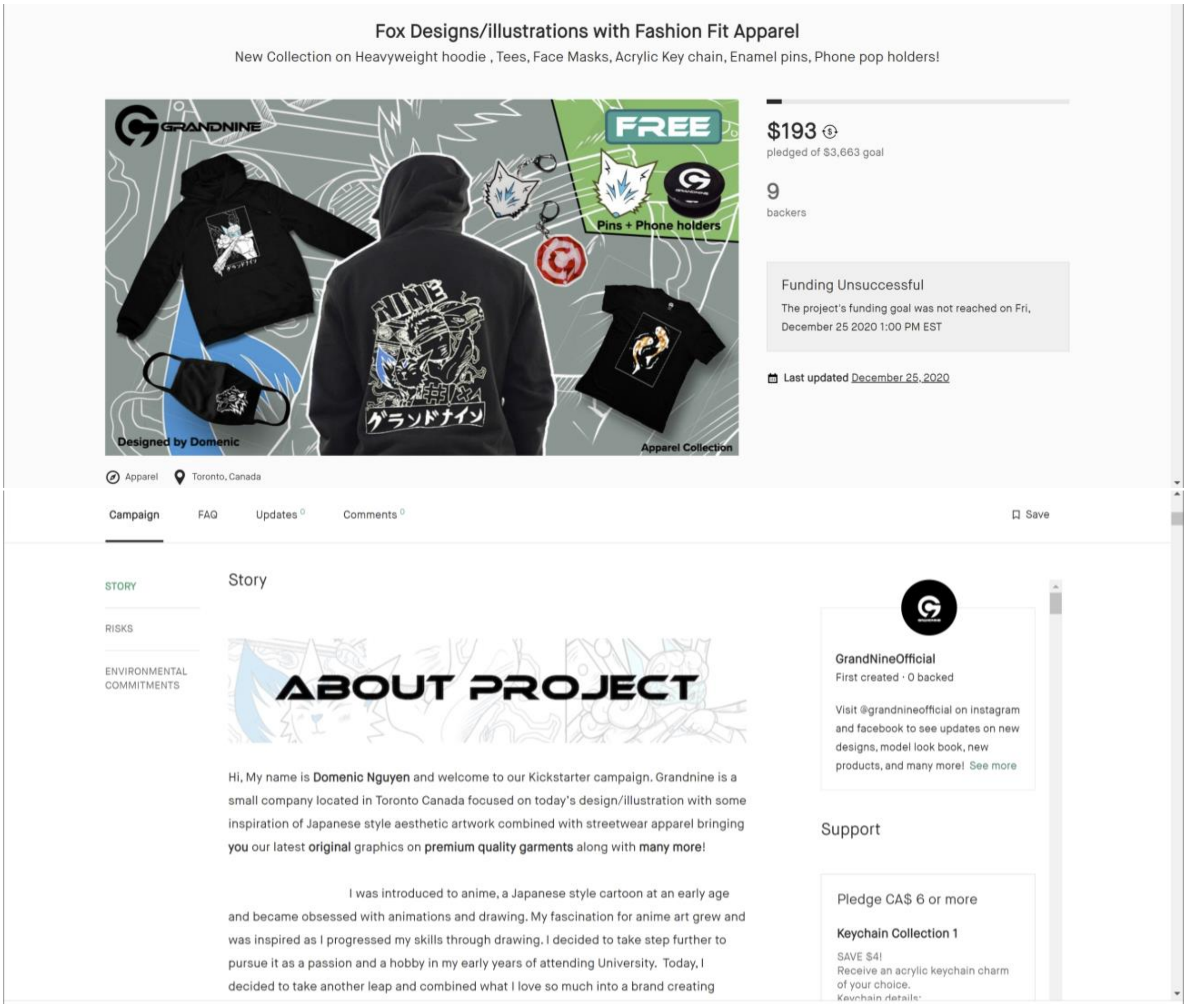
Figure 1. Sample Project Main Pages (9 vs. 10 Backers)

This figure shows the screenshots of two projects from Kickstarter. The first one – Project A, titled "Fox Designs/illustrations with Fashion Fit Apparel" is an unsuccessful project with only 9 backers. The second one– Project B, titled "Step Outside" is an unsuccessful project with 10 backers. Backer information is disclosed under "community" tab for Project B, while backer information is not available for Project A as its number of backers is below the disclosure threshold (i.e., 10 backers).

Project A



Project B

Step Outside

It's better to say, "I remember" rather than "I wish I would've." Inspiring to explore now, before its too late.

$462
pledged of $6,000 goal

10
backers

Funding Unsuccessful

The project's funding goal was not reached on Mon, January 29 2018 11:21 AM EST

Last updated January 29, 2018

Places Oslo, Norway

Campaign Rewards FAQ Updates 0 Comments 0 Community

10 people are supporting Aaron & Isaac

Where Backers Come From
Top Cities

Manama	Bahrain	1 backer
Anaheim	United States	1 backer
Kailua	United States	1 backer
Littleton	United States	1 backer
Overland Park	United States	1 backer
Richmond	United States	1 backer
Seattle	United States	1 backer
Taylorsville	United States	1 backer
West Jordan	United States	1 backer

Where Backers Come From
Top Countries

United States	8 backers
Bahrain	1 backer

New Backers	Returning Backers
7	3
backers had never backed a project on Kickstarter before	backers had backed a project on Kickstarter before

Figure 2. Funding Success and Pledges around the IB disclosure Threshold

This figure graphs the fitted line and 95% confidence interval for average success rates (Figure 2.1) and average pledge percentage (Figure 2.2) for projects with 7-9 backers and 11-13 backers.

Figure 2.1 Average success rate

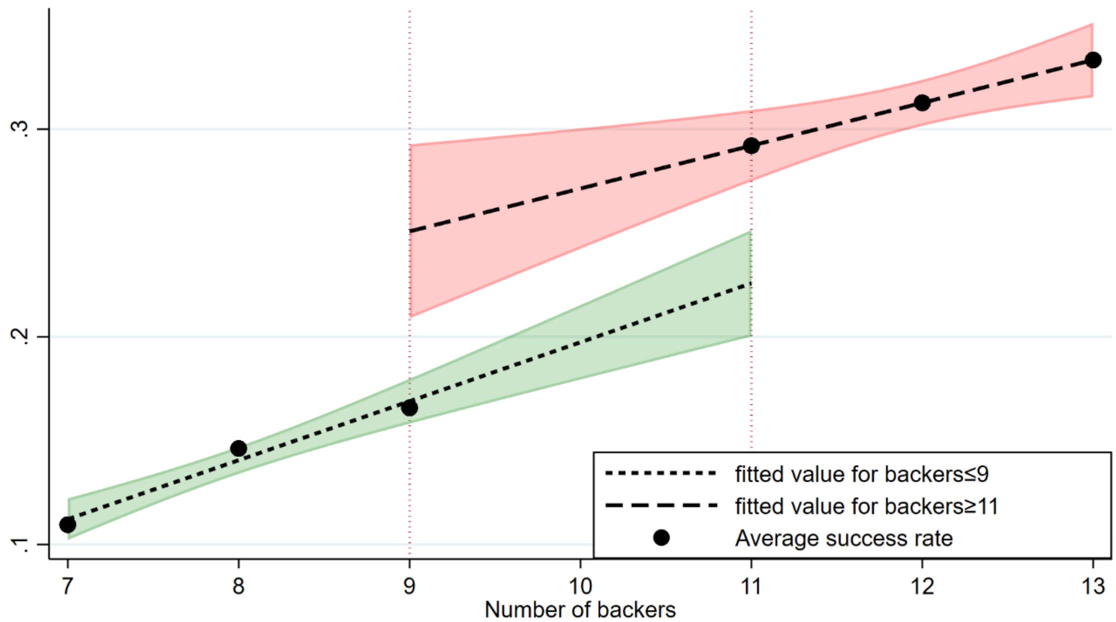


Figure 2.2 Average pledged percentage

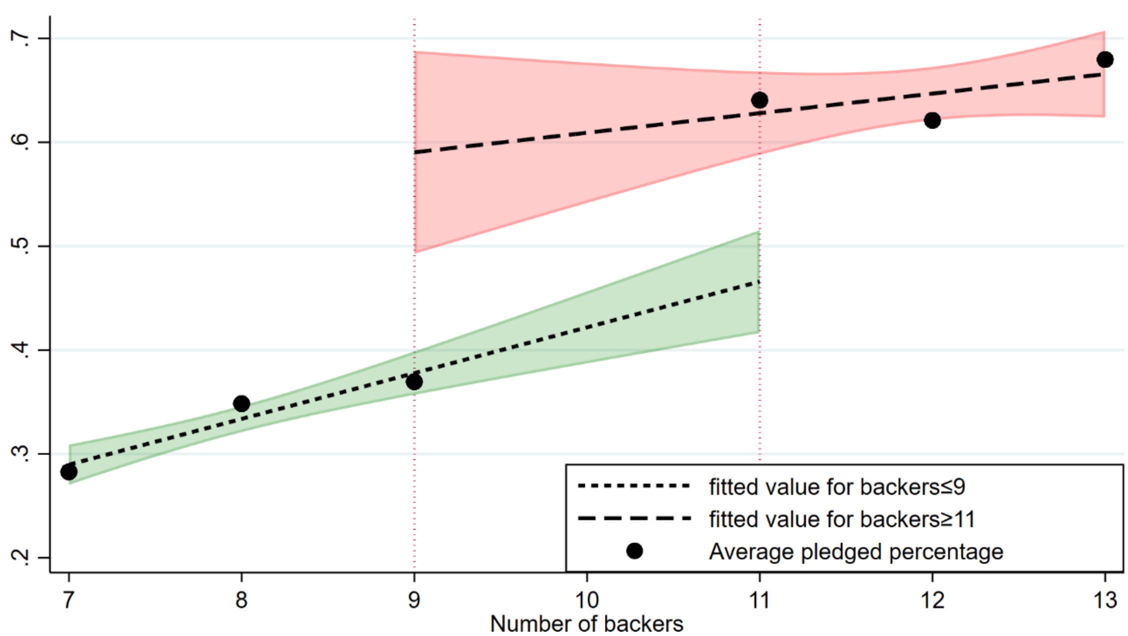


Figure 3. Funding Success and Pledges around the IB disclosure Threshold: Falsification Tests

The figures 3.1 and 3.2 graph the fitted line and 95% confidence interval for average success rates and average pledge percentage, respectively, for projects with 7-9 backers and 11-13 backers for the backfilled projects (*non-IB disclosure regime*) before the community tab was introduced (i.e., projects launched and completed between March 2012 and January 2016). Figures 3.3 and 3.4 graph the fitted line and 95% confidence interval for average success rates and average pledge percentage, respectively, for projects with 7-9 backers and 11-13 backers for the period before March 2012, in which IB information is disclosed for *all* projects (*full IB-disclosure regime*). Details of this institutional feature are contained in Section 4.2.1.

Figure 3.1 ***Non IB-disclosure regime*****: Average success rate**

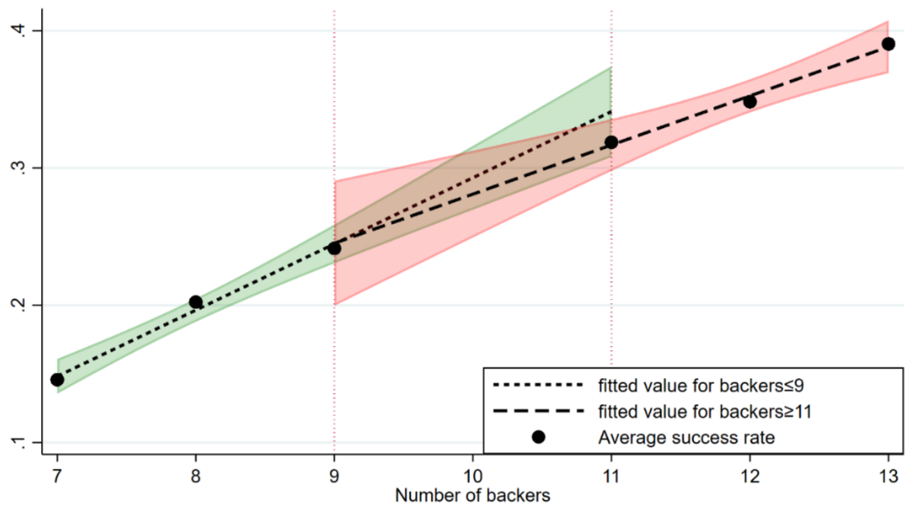


Figure 3.2 ***Non IB-disclosure regime*****: Average pledged percentage**

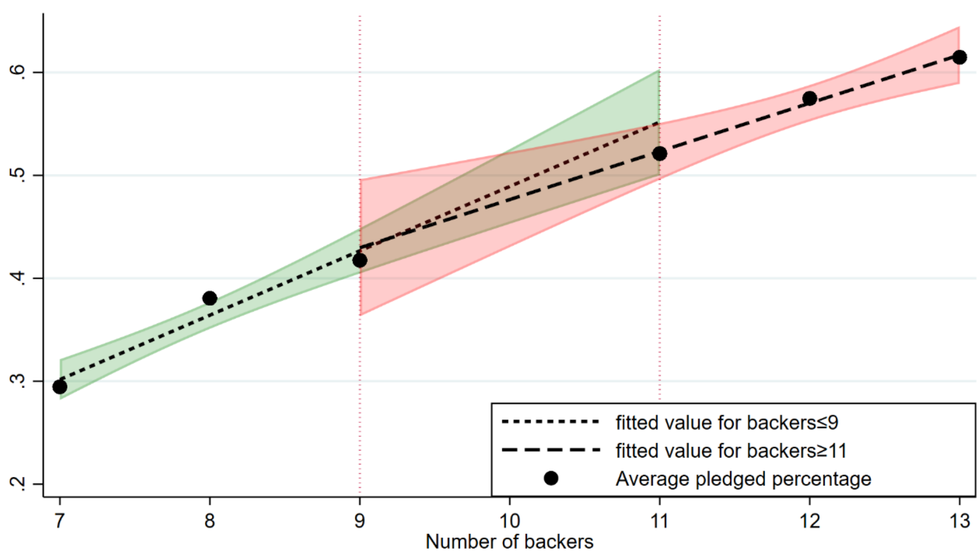


Figure 3.3 ***Full IB-disclosure regime*****: Average success rate**

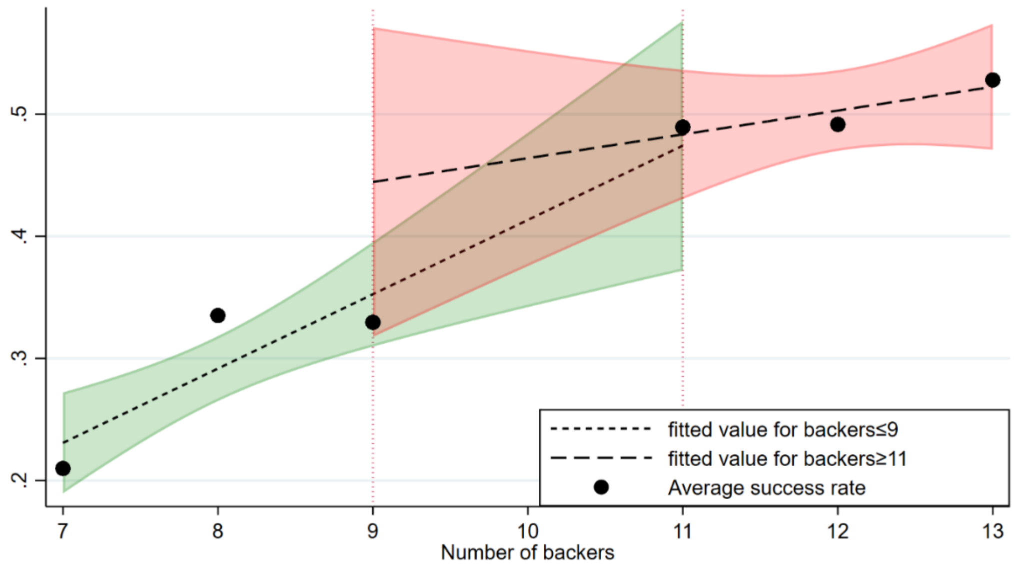


Figure 3.4 ***Full IB-disclosure regime*****: Average pledged percentage**

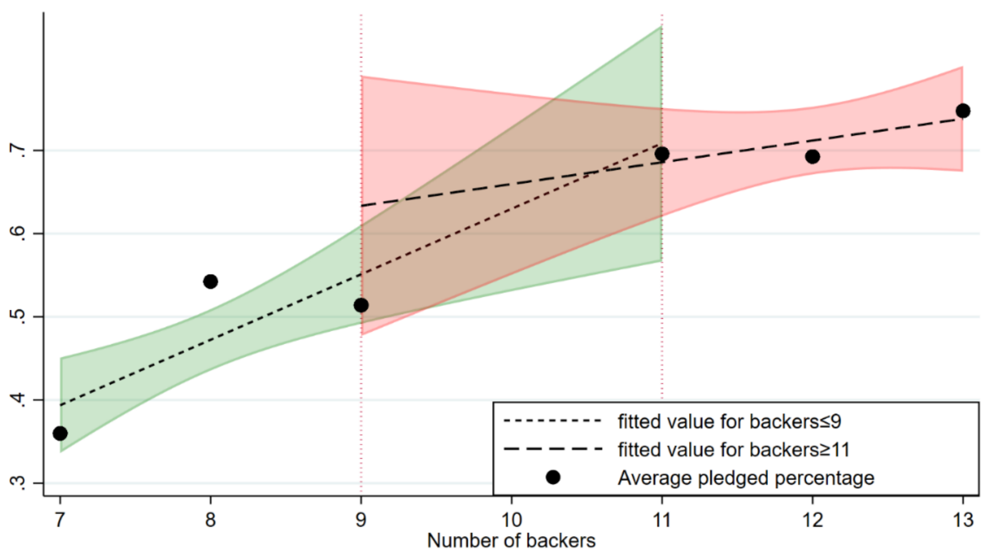
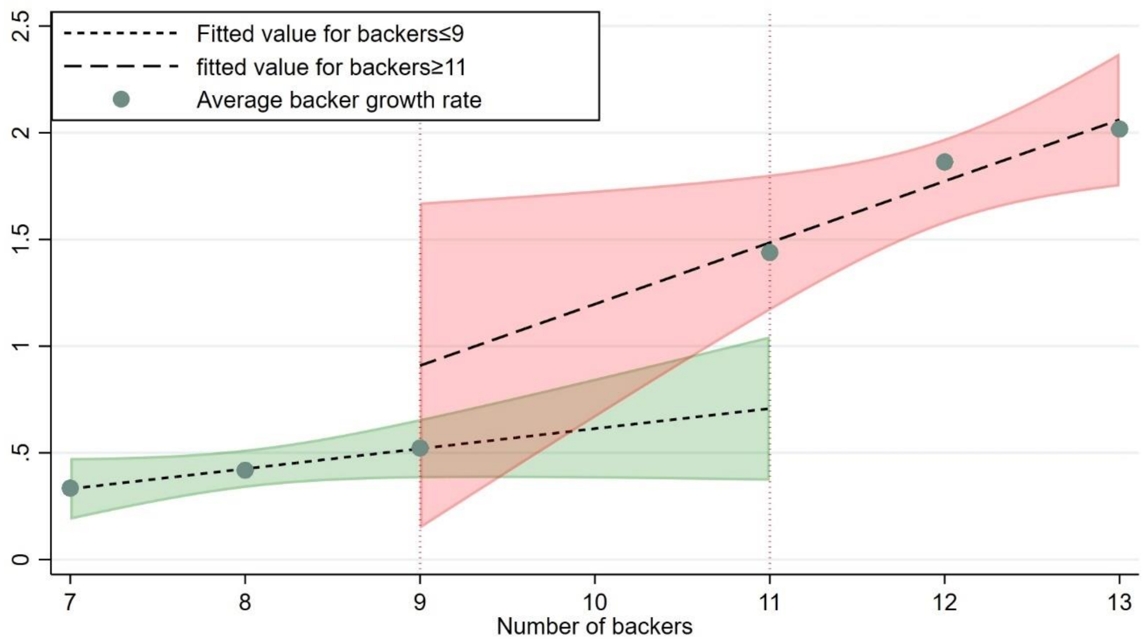


Figure 4. Dynamic Changes in Backers and Funding

This figure graphs the fitted line for average daily addition in number of backers (Figure 4.1) and average daily growth rate in *Pledges* (Figure 4.2) for projects with 7-9 backers and 11-13 backers that were active between May 11 to June 15 of 2022.

4.1 Dynamic addition of new backers



4.2 Dynamic pledge growth rates

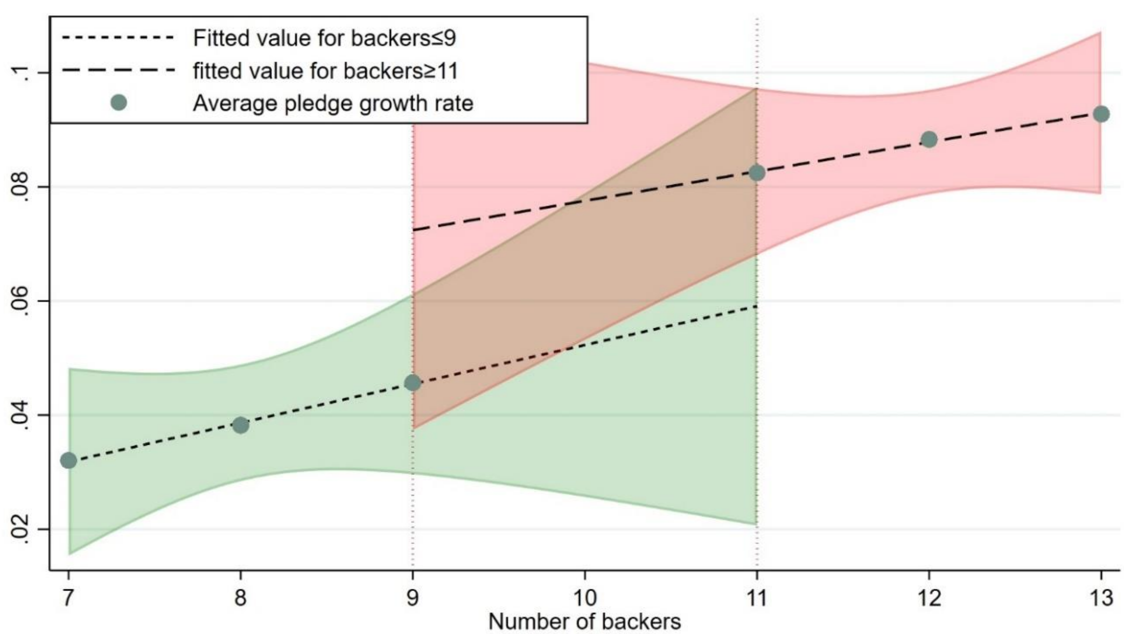


Table 1. Variable Definitions

Crowding Funding Outcome	
Success	An indicator equal to one if the project is successfully funded.
Pledges	Total amount pledged to the project, scaled by the project's stated goal.
Other Outcome Variables	
Product Delivery	We parse all updates issued in the year after the end of fund raising. Product delivery is an indicator variable, coded as one if one or more sentences in those subsequent updates does not contain negation ("not" or "n't") and has one of the following word stems, "ship", "sent", "send", "mail", and "receive".
Creator characteristics	
Minority	An indicator equal to one if the project creator is non-white. It is inferred by using the NamePrism algorithm. The algorithm predicts race probabilities based on six categories: White, Black, Hispanic, Asian, AIAN (American Indian or Alaska Native) and 2PRACE
Female	An indicator equal to one if the project creator is Female. It is inferred by matching the creator's name with the gender data published on https://github.com/lmullen/gender by Lincoln Mullen (2021).
Previous success	The total number of previously successfully funded projects belong to the project creator.
Total projects	Number of total projects submitted by the same creator in the same year-quarter.
Project characteristics	
IB_DISCL	An indicator variable equal to 1 if the total number of backers is greater than the disclosure threshold of 10, 0 otherwise
Backers	The total number of backers at the end of fund raising
Goal	The target dollar amount of funding determined by the project creator.
Horizon	The duration that the project is available for funding on Kickstarter.
HHI _backer	Geographical concentration of backers, calculated by squaring the percentage of backers in each top 10 city and then summing the resulting numbers
Blurb Length	The length of the project blurb (i.e., the short project summary underneath the project title).
Self-mention	An indicator equal to one if the project creator self-mentioned himself/herself in the project description.
Staff picked	An indicator equal to one if the project is staff picked.
Novelty	The percentage of innovation-related words in the project description. The innovation-related word list is obtained from Cascino, Correia, and Tamayo (2019, Appendix C)
Fog index	The Fog index of project description. Defined as 0.4×(average words per sentence + percent of complex words).
Average reward size	The average size of rewards offered in a project.

Table 2. Summary Statistics & Correlation Matrix

This table reports the summary statistics of the sample with a bandwidth of 3 (the finite-sample mean square error (MSE) optimal bandwidth), including all Kickstarter projects with the number of backers varying from 7 to 9 and 11 to 13 and launched between February 16, 2016 and December 31, 2021.

Panel A. Summary Statistics

	Obs	Mean	Std. Dev.	Q1	Median	Q3
Outcome variables						
Funding success (*Success*)	19,407	0.2224	0.4158	0.0000	0.0000	0.0000
Total fund pledged (%) (*Pledges*)	19,407	0.3574	0.4411	0.0375	0.1236	0.5300
Total fund pledged ($)	19,407	1251.0	2858.6	242	461	974
Product delivery[a]	15,602	0.0790	0.2697	0	0	0
Creator characteristics						
Minority	19,407	0.1232	0.3287	0	0	0
Female	19,407	0.1995	0.3996	0	0	0
Previous success	19,407	0.2686	1.0956	0	0	0
Total projects	19,407	0.2530	0.6282	0	0	0
Project characteristics						
IB DISCLOSE (*IB_DISCL*)	19,407	0.4526	0.4978	0	1	1
# of backers (*Backers*)	19,407	9.5232	1.9932	8	9	11
Proportion of returning backers[b]	8,784	0.5928	0.2918	0.3529	0.5833	0.8571
Geographical concentration of backers (*HHI_backer*)[b]	8,784	0.1294	0.0890	0.0694	0.0947	0.1479
Goal	19,407	39811.1	503040.7	1000	5000	15000
Horizon	19,407	34.4255	13.0453	30	30	40
Blurb Length	19,407	15.9271	6.0199	12	17	21
Self-mention	19,407	0.1313	0.3378	0	0	0
Staff picked	19,407	0.0186	0.1349	0	0	0
Novelty	19,407	0.3906	0.5628	0	0.2389	0.6012
Fog index	19,407	11.7496	3.8812	9.7	11.280	13.2
Average reward size	19,407	2257.5	244332.7	32.1	81.0	256.0

[a] For Product delivery, we limit our sample to projects with fund-raising campaign ending before 12/31/2020 to avoid the truncation bias (i.e., projects created more recently have had enough time to deliver the product).

[b] These two variables only apply to those projects that exceed the IB disclosure threshold.

Panel B. Correlation Matrix of Key Variables	(1)	(2)	(3)	(4)	(5)
(1) Funding success(*Success)*	1				
(2) Total fund pledged (%)(*Pledges*)	0.9442***	1			
(3) Product delivery	0.5459***	0.5729***	1		
(4) Proportion of returning backers	0.1072***	0.0605***	0.1623***	1	
(5) Geographical concentration of backers	-0.1289***	-0.1348***	-0.0399***	-0.3999***	1

Table 3. Investor Base Disclosure and Funding Outcomes

This table presents regression results of the effect of IB DISCLOSE (*IB_DISCL*) on funding outcomes (Equation (1)). In Panels A and B, the reported results are based on discrete RDD (Kolesár and Rothe 2018) and use a local polynomial of order 1 for estimation. The bandwidth of 3 (column (1)) is the finite-sample mean square error (MSE) optimal bandwidth. In Panel C, we augment Equation (1) with a set of control variables detailed in Table 1 and report the results based on conventional RDD without considering the discreteness of the running variable. The optimal bandwidths in Columns 1-2 and 4-5 of Panel C are based on the triangular kernel and a local polynomial of order 1; The bandwidth in Columns (3) and (6) is specified as 3. All specifications in Panel C include year and category fixed effects. Moreover, the inference of Columns (2) and (5) is clustered at the product category level. The z scores are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Funding Success (*Success)*

	Success	Success	Success
	(1)	(2)	(3)
Kernel: triangular			
IB_DISCL	0.1029***	0.1067***	0.0963***
	(6.858)	(6.241)	(7.804)
Kernel: uniform			
IB_DISCL	0.0932***	0.1068***	0.0923***
	(7.481)	(6.336)	(8.783)
Kernel: Epanechnikov			
IB_DISCL	0.1020***	0.1067***	0.0951***
	(7.001)	(6.274)	(7.939)
Bandwidth	3	2	4
Observations	19,407	13,486	26,052

Panel B. Total Fund Pledged Scaled by Project Goals (*Pledges*)

	Pledges	Pledges	Pledges
	(1)	(2)	(3)
Kernel: triangular			
IB_DISCL	0.1348***	0.1402***	0.1239***
	(7.087)	(6.456)	(7.924)
Kernel: uniform			
IB_DISCL	0.1197***	0.1421***	0.1040***
	(7.565)	(6.640)	(7.386)
Kernel: Epanechnikov			
IB_DISCL	0.1338***	0.1406***	0.1215***
	(7.248)	(6.504)	(8.001)
Bandwidth	3	2	4
Observations	19,407	13,486	26,052

Panel C. Conventional RDD without Considering the Discreteness of the Running Variable

	Success	Success	Success	Pledges	Pledges	Pledges
	(1)	(2)	(3)	(4)	(5)	(6)
IB_DISCL	0.0749***	0.1004***	0.0525***	0.1299***	0.1471***	0.1152***
	(12.167)	(4.657)	(4.038)	(10.176)	(4.452)	(4.326)
Bandwidth	8.535	15.753	3	10.706	17.995	3
Observations	69,733	110,750	13,486	103,375	113,358	13,486

Table 4. Falsification Tests

This table presents two falsification test results of the effect of IB DISCLOSE (*IB_DISCL*) on funding outcomes. Panel A and B report the results for the backfilled projects (*non-IB disclosure regime*) before the community tab was introduced (i.e., projects launched and completed between March 2012 and January 2016); Panel C and D report the results for projects launched and completed before March 2012, in which IB information is disclosed for *all* projects (*full IB-disclosure regime*). Details of this institutional feature are contained in Section 4.2.1. The reported results are based on Equation (1) using the discrete RDD (Kolesár and Rothe 2018). The estimates are based on a triangular kernel and a local polynomial of order 1. The bandwidth of 3 is the finite-sample mean square error (MSE) optimal bandwidth. The z scores are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. *Non IB-disclosure regime*: Funding Success (*Success*)

	Success (1)	Success (2)	Success (3)
IB_DISCL	0.0023 (0.089)	0.0086 (0.288)	-0.0047 (-0.005)
Bandwidth	3	2	4
Observations	14,294	9,159	19,725

Panel B. *Non IB-disclosure regime*: Total Fund Pledged Scaled by Project Goals (*Pledges*)

	Pledges (1)	Pledges (2)	Pledges (3)
IB_DISCL	0.0046 (0.125)	0.0130 (0.297)	-0.0052 (-0.183)
Bandwidth	3	2	4
Observations	14,294	9,159	19,725

Panel C. *Full IB-disclosure regime*: Funding Success (*Success*)

	Success (1)	Success (2)	Success (3)
IB_DISCL	0.0261 (0.967)	0.0275 (1.066)	0.0280 (0.464)
Bandwidth	3	2	4
Observations	2,230	1,466	3,031

Panel D. *Full IB-disclosure regime*: Total Fund Pledged Scaled by Project Goals (*Pledges*)

	Pledges (1)	Pledges (2)	Pledges (3)
IB_DISCL	0.0364 (0.836)	0.0385 (0.940)	0.0570 (0.342)
Bandwidth	3	2	4
Observations	2,230	1,466	3,031

Table 5. RDD using Matched Sample

This table presents regression results of Equation (1) using the discrete RDD (Kolesár and Rothe 2018) with a matched sample. We use Mahalanobis 1-to-1 matching, which is based on project and creator characteristics in Panel A as well as project category with a caliper of 0.1. Panel A compares the differences in observables of the matched samples. Hotelling's T-squared test is the joint test of equality of means between groups (i.e., backers ∈[11,13] vs backers ∈ [7,9]). In Panels B and C, the reported results are based on a local polynomial of order 1. The z scores are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Difference in Observable Characteristics

	11-13 backers	7-9 backers	Difference	p-value
Minority	0.117	0.117	0	0.979
Female	0.203	0.202	0.001	0.949
Goal	13269.2	13163.4	105.8	0.840
Horizon	33.30	33.43	-0.133	0.549
Blurb Length	15.95	15.96	-0.014	0.895
Self-mention	0.136	0.136	0	1
Staff picked	0.022	0.022	0	1
Ln(1+Previous success)	0.150	0.144	0.007	0.326
Total projects	0.722	0.717	0.005	0.890
Hotelling's T-squared test				0.996

Panel B. Funding Success (*Success*)

	Success (1)	Success (2)	Success (3)
Kernel: triangular			
IB_DISCL	0.0667***	0.0749***	0.0508***
	(3.507)	(3.537)	(3.248)
Kernel: uniform			
IB_DISCL	0.0399**	0.0749***	0.0314**
	(2.537)	(3.537)	(2.363)
Kernel: Epanechnikov			
IB_DISCL	0.0642***	0.0749***	0.0458***
	(3.476)	(3.537)	(3.022)
Bandwidth	3	2	4
Observations	13,426	9,240	17,562

Panel C. Total Fund Pledged Scaled by Project Goals (*Pledges*)

	Pledges (1)	Pledges (2)	Pledges (3)
Kernel: triangular			
IB_DISCL	0.0828***	0.0935***	0.0586***
	(3.472)	(3.415)	(2.985)
Kernel: uniform			
IB_DISCL	0.0351*	0.0935***	0.0300*
	(1.775)	(3.415)	(1.773)
Kernel: Epanechnikov			
IB_DISCL	0.0788***	0.0935***	0.0510***
	(3.403)	(3.415)	(2.871)
Bandwidth	3	2	4
Observations	13,426	9,240	17,562

Table 6. A disclosure policy change test

This table presents the 2016 policy change test of the effect of IB DISCLOSE on funding outcomes (Equation 2). To ensure comparability between projects under the pre- and post-2016 period, we match projects launched after February 2016 (post-IB disclosure period, i.e., the treated group) with those launched between March 2012 and January 2016 (pre-IB disclosure period, i.e., the control group). Specifically, each project in the post-IB disclosure period is matched with replacement with the pre-IB period project, with which, the Mahalanobis distance of all covariates listed in Table 5, Panel A as well as the number of backers is minimized. The caliper width is set to 0.1. We then estimate linear regression with *IB DISCLOSE*, the full set of control variables, and product category and year fixed effects. *IB DISCLOSE* takes the value of zero for all projects launched in the pre-IB disclosure period. Standard errors are clustered by product categories. Coefficient estimates are reported in the row above the *t*-statistics, which are in parentheses. ***, **, and * denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Success	*Pledges*
IB DISCLOSE	**0.015*** **	**0.035*** **
	(8.24)	**(18.51)**
log(1 + # of backers)	0.194***	0.253***
	(78.52)	(22.10)
Female	0.020***	0.006***
	(14.25)	(4.11)
Minority	0.005***	-0.002
	(2.89)	(-1.35)
log(Goal)	-0.102***	-0.144***
	(-268.74)	(-380.51)
log(Horizon)	-0.050***	-0.048***
	(-28.56)	(-27.46)
log(Blurb Length)	0.004***	0.004***
	(2.61)	(2.85)
Self-mention	0.027***	0.019***
	(10.15)	(7.12)
Staff picked	0.032***	0.033***
	(15.84)	(16.18)
log(1 + # Previous success)	0.063***	0.103***
	(31.32)	(51.74)
log(Total projects)	0.003***	0.004***
	(6.96)	(7.76)
Category FE	Y	Y
Year FE	Y	Y
Observations	321,952	321,952
Adj. R^2	0.644	0.756

Table 7. IB Heterogeneity: Share of Returning Backers & Backers' Geographic Dispersion

This table presents the regression results of Equation (1) using the discrete RDD (Kolesár and Rothe 2018) for different subsamples of share of returning backers (Panel A) and backers' geographic dispersion (Panel B). We calculate the median share of returning backers in the subsample of backers∈[11, 10+bandwidth]. The sample of 'more returning backers' ('fewer returning backers') combines the subsample with backers∈[10–bandwidth, 9] and that with backers∈[11, 10+bandwidth] and the share of returning backers equal to or greater than (smaller than) the median. We measure backers' geographic concentration (*HHI _backer*) by squaring the percentage of backers in each top 10 city and then summing the resulting numbers, and calculate the median *HHI_backer* in the subsample of backers∈[11, 10+bandwidth].The sample of 'diverse backers' ('concentrated backers') combines the subsample with backers∈ [10–bandwidth, 9] and that with backers∈ [11, 10+bandwidth] and *HHI_backer* equal to or less than (greater than) the median. The estimates are based on a triangular kernel and a local polynomial of order 1. The z scores are reported in parentheses. The last row reports the paired t-test resampling statistics (with 100 bootstrap runs) for the null hypothesis of the IB coefficient equality between two subsamples (Konietschke and Pauly, 2014; Eq. 2.5). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. IB Heterogeneity: Share of Returning Backers
Panel A1. Funding Success (*Success*)

.	Success	Success	Success
	(1)	(2)	(3)
	More returning backers		
IB_DISCL	0.1091***	0.1141***	0.1028***
	(6.348)	(5.886)	(6.958)
Discrete bandwidth	3	2	4
Observations	15,154	10,130	20,683
	Fewer returning backers		
IB_DISCL	0.0960***	0.0990***	0.0897***
	(5.527)	(5.108)	(6.110)
Discrete bandwidth	3	2	4
Observations	14,876	10,126	20,674
Test of IB equality	10.29	7.860	7.211

Panel A2. Total Funding Pledges Scaled by Project Goals (*Pledges*)

	Pledges	Pledges	Pledges
	(1)	(2)	(3)
	More returning backers		
IB_DISCL	0.3690***	0.3977***	0.3565***
	(8.369)	(8.068)	(9.013)
Discrete bandwidth	3	2	4
Observations	15,154	10,130	20,683
	Fewer returning backers		
IB_DISCL	0.0838***	0.0925***	0.0649**
	(2.704)	(2.647)	(2.510)
Discrete bandwidth	3	2	4
Observations	14,876	10,126	20,674
Test of IB equality	62.61	63.34	74.75

Panel B. IB Heterogeneity: Backers' Geographic Dispersion

Panel B1. Funding Success (*Success*)

	Success	Success	Success
	(1)	(2)	(3)
	Diverse backers		
IB_DISCL	0.1381***	0.1775***	0.1113***
	(4.330)	(4.882)	(4.523)
Discrete bandwidth	3	2	4
Observations	13,916	8,977	19,682
	Concentrated backers		
IB_DISCL	0.0512*	0.0280	0.0576***
	(1.924)	(0.902)	(2.817)
Discrete bandwidth	3	2	4
Observations	14,059	9,192	19,726
Test of IB equality	22.07	38.66	18.02

Panel B2. Total Funding Pledges Scaled by Project Goals (*Pledges*)

	Pledges	Pledges	Pledges
	(1)	(2)	(3)
	Diverse Backers		
IB_DISCL	0.5624***	0.6450***	0.4347***
	(5.762)	(6.002)	(5.740)
Discrete bandwidth	3	2	4
Observations	13,916	8,977	19,682
	Concentrated Backers		
IB_DISCL	0.0956*	0.0543	0.0855**
	(1.857)	(0.963)	(2.122)
Discrete bandwidth	3	2	4
Observations	14,059	9,192	19,726
Test of IB equality	33.49	44.65	36.69

Table 8. More IB Heterogeneity: The role of other project characteristics

This table presents additional cross-sectional test results using the discrete RDD (Kolesár and Rothe 2018) for subsamples based on the partitioning variable of interest. In Column (1), the partitioning variable of interest is ex-ante credibility of creators, proxied by the total number of previously successfully funded projects belonging to the project creator (*Previous Success*). The creator is considered as more reputable if *Previous Success* >0, and less reputable if *Previous Success*=0. In Column (2), the partitioning variable of interest is ex-ante uncertainty of project outcomes, measured by the percentage of innovation-related words in the project description (e.g., Casino et al 2019). Projects with more innovation-related words are considered as having greater ex-ante uncertainty. In Column (3),, the partitioning variable of interest is the readability of project description as measured by FOG index. The higher the FOG index, the lower the readability. In Column (4), the partitioning variable of interest is the expected payoff to the backers, as measured by the average reward size of the project. For all cross-sectional tests, we first calculate the median value of the partitioning variable of interest in the subsample of backers∈ [11, 10+bandwidth]. We then combine the subsample of projects without IB disclosure (i.e., backers∈ [10–bandwidth, 9]) and the subsample of projects with IB disclosure (i.e., backers∈ [11, 10+bandwidth]) that have the partitioning variable of interest greater (smaller) than its median value to create two subsamples. The estimates are based on a triangular kernel and a local polynomial of order 1. The z scores are reported in parentheses. The last row reports the paired t-test resampling statistics (with 100 bootstrap runs) for the null hypothesis of the IB coefficient equality between two subsamples (Konietschke and Pauly, 2014; Eq. 2.5). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Funding Success (*Success*)

	Success	Success	Success	Success
	(1)	(2)	(3)	(4)
	Less reputable creators	**High Ex-ante Uncertainty**	**Low readability**	**Larger Average Reward Size**
IB_DISCL	0.1677***	0.1364***	0.1452***	0.1863***
	(8.68)	(7.03)	(8.12)	(10.42)
Discrete bandwidth	3	3	3	3
Observations	18,243	13,351	14593	14,838
	More reputable creators	**Low Ex-ante Uncertainty**	**High readability**	**Smaller Average Reward Size**
IB_DISCL	0.0648***	0.0880***	0.0669***	0.02206
	(4.30)	(5.34)	(3.89)	(1.34)
Discrete bandwidth	3	3	3	3
Observations	11,787	15,849	14,607	14,842
Test of IB_DISCL equality	14.9	26.12	41.45	104.2

Panel B. Total fund Pledged Scaled by Project Goals (*Pledges*)

	Pledges	Pledges	Pledges	Pledges
	(1)	(2)	(3)	(4)
	Less reputable creators	**High Ex-ante Uncertainty**	**Low readability**	**Larger Average Reward Size**
IB_DISCL	0.1706***	0.2291***	0.2029***	0.2518***

	(8.55)	(5.95)	(9.03)	(11.25)
Discrete bandwidth	3	3	3	3
Observations	18,243	13,351	14,593	14,838

	More reputable creators	**Low Ex-ante Uncertainty**	**High readability**	**Smaller Average Reward Size**
IB_DISCL	0.0722***	0.1634***	0.0766***	0.02356
	(3.81)	(6.83)	(3.51)	(1.12)
Discrete bandwidth	3	3	3	3
Observations	11,787	15,849	14,607	14,842
Test of IB_DISCL equality	42.6	21.51	59.3	107.3

Table 9. Investor Base Disclosure and Product Delivery

This table presents regression results of Equation (1) using the discrete RDD (Kolesár and Rothe 2018) with the dependent variable replaced by Product Delivery for successfully funded projects. Product delivery is an indicated variable, recorded as 1 if one or more sentences in those subsequent updates does not contain negation ("not" or "n't") and has one of the following word stems, "ship", "sent", "send", "mail", and "receive". We limit our sample to projects with fund-raising campaign ending before 12/31/2020 to avoid the truncation bias (i.e., projects created more recently have had enough time to deliver the products).The estimates are based on a triangular kernel and a local polynomial of order 1. The z scores are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Delivery (1)	Delivery (2)	Delivery (3)
IB_DISCL	0.1208 (2.208)	0.1397** (2.206)	0.0763* (1.804)
Bandwidth	3	2	4
Observations	3,230	2,212	4,269

Appendix

Table A1. Earlier vs. Later Sample Period

This table re-estimates Equation (1) using the discrete RDD (Kolesár and Rothe 2018) for the earlier (i.e., 02/17/2016 - 12/31/2017) versus later sample period (i.e., 01/01/2018 - 12/31/2021). The estimates are based on the finite-sample MSE optimal bandwidth of 3 and a local polynomial of order 1. The z scores are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Earlier Sample Period (02/17/2016 - 12/31/2017)

	Success	**Pledges**
	(1)	(2)
Kernel: triangular		
IB_DISCL	0.0939***	0.1342***
	(3.764)	(4.398)
Kernel: uniform		
IB_DISCL	0.0976***	0.1260***
	(4.709)	(4.951)
Kernel: Epanechnikov		
IB_DISCL	0.0951***	0.1346***
	(3.924)	(4.542)
Bandwidth	3	3
Observations	7201	7201

Panel B. Later Sample Period (01/01/2018 - 12/31/2021)

	Success	Pledges
	(1)	(2)
Kernel: triangular		
IB_DISCL	0.1084***	0.1350***
	(5.775)	(5.551)
Kernel: uniform		
IB_DISCL	0.0907***	0.1116***
	(5.814)	(5.725)
Kernel: Epanechnikov		
IB_DISCL	0.1062***	0.1332***
	(5.830)	(5.645)
Bandwidth	3	2
Observations	12206	12206