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Risk Disclosure in Crowdfunding

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Abstract. How should crowdfunding platforms alleviate information asymmetry between creators and crowdfunders? In traditional financial markets, public companies are required to disclose potential risks to their investors, and such risk disclosure requirements are enforced by legal and fiduciary regulations. In the crowdfunding context, however, such information asymmetry concerns are often addressed by crowd-based platforms. In this study, we examine whether and how a regulation to increase the salience of project risks in crowdfunding affects crowdfunders' funding decisions. Leveraging a policy change as an exogenous event, we adopt a difference-in-differences empirical strategy with a matching sample to compare funding decisions before and after the regulation was mandated and show differential effects between high- and low-risk projects. In addition, to strengthen the causality, we directly test individuals' intention to pledge after reading project descriptions with and without risk disclosure in online experiments. We find that increasing the awareness of project risks is associated with inferior funding outcomes of crowdfunding projects, and the effect exists mainly for high-risk projects but not much for low-risk projects. In addition, high-risk projects benefit from a risk disclosure with relevant information, authentic language, and balanced tones that are not overly negative or optimistic. Despite the negative short-term effects, technology funders tend to interpret risk disclosures rationally over time, suggesting a positive long-term effect. Implications for research and insights for practitioners are discussed, particularly the fact that disclosure policies may make crowdfunding markets more sustainable by reducing information asymmetry and helping crowdfunders make more informed decisions.

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Keywords: credibility • crowdfunding • machine learning • natural experiment • risk disclosure

1. Introduction

Crowdfunding, a novel way for project creators to solicit funding online from many individual funders, offers various financial and nonfinancial benefits for project creators, funders, and crowdfunding platforms (Agrawal et al. 2014, Lin and Viswanathan 2016, Hendershott et al. 2021). Project creators who might otherwise struggle to fund their projects can use crowdfunding to raise early subsidies (Younkin and Kuppuswamy 2017, Kim and Hann 2019), gain public exposure, and predict demand for their proposed products (Agrawal et al. 2014). Crowdfunders are often motivated to obtain tangible rewards, but they are sometimes motivated to support friends, family members, and causes they value or to gain early access to innovative products (Burtch et al. 2013, Ryu et al. 2020). For example, they might back a novel 3-D printer project in return for promises to receive the developed product.

Although crowdfunding can be beneficial, funders may lose money from fraud, project failure, or delayed rewards (Agrawal et al. 2014), especially in early stages when project creators lack experience in developing products, dealing with logistics, and handling suppliers. The concerns are exacerbated when project creators fail to provide symmetric information or when the platform appears to have minimal oversight and regulation (Agrawal et al. 2014), which is highly likely given that crowdfunders are inexperienced and lack knowledge about investing. Indeed, a significant proportion of successfully funded design or technology projects on Kickstarter were delivered later than expected (Mollick and Kuppuswamy 2014) although the proportion has declined recently because platforms are imposing tighter requirements.

In traditional financial markets, public companies are required to tell investors about potential risks. Legal and fiduciary regulations enforce risk disclosure requirements to ensure that individual investors are properly informed and avoid overly risky investment behaviors (Xu and Zhang 2013, Zhang and Zhang 2015). In the reward-based crowdfunding context, however, platforms are free from such legal restrictions and regulations. Instead, platform-wide rules and policies are made to help address information asymmetries between creators and funders.

In September 2012, Kickstarter announced a new policy requiring that every campaign page must include a section that discloses risks and challenges and plans for overcoming both. The policy was intended mainly to prevent funders from perceiving the platform as a store for developed products and to ensure that they have the information they need to judge whether projects will be completed as promised. However, the platform does not evaluate or verify the disclosed information and does not resolve disputes caused by misinformation. Instead, creators have full discretion over actual disclosures.

To remain sustainable, the crowdfunding industry must know the effects of reduced information asymmetry (Agrawal et al. 2014, Hildebrand et al. 2016). Funders may distrust the crowdfunding business model if they have to make funding decisions without adequate information, and then promises are unfulfilled. We do not know, however, whether efforts to increase the salience of project risks affect funding responses and, if so, how (Ahlers et al. 2015). Platforms or crowdfunders rarely verify creator-provided information, including risk disclosure. Risk disclosure might be restricted to what is voluntarily disclosed on the project's campaign page, such as project descriptions or pitch videos. As such, funders might neglect the disclosed risk information when making their funding decisions.

Consequently, we wondered whether increased awareness of project risks would affect funding decisions, whether observably high- or low-risk projects would be more affected, and how the content and presentation of risk disclosure would affect risk perceptions. Those questions led us to use both observational and experimental data to examine how Kickstarter's platform policy for reducing information asymmetry affected project perceptions and funding decisions. We drew a natural experiment sample from data regarding projects that started after the policy was introduced. After using a matching technique to form a matched sample, we examined whether mandatory inclusion of risk affected funding decisions and, if so, how the effect differed for high- and low-risk projects. Because risk disclosure is self-disclosed and only available in projects after the policy introduction, we relied on a more objective measure of risk from several ex ante observable characteristics rather than risk disclosure. Furthermore, we examined how the content and the presentation of risk disclosure could mitigate the negative effect by using text mining to show that authenticity, sentiment, and consistency are essential if disclosure is to appear credible. To corroborate findings from the observational data analysis, we conducted two experiments directly examining pledge intentions. By combining the data and methodologies from all analyses, we triangulated our findings to reach conclusions and provide deeper understandings of risk disclosure.

Our analysis of Kickstarter's policy change revealed that it caused project funding to decline but less so when projects were observably less risky. Specifically, on average, the policy decreased total funding by 29.5% and funding success by 8.5% although the decrease occurred mainly in high-risk projects. On a positive note, the policy apparently reduced information asymmetry between creators and funders because crowdfunders became less willing to contribute to high-risk projects after the policy. In the postdisclosure period, inherently risky projects received more negative responses if risk disclosures appeared to be inauthentic or highly optimistic and if product descriptions were inconsistent with risk disclosures. The experimental data show that funders are more willing to pledge when creators of high-risk projects include credible content in their risk disclosures. Importantly, the policy's negative effect apparently fades over time for low-risk technology projects but lasts for nontechnology projects. The effects may have occurred because funders interested in technology projects were aware of potential risks even before the policy and were better able to analyze risk disclosure rationally as time passed. In contrast, funders interested in nontechnology projects were surprised when they read about possible risks and lost interest. In the long term, the policy should benefit the platform by attracting more innovative technology projects that are likely to show higher growth.

Our findings make several academic and practical contributions. Although research has indicated that risk disclosure in public firms has greatly varying effects, even under mandatory disclosure rules, we lack research showing how inexperienced individuals respond to risk disclosure made by early stage private ventures. We provide systematic evidence that early stage ventures affect funding decisions through risk disclosure and that funders' responses vary by project riskiness.

We know that risk information evokes reactions, but research provides scant explanations about the effects of content and presentation. We add to risk disclosure studies by combining text-based techniques to show that the credibility of content and presentation affect funding decisions. That is, mandatory risk disclosure is less harmful and more credible if creators write risk disclosures that appear authentic and are appropriately balanced regarding negativity and positivity and consistent with the main description of the project. We argue that the key is to write risk disclosures strategically.

We extend the crowdfunding literature by highlighting that risk disclosure gives funders valuable information, but we concur that it is subjective, unverified, and potentially misleading. By using various text-based machine learning techniques, we reveal strategies for writing risk disclosures (Gorbatai and Nelson 2015, Gao et al. 2022). As such, we complement previous entrepreneurship research that relies mostly on surveys (Cholakova and Clarysse 2015) and laboratory/field experiments (Brooks et al. 2014, Greenberg and Mollick 2017). Our work is also relevant for researchers and practitioners in the information systems community (Brynjolfsson et al. 2021). The text-based machine learning techniques can be easily generalized to other related domains for analysis.

2. Theory and Literature Review

Researchers examine individual responses to information disclosure. A review of the literature on quality disclosure and certification concludes that, if consumers are dissatisfied with the quality of the disclosure, they switch to higher quality options (Dranove and Jin 2010). A study of the effects of a mandatory disclosure of fat content shows that high-fat dressings lost market share (Mathios 2000). Some studies show that consumers respond inconsistently to information disclosure. A study of moviegoers, for example, indicates that they tend to discount movies that critics have not screened before release (Brown et al. 2012). Disclosure of shipping charges is also shown to affect bidding behaviors: attentive bidders who were aware of exact shipping charges reduced their bids accordingly, but naïve bidders did not (Brown et al. 2010). The mixed findings make it difficult to predict how individuals will react to risk disclosure.

The accounting and finance literatures examine information disclosure in public firms and find that it lowers costs of capital and governance (Healy and Palepu 2001). Mandatory risk disclosure, however, is inherently subjective, nonverifiable, and discretionary, implying that risk reporting rules must include incentives for disclosure (Lajili and Zéghal 2005, Linsley and Shrives 2006, Xu and Zhang 2013). Moreover, they fear that their investments may have adverse outcomes as they perceive greater risk; disclosure often harms firms if it is mainly about downside risks.

When corporate firms are mandated to disclose risks publicly or encouraged to do so voluntarily, the new information increases investors' risk perceptions. For example, an increase in the number of keywords indicating risk is shown to increase uncertainty as indicated by stock return volatility, trading volume, and earnings forecast dispersion (Kravet and Muslu 2013). Required risk factor disclosures are positively related to postdisclosure market-based measures of firm risk and negatively related to postdisclosure information asymmetry (Campbell et al. 2014). We complement those studies by investigating risk disclosure effects on a crowdfunding platform. We examine very early stage crowdfunding projects for which funders are generally nonprofessionals and driven by more than financial considerations.

Disclosure must have *credibility* if investors are to perceive that it is believable, useful, and relevant (Sobel 1985, Mercer 2004, Wang et al. 2018). For corporate firms, market reactions to management disclosure depend on credibility as much as on the amount of new information (Jennings 1987). A synthesis of current research identifies four factors that influence disclosure credibility: management incentives to mislead, management credibility, external and internal assurance, and disclosure characteristics (Mercer 2004). Insider stock purchase can also enhance the credibility of voluntary disclosure (Gu and Li 2007). We add to these studies by examining risk disclosure credibility on a crowdfunding platform, particularly focusing on whether the disclosure aligns with the main description, is authentic, and is presented with a tone that is not too negative or too positive.

Research shows that consumers show protective and avoidant behavior in response to risk information about products and services (Zhu et al. 2012). A survey study, for example, indicates that online shoppers react negatively to perceived risk (Bhatnagar et al. 2000). Consumers are shown to be generally averse to product risk regardless of the seriousness, especially when the risk is framed in terms of losses rather than gains (Bolton et al. 2006, Cox et al. 2006). Disclosure is shown to decrease risk perception and avoidance in an examination of advertisements about remedies for decreasing the severity or likelihood of risk (Bolton et al. 2006). Although those literatures demonstrate how consumers react to risk information about commercial products, they mostly measure behavioral intentions in laboratory experiments instead of observing actual behavior. In contrast, we used risk disclosure data regarding actual early stage ventures to identify how individual funders respond to risk disclosure associated with engineering and manufacturing in project and product development.

Studies on crowdfunding examine how funders assess and use information (Ahlers et al. 2015, Gorbatai and Nelson 2015, Bapna 2019, Kim and Viswanathan 2019). A study of loan requests, for example, observes that funders consider textual information but may fail to correctly assess the economic values related to loan defaults (Gao et al. 2022). Funders are shown to have unconscious biases against African American founders even when campaign pages include somewhat obscure race information (Younkin and Kuppuswamy 2017). Examinations of objective information, such as the number of current backers, the use of videos, and creators' platform activities, provide useful insights for understanding backing decisions and crowdfunding behavior. However, risk disclosure differs in that creators subjectively and voluntarily self-disclose potential risks and challenges associated with their project. Potential funders are more likely to form various interpretations of such subjective and unverifiable disclosures. Some may be repelled; others might form greater trust toward funders.

Risk disclosure is highly likely to cause investors to infer risk, but it is unverifiable, voluntary, and potentially misleading. One of the first papers to examine the risks of early stage firms/projects reveals that, when funders were offered a lower share of equity and could view financial forecasts, they increased funding (Ahlers et al. 2015). The study examines risks associated with ventures but possesses several limitations. It uses a rather crude measure of risk disclosure, fails to indicate a possible mechanism, lacks a good identification strategy, and does not examine risk disclosure contents. In contrast, we use topic modeling, sentiment analysis, and Linguistic Inquiry and Word Count (LIWC) to comprehensively understand the contents of risk disclosure.

3. Study Context and Empirical Setting

3.1. Research Background

On crowdfunding sites, such as Kickstarter, creators host campaigns to raise funds from individual funders. To promote campaigns, creators often post professional videos about their projects, describe the projects in detail, profile their team members, and list reward options (see Online Figure A1, left screenshot). Ideally, crowdfunders can use the information to decide whether to participate in funding. In reality, however, projects are often delayed or fail, so it is difficult for funders to accurately predict success even with disclosed information.

When Kickstarter managers realized that many projects were delayed or eventually fail (Mollick and Kuppuswamy 2014), on September 20, 2012, they mandated that campaign pages must include a new section, called "Risks and Challenges" (Online Figure A1, right screenshot). However, they gave creators full discretion over the self-reported content. Platform managers do not evaluate or verify the disclosed information and do not resolve disputes because of misinformation.

Kickstarter's new disclosure policy provided an exogenous event for a natural experiment setting to study funders' responses to risk disclosure. The policy was announced instantaneously. Most creators were surprised and unprepared as indicated by a plethora of questions and expressions of frustration in the comments.[1] Creators rather quickly complied with the policy.[2] Figure 1 shows a significant amount of disclosure in the first 15 days after the policy was enacted. Online Figure C1 shows the same information for the 24-month window. The risk disclosure section was about one third as long as the main description section.

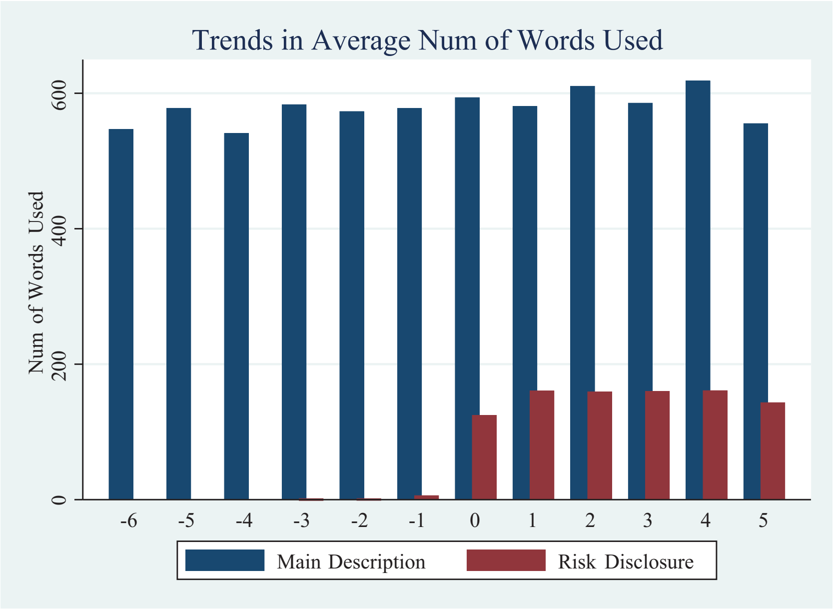
Creators of technology-related projects generally disclosed risks in production, engineering, and distribution, such as prototype development. Creators of nontechnology projects, such as music, disclosed risks related to production and distribution, such as difficulties in finding and/or working with musicians/studios.[3]

3.2. Empirical Strategy

We examine how funders responded to Kickstarter's new policy requiring creators to disclose potential risks and challenges involved in their projects. For our main analysis, we used projects launched from September 20, 2012, to December 20, 2012 (three months after the policy announcement) and compared them with projects initiated in the same period of three months in 2011. Our main reason for using projects created in the previous year is that they were less likely to be contaminated when the new policy was introduced. In addition, we could control for seasonal trends. The main analysis included 5,445 projects launched in the prepolicy period in 2011 and 7,655 projects launched in the postpolicy period.

We adopted several matching methods and algorithms to find the two most comparable groups. The two groups comprise essentially different projects. To rule out the possibility that project characteristics drove our results, we estimated the effect of disclosed risk information using several matching variations. First, we found similar projects through a distance metric that measures the proximity between projects in the multivariate space of observed variables, called *multivariate distance* (MD) (Cochran and Rubin 1973). After calculating MD, we applied two algorithms to find potential matches based on the distances: the nearest-neighbor (NN) matching algorithm and kernel matching algorithm. Propensity score (PS) matching was another strategy to simplify the matching tasks to

Figure 1. (Color online) Trends in Average Number of Words Used in Main Description and Risk Disclosure



Notes. We grouped data by 15-day intervals. The first day in group 0 represents the introduction date of the risk disclosure policy.

one dimension and check robustness. Finally, we used coarsened exact matching for the robustness checks.

Building on prior studies (Geva et al. 2019, Madsen and McMullin 2020, Gong et al. 2021), we included three sets of variables that are shown to affect project outcomes. First, we included variables related to creators' experience: the number of prior backings of the creator and the number of prior projects attributed to the creator. Second, we considered a set of project characteristics expected to affect campaign performance: goal amount, project duration, number of videos, median level of rewards, foreign project, category, and project complexity.[4] Third, we added the textual features of the main description, such as the number of total words used. Together, we matched our samples with a comprehensive set of 11 variables from three dimensions of a crowdfunding project. Foreign project (i.e., those located outside of the United States) and category are exactly matched. Table 1 presents detailed descriptions and descriptive statistics for our variables. Online Table C1 reports balance checks between the prepolicy and postpolicy project groups after MD matching with the NN algorithm as our main sample. After matching, the sample of the prepolicy project group included 5,294 projects; the sample of the postpolicy project group included 3,876. The table indicates that our matching provided comparable samples. Using this matching, we examined how campaign performances changed after the policy.

3.3. Model Specification and Main Variables

Next, we conducted a difference-in-differences (DID) analysis on matched samples to examine how the change in campaign performances differed for high- and low-risk projects after the policy. We estimated the following DID model at the project level:

$$\begin{aligned} \textit{Funding Outcome} = \alpha &+ \beta_1 \textit{Post Disclosure} \\ &+ \beta_2 \textit{Post Disclosure} \\ &\times \textit{Project Risk Index High} \\ &+ \beta_3 \textit{Project Risk Index High} + \boldsymbol{X\delta} \\ &+ \textit{Category FE} + \textit{DW FE} + \textit{MY FE} \\ &+ \epsilon, \end{aligned} \tag{1}$$

where *funding outcome* dependent variables were two project performance outcomes directly related to funding decisions. Log-transformed *amount raised*, measures the total U.S. dollars funding raised, and *campaign success* is a dummy variable equal to one if a campaign is successfully funded. *Post disclosure* equals one if a project is launched after the policy. *Project risk index high* is dummy equal to one if a project has a *project risk index* (the details of construction of *project risk index* are provided in Online Appendix B) greater than two, which is the median of this measure. Our main interest is the interaction between *post disclosure* and *project risk index high*. The regressions also include project- and creator-specific control variables (denoted $\boldsymbol{X}$)—same as the variables used for the matching. We included several variables to control for possible

Table 1. Variable Descriptions and Summary Statistics

Variable	Description	Mean	Standard deviation	Minimum	Maximum
Amount raised	Total amount (in U.S. dollars) raised by the project	8,515	53,371	0	2.9M
Ln(amount raised)	Ln(amount raised+1)	7.30	2.08	0	14.89
Num pledges	Number of pledges in the campaign	112	580	0	34,397
Ln(num pledges)	Ln(num pledges+1)	3.44	1.47	0	10.44
Campaign success	Whether a campaign is successfully funded	0.54	0.50	0	1
Goal amount	Amount (in U.S. dollars) of target funding	15,889	150,920	1	16M
Ln(goal amount)	Ln(goal amount)	8.50	1.41	0	16.59
Num video	Number of videos in the campaign	0.95	1.07	0	41
Ln(num video)	Ln(num video+1)	0.57	0.42	0	3.74
Total words	Number of words used in the campaign description	529	479	3	3,979
Ln(total words)	Ln(total words)	5.95	0.83	1.10	8.70
Median reward	Median reward level (in U.S. dollars) for the project	109	183	1	7,988
Ln(median reward)	Ln(median reward+1)	4.26	0.88	0	8.99
Num own backing	Number of projects previously backed by the campaign's owner	2.00	6.06	0	173
Ln(num own backing)	Ln(num own backing+1)	0.60	0.82	0	5.16
Project duration	Project duration (in days) of a campaign	35	13	1	61
Foreign project	Whether a project is foreign project	0.08	0.27	0	1
Num own projects	Number of projects created by the campaign's owner	0.28	1.77	0	63
Ln(num own projects)	Ln(num own projects+1)	0.13	0.36	0	4.16
Project complexity	Level of complexity of a project	3.79	0.52	2.48	5.57
Daily num projects	Daily number of new projects	89	38	13	217
Project risk index	The sum of the following six dummy variables: inexperienced creator, foreign project, high complex, short main description, no video, no prior backing	2.18	1.06	0	6
Project risk index high	Whether project risk index is greater than 2 (median)	0.38	0.49	0	1
Topic consistency	Topic consistency between the main description and the risk disclosure	0.44	0.27	0	1
Topic consistency low	Whether Topic Consistency is at the bottom 25th percentile	0.25	0.43	0	1
Authenticity	Standardized score to measure writing that is personal and honest in the risk disclosure	32.90	25.22	1	99
Authenticity low	Whether authenticity is at the bottom 25th percentile	0.25	0.43	0	1
Negative tone	A score of how negative the risk disclosure is	0.04	0.04	0	0.81
Negative tone low	Whether negative tone is at the bottom 25th percentile	0.25	0.43	0	1

Notes. The summary statistics are based on a sample of 13,100 projects that covers three months after the risk disclosure policy is introduced in September 2012 and the same period in 2011. The bottom six variables using risk disclosure are available only in postpolicy periods.

changes in external environments around the policy introduction. Two projects might have the same characteristics but have different funding outcomes under different external environments. For example, on a day when the platform has more projects, intense competition could lead to lower funding. Thus, we computed and added the daily number of new projects.[5] We also included day-of-week and month-of-year fixed effects (FEs). Finally, we included category FEs. We clustered standard errors at the category level.[6]

In order to understand if risk disclosure benefited or hindered risky projects more than others, we developed a measure to capture the inherent project risk: *project risk*

Table 2. Validation Tests of Project Risk Index

Variables	(1) Delay	(2) Refund	(3) Negative sentiment
	Panel A: Using crowdfunder comments		
Project risk index	0.025***	0.021**	0.010**
	(0.005)	(0.007)	(0.004)
Ln(num pledges)	0.077***	0.053***	0.008***
	(0.017)	(0.016)	(0.001)
Excess Funding	0.089***	0.051***	0.011**
	(0.013)	(0.009)	(0.004)
Category fixed effects	Yes	Yes	Yes
Monthly fixed effects	Yes	Yes	Yes
Observations	35,656	35,656	13,572
Adjusted R^2	0.327	0.212	0.024
	Panel B: Using data from online survey		
	Delivery likelihood	Overall Risk	
Project risk index	−0.187**	0.164**	
	(0.078)	(0.076)	
Controls	Yes	Yes	
Observations	313	313	
Adjusted R^2	0.016	0.023	

Notes. Panel A reports linear regression estimates. We include two control variables: the log of the total number of pledges (*ln(num pledges)*) and a dummy equal to one if a project received greater than 200% of its funding goal (*excess funding*). More backers can mechanically mean more comments that are likely to have negative comments. Also, when a project has overfunding, it can cause delivery issues. We also include category and month fixed effects. Standard errors are clustered at the category level for panel A and are robust for panel B. In panel B, we included as controls gender, age, education, and crowdfunding familiarity.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

index, which includes several observable project and creator characteristics. The underlying rationale behind this is that project and creator characteristics can contain valuable information to reflect underlying project risks. Generally, three major components can affect project risks: first, project creators, various levels of experience and expertise in crowdfunding and, more generally, entrepreneurship; second, projects themselves as some are inherently more complex and complicated; third, the level of effort creators put into launching campaigns. Building on these insights, we created the measure (*project risk index*) by developing six dummy variables that likely lead to higher project risk and summing them up. We created two dummy variables (*inexperienced*, *no prior backing*) for project creators. *Inexperienced* is equal to one if a creator has not previously launched a project on the platform. We can expect that inexperienced creators are not familiar with crowdfunding and generally have less experience and expertise in creating and managing projects and ventures, thus being likely to have high delivery risks. *No prior backing* is equal to one if a creator has no prior backing on the platform. When creators contribute to other projects they like, they become more engaged with the platform community, accumulate social capital (Zvilichovsky et al. 2015), and are willing to put more effort into their projects and try to deliver on their promises. We should expect the opposite when creators have no prior backing.

Two dummy variables (*high complexity*, *foreign project*) are from project characteristics. *High complexity* is a dummy variable equal to one if a project is at the top 25% in terms of *project complexity*. More complex projects should have inherently higher risks and be less likely to deliver promised rewards. *Foreign project* is another indicator equal to one if a project is located outside of the United States. Foreign projects are likely to have more uncertainties in delivery because of greater geographic distances and cultural and language barriers. Finally, we included two more variables (*no video*, *short main description*) to capture the level of efforts creators put into launching campaigns. When creators use videos to promote projects, this may indicate that creators are sincerely committed and offering a high-quality project (Li et al. 2017). Hence, we created *no video* equal to one if a project has no video in its campaign page on the platform. We generated *short main description* to indicate projects with short main descriptions for which the length of their main descriptions is at the bottom 25%. Projects with short main descriptions can have high uncertainties and indicate low engagement of project creators. We then summed all six dummies to create *product risk index*.

Overall, we generated a measure of project risks by relying on the six observable characteristics. This measure has several advantages. First, this measure is easily computable and scalable because all the variables

Table 3. Matching Estimates of Disclosure Effects

	(1) Nearest-neighbor algorithm	(2) Kernel matching algorithm	(3) Nearest-neighbor algorithm	(4) Kernel matching algorithm
Dependent variable	*Ln(amount raised)*	*Ln(amount raised)*	*Campaign success*	*Campaign success*
Post disclosure	−0.349***	−0.383**	−0.085***	−0.087***
	(0.045)	(0.039)	(0.012)	(0.010)
Observations	13,100	13,100	13,100	13,100

Notes. This table reports estimates of the disclosure effects in a matched sample based on multivariate distance matching. In columns (1) and (3), the number of matches to be searched is three. We use the following project characteristics for matching: log of the goal amount, log of the number of videos, log of the total words, log of the median reward, project duration, foreign project, project complexity, log of the number of prior backing by a focal project creator, log of the number of projects created by a focal creator, and category dummies. We make the category and foreign project exactly matched. Standard errors are computed with bias adjustment as suggested by Abadie and Imbens (2011).

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

rely on machine-readable data. Second, it combines the three sources of project risks (projects, creators, and the effort put into a project). Third, it is available in both prepolicy and postpolicy periods. In contrast, risk disclosure is a self-reported risk and only available in postpolicy periods. Therefore, we believe the measure reflects underlying differences in project risks in a meaningful way.

Further, we adopt two validation tests for our key measure of risk: *product risk index*. First, we show that *project risk index* is significantly correlated with negative words from backers' comments, including feedback and complaints indicating dissatisfaction with the project status. We focus only on successfully funded projects because they are the only ones to have delivery risks. We include 35,656 successfully funded projects within one year before and after the policy introduction for this validation analysis. We extracted all backers' comments and created three dummy variables to indicate the status of project delivery.[7] *Delay* and *refund* are dummies equal to one if comments include the words "delay" or "refund," respectively. *Negative tone* is the number of negatively toned backer comments divided by the number of total backer comments. More negative comments are likely to represent dissatisfaction. Panel A of Table 2 shows that our *project risk index* is positively associated with all three variables regarding issues with reward delivery. High-risk projects are likely to have more comments including the words "delay" or "refund" and more negative comments indicating poor delivery of promised rewards. The findings indicate that our risk measure is meaningful for capturing ex ante project risks.

Second, we conducted a survey to provide additional evidence on the validation of our measure.[8] Three hundred thirteen participants were recruited via Amazon Mechanical Turk (165 males and 148 females; the average age is 38.43). Participants were asked to indicate how likely it is that they would receive the promised rewards on time (1 = very unlikely, 7 = very likely) and how much risk they thought the project would involve (1 = little, 7 = very much). The results in panel B of Table 2 show that our risk index is negatively associated with an expected delivery of the reward and positively with perceived risk, providing additional evidence that our index meaningfully captured funders' perceptions about project risks.

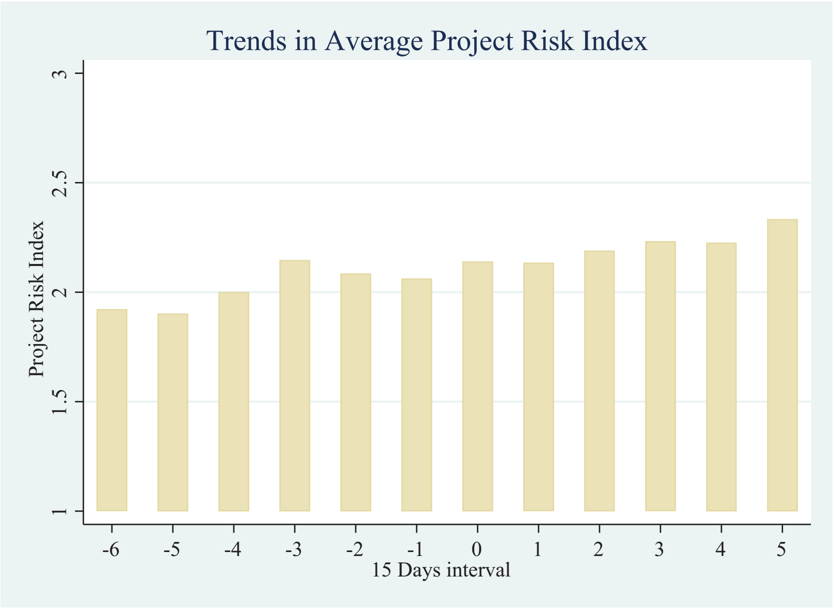
Figure 2 shows the average of *project risk index* in the three months before and after the policy introduction. It exhibits a slightly increasing trend in *project risk index* during this period. When we consider two years, one year before and after the policy, Online Figure C2 shows no significant trend, which suggests that the policy had a minimal effect on the composition of high- and low-risk projects.

4. How Does the Risk Disclosure Policy Affect Funding Decisions?

4.1. Main Effects of the Policy Introduction

Table 3 shows the matching estimates of the policy effects. In column (1), we used the matched sample based on the MD matching algorithm and estimated the average effect of the policy on *Ln(amount raised)*. The policy had a significantly negative effect on the amount of pledges raised. Interpreting the coefficient of *post disclosure*, projects initiated after the policy attracted 29.5% less funding than comparable projects before the policy, a decrease equal to US$2,509. In column (2), we used kernel matching with replacement. The policy again had a negative and significant effect. We then turned to the dependent variable *campaign success*. In column (3), the policy had a consistently negative effect when we used the alternative dependent variable: campaign success. Projects launched after the policy were 8.5% less likely to get successful funding than comparable projects before the policy. Column (4) shows that the result is robust to the alternative matching algorithm. In sum, the risk disclosure policy had a significant and negative effect on project outcomes. After disclosing risks and challenges, creators were more challenged in their efforts to raise funding.

Figure 2. (Color online) Trends in Average Project Risk Index



Note. The first day in group 0 represents the introduction date of the risk disclosure policy.

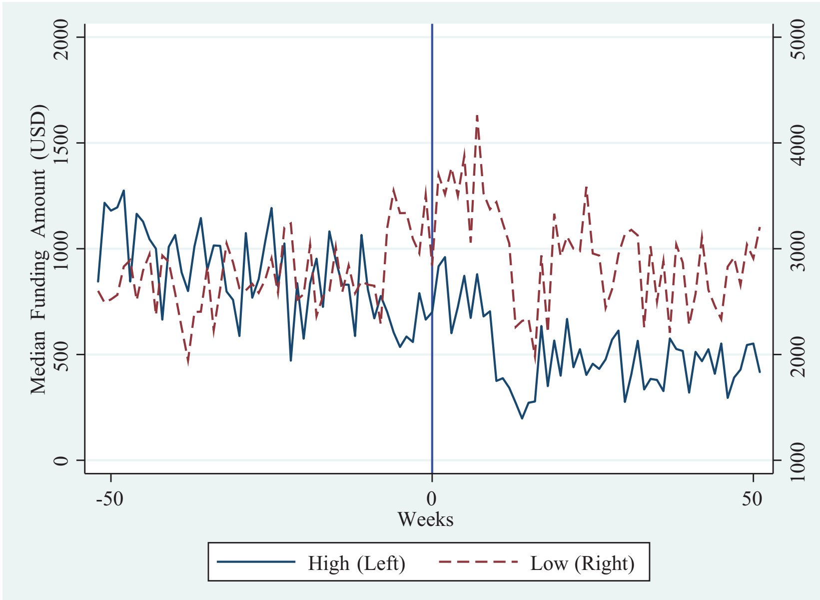
We conducted regression-based analyses using our matched sample. Columns (1) and (3) reconfirm the overall negative effects of the policy for all projects on the amount of funding raised and campaign success as in Table 3 after controlling for project and creator characteristics and external environments in regression models. We then conducted a DID analysis in Equation (1) on the matched sample to examine whether policy effects vary between observably high- and low-risk projects.[9] Essentially, we added the interaction term of *post disclosure* with *project risk index high* to models in columns (1) and (3). Figure 3 shows the weekly median funding amounts in the two-year period. We generally observed no significantly different trends between high- and low-risk projects before the policy but a significant divergence after although the divergence started about two months before the policy, implying that events occurring before but closer to the policy adoption may have deterred funding for some high-risk projects.[10] Therefore, it was unreasonable to use projects right before the policy, which justifies our choice of projects created one year before.[11] We show DID regression results in columns (2) and (4) of Table 4. We examined the interaction terms between *post disclosure* and *project risk index high* and found that, after the policy was introduced, high-risk projects received less funding and had less chance of success relative to low-risk projects. The results suggest that risk disclosure made risk salient, and backers may have more concerns about projects with high risk. The nonsignificant coefficient estimates on *post disclosure* (columns (2) and (4)) indicate that the risk disclosure did not significantly damage low-risk projects. The main results in Tables 3 and 4 indicate that the risk disclosure policy had overall negative outcomes for project creators, but it may have reduced information asymmetry between creators and funders by providing valuable risk information. The crowdfunding market should be more sustainable if funders can leverage such information to differentiate between low- and high-risk projects and avoid high-risk investments.

4.2. Robustness Checks

In this section, we use a set of robustness tests to strengthen our main findings and rule out alternative explanations. We started with alternative matching methods.

4.2.1. Use of PS Matching and Coarsened Exact Matching. As a robustness check, we used PS and coarsened exact matching to construct a comparable sample. Online Tables C2 and C3 contain results from PS matching showing that our main findings are robust to PS matching. Projects, on average, raised smaller funding after the policy; projects with high-risk characteristics showed the strongest decreases. The average effects with PS matching were similar to those with MD matching. We report results from coarsened exact matching in Online Tables C4 and C5. Our main results are again robust to using the coarsened exact matching method.

Figure 3. (Color online) Weekly Median Funding Amount Between High- and Low-Risk Projects



Notes. The first day in week 0 represents the introduction date of the risk disclosure policy. High (low) risk projects have high (low) *project risk index*.

4.2.2. Time-Varying Effects of Disclosure Policy. We examined time-varying effects of the risk disclosure policy by dividing the three-month postpolicy period into the first, second, and final months to observe how the negative effect changed over time. Online Table C6 shows significant effects in each of three months after the policy. The highest negative effect occurred in the final month although the effect remained for three months. When we observed the effects between high- and low-risk projects, as expected, the policy had larger negative effects for high-risk projects and had little negative effects for low-risk projects during the whole period, again confirming that risk disclosures do not significantly harm low-risk projects.

4.2.3. Excluding Technology and Design Categories. On the day Kickstarter.com announced the new policy, it also announced that hardware and product design projects could no longer include product simulations, renderings, or offers of multiple rewards. The prohibitions applied only to hardware and product design projects, so we excluded all projects in the technology and design categories and redid the main analyses. Online Table C7 shows a similar main finding. If the two new guidelines drove the findings, we should not observe a significant effect when we exclude the two categories from the sample.

4.2.4. Falsification Tests. One could argue that risk disclosure had negative effects because the platform faced an increasing rate of delivery issues and had decreased overall funding. Indeed, the delivery issue problem was the catalyst for the new policy. To address the issue, we conducted falsification tests using different hypothetical disclosure dates. We compared projects launched within three months before and after each hypothetical disclosure date. We chose three disclosure dates: June 20, 2012, three months before the policy introduction; March 20, 2012, six months before; and December 20, 2011, nine months before. Online Table C10 shows results of the falsification tests: the interaction terms between *post disclosure* and *project risk index high* were generally not significant for the three dates. When we used June 20, 2012, we observed a significant interaction effect for campaign success, suggesting that funders might have already been aware of potential risks and acted accordingly in months closer to the actual policy introduction date.

4.2.5. Alternative Comparison Group. Although we believe that our main comparison group has advantages, we considered an alternative comparison group, comprising projects launched within three months before the policy in a robustness check. Panel A of Online Table C11 shows that the policy had no significant negative effect between three months before and after the policy. However, it still had more negative effects for high- rather than low-risk projects. Finding no significant overall effect suggests that confounding factors may have contaminated our sample probably because the projects were closer to the actual policy adoption date. When we examined a 12-month

Table 4. Regression Estimates of Disclosure Effects Interacting with Project Risk Index

Variables	(1) *Ln(amount raised)*	(2) *Ln(amount raised)*	(3) *Campaign success*	(4) *Campaign success*
Post disclosure	−0.339***	−0.112	−0.070***	0.005
	(0.060)	(0.072)	(0.017)	(0.017)
Post disclosure × project risk index high		−0.582***		−0.198***
		(0.102)		(0.029)
Project risk index high		−0.004		0.039*
		(0.063)		(0.020)
Ln(goal amount)	0.198***	0.201***	−0.163***	−0.161***
	(0.036)	(0.037)	(0.005)	(0.005)
Ln(num video)	1.206***	1.062***	0.354***	0.325***
	(0.060)	(0.050)	(0.023)	(0.023)
Ln(total words)	0.328***	0.257***	0.050***	0.034**
	(0.048)	(0.057)	(0.013)	(0.014)
Ln(median reward)	0.435***	0.438***	0.084***	0.085***
	(0.037)	(0.036)	(0.007)	(0.006)
Ln(num own backing)	0.623***	0.558***	0.123***	0.109***
	(0.047)	(0.049)	(0.007)	(0.009)
Project duration	−0.015***	−0.015***	−0.004***	−0.004***
	(0.002)	(0.002)	(0.000)	(0.000)
Foreign project	0.418***	0.535***	0.066***	0.091***
	(0.087)	(0.092)	(0.016)	(0.013)
Ln(num own projects)	−0.170**	−0.273***	−0.065***	−0.086***
	(0.074)	(0.082)	(0.010)	(0.014)
Project complexity	−0.140**	−0.087	−0.014	−0.002
	(0.060)	(0.061)	(0.020)	(0.019)
Daily num of projects	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Category fixed effects	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes
Month-of-year fixed effects	Yes	Yes	Yes	Yes
Observations	9,170	9,170	9,170	9,170
Adjusted R^2	0.328	0.335	0.264	0.274

Notes. This table reports linear regression estimates based on a new sample from multivariate distance NN matching estimates. For each column, we use the following project characteristics for matching: log of the goal amount, log of the number of videos, log of the total words, log of the median reward, project duration, foreign project, project complexity, log of the number of prior backing by a focal project creator, log of the number of projects created by a focal creator, and category dummies. Standard errors are clustered at the category level.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

window centered on the policy, we found in panel B of Online Table C11 that the effect was usually negative and stronger for high-risk projects.

5. How Should Creators Disclose Risk Information?

Considering that projects are preliminary and immature, how should creators disclose risks without losing crowdfunders? We examined how creators should disclose risk information to draw the most positive funder responses. We constructed several risk disclosure variables to identify the most credible styles of disclosure, and then interacted them with our observable risk measure, *project risk index high*. The analysis is based on the main rationale that contents and presentations determine whether high risk negatively affects project outcomes. We conducted the analysis using only postpolicy projects because of the availability of risk disclosure data.

To investigate how disclosure content interacts with project risks, we constructed three variables. *Topic consistency* measures the similarity between the main description and the disclosure. Specifically, we first combined risk disclosures and main descriptions to form documents for applying topic modeling (e.g., latent Dirichlet allocation). Each document, whether risk disclosure or main description, is represented as a topic–document distribution. We then obtained topic consistency by calculating similarities, measured by the Kullback–Leibler (KL) divergence of two corresponding topic vectors.[12] Second, we used the LIWC category *authenticity* to measure how extensively the document used personal and self-revealing language rather than detached and guarded language (Pennebaker et al. 2015). *Negative sentiment* captured negative emotion in risk disclosure.

We estimated the following ordinary least squares (OLS) regression for the postpolicy sample:

$$\begin{aligned} \textit{Funding Outcome} = \alpha &+ \beta_1 \textit{Project Risk Index High} \\ &+ \beta_2 \textit{Risk Disclosure} \\ &\times \textit{Project Risk Index High} + \boldsymbol{X\delta} \\ &+ \textit{Category FE} + \textit{DW FE} + \textit{MY FE} \\ &+ \epsilon, \end{aligned} \tag{2}$$

where *funding outcome* is one of the two main project outcome variables: *amount raised* and *campaign success*. We included the same set of control variables and fixed effects as in our main analysis, and clustered standard errors at the category level. Our main interest is the interaction terms between *risk disclosure* and *project risk index high*. *Risk disclosure* is one of the three variables created from risk disclosure content. The interaction allowed us to investigate whether the presentation and the content worsens or mitigates the negative effect of high risk on project outcomes.

Table 5 presents coefficient estimates of Equation (2). An examination of the coefficient estimates on *project risk index high* showed that high-risk projects with low *topic consistency* (columns (1) and (4)), low *authenticity* (columns (2) and (5)), and low *negative sentiment* (columns (3) and (6)) draw worse funding.[13] Examining the interaction terms, in column (1), we found a 14.1% decrease in funding for high-risk projects in which the main description was dissimilar to the risk disclosure relative to high-risk projects in which the two were highly similar. In column (2), when high-risk projects were interacted with *authenticity low*, funding decreased by 18.7%. Finally, in column (3), we found significantly decreased funding by 23.8% for high-risk projects with less negative risk disclosure. Findings were generally similar for *campaign success* in columns (4)–(6).

Negative sentiments results suggest that risk disclosures may appear less credible if they are too positive. To further investigate that possibility, we divided projects into three groups: *negative sentiment high* represents the most negative disclosures; *negative sentiment low* represents the least negative. We then interacted them with *project risk index high*. In Online Table C12, we observed the positive interaction coefficient of *high risk index high* and *negative sentiment medium* but not for *high risk index high* and *negative sentiment low*, showing that for high-risk projects, risk disclosure that is too optimistic is as unfavorable as the most negative disclosure, possibly because funders expected project creators to prudently assess and honestly disclose project risk. If they are too negative, funders assume that creators lack confidence; if they are too optimistic, funders assume that creators are cavalier about risks or are hiding them.

6. More Evidence from Online Experiments

From secondary data analysis, we find that projects raised less money and were less likely to succeed after the policy, but the content and credibility of risk disclosure help mitigate the negative effect. In this section, to strengthen the causal inference, we examine individual funders' willingness to pledge in response to risk disclosure by conducting two controlled online experiments on Amazon Mechanical Turk. In experiment 1, we examined the willingness to pledge with/without risk disclosure. Experiment 2 further examined how the content of risk disclosure evokes different perceptions of risk and, in turn, affects funding decisions.

In experiment 1, we compared three conditions. To test the direct impact of risk disclosure, we included the risk disclosure alone and no risk disclosure conditions. To mitigate risk perceptions, many creators provide information about how they will avoid or overcome potential risks. Assuming that remedy information would lower the impact of risk disclosure, we added the risk disclosure with overcome statements. To proxy a project risk, we used real Kickstarter projects and identified high risk for the technology category and low risk for the music category.[14] Our pretest confirmed that technology projects are perceived as more risky than music projects. Thus, we used a 3 (risk disclosure conditions: no risk disclosure versus only risk disclosure versus risk disclosure with overcome statements) × 2 (project categories: a technology project versus a music project) between-participants design. As in an actual crowdfunding platform, the project included detailed descriptions and images. After the project information, participants indicated their willingness to fund a project on a seven-point scale (1 = not at all, 7 = very much). Participants answered several questions and provided demographic information. (Online Appendix E provides more details about experiment 1.)

Results from experiment 1 are summarized in Table 6. First, comparing with and without disclosure conditions for the high-risk technology projects, panel A of Table 6 shows that participants in the risk conditions had significantly lower funding intentions, suggesting that explicit risk disclosure discourages funding for high-risk projects, consistent with our main hypothesis in Section 4. In addition, when we further divided risk conditions into risk disclosure only and risk disclosure with remedies, planned contrasts revealed that participants in the risk disclosure only condition had significantly lower funding intentions, whereas participants in the risk disclosure with remedies did not, implying that disclosure content may moderate the negative impact. In contrast, we found no significant differences across the three conditions for the low-risk music projects in panel B of Table 7. This suggests that disclosure and content matter more for high-risk projects, consistent with our Kickstarter data.

In Section 5, secondary data indicate that topic consistency, authenticity, and negative sentiment indeed

Table 5. Regression Estimates of Project Risk Index Interacting with Risk Disclosure

Variables	(1) *Ln(amount raised)*	(2) *Ln(amount raised)*	(3) *Ln(amount raised)*	(4) *Ln(amount raised)*	(5) *Campaign success*	(6) *Campaign success*	(7) *Campaign success*	(8) *Campaign success*
Project risk index high	−0.349***	−0.333***	−0.318***	−0.247***	−0.102***	−0.098**	−0.108***	−0.078***
	(0.085)	(0.107)	(0.072)	(0.079)	(0.028)	(0.032)	(0.026)	(0.024)
Project risk index high × topic consistency low	−0.141**			−0.131**	−0.066***			−0.065***
	(0.059)			(0.060)	(0.018)			(0.017)
Project risk index high × authenticity low		−0.187*		−0.178*		−0.068***		−0.067***
		(0.095)		(0.100)		(0.016)		(0.017)
Project risk index high × negative sentiment low			−0.238**	−0.222*			−0.029	−0.023
			(0.104)	(0.105)			(0.028)	(0.026)
Project characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,655	7,655	7,655	7,655	7,655	7,655	7,655	7,655
Adjusted R^2	0.397	0.398	0.397	0.398	0.381	0.381	0.380	0.382

Notes. This table reports linear regression estimates based on a sample of projects initiated within three months after the risk disclosure policy. For each column, we use the following project characteristics: log of the goal amount, log of the number of videos, log of the total words, log of the median reward, project duration, foreign project, project complexity, log of the number of prior backing by a focal project creator, log of the number of projects created by a focal creator, daily number of new projects, and category dummies. Standard errors are clustered at the category level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

matter in risk disclosure, consistent with risk disclosure research emphasizing that disclosure information must be reliable and relevant (Campbell et al. 2014, Yang et al. 2014). To make causal inferences and, more importantly, to examine the underlying mechanism of the risk disclosure impact on funding decisions, we conducted experiment 2. Besides, we diverged from experiment 1 by systematically manipulating disclosure content both quantitatively and qualitatively (Hope et al. 2016). Because consumers often infer risk from the product category (Swaminathan 2003), we used target projects of different categories in experiment 1. However, risk varies across different types of projects even within the same category, and different

Table 6. Impact of Risk Disclosure on Crowdfunders' Pledge

Dependent variable	(1) Pledge	(2) Pledge	(3) Pledge	(4) Pledge
	Panel A: Technology			
With risk disclosure	−0.524*	−0.460*		
	(0.273)	(0.277)		
Only risk disclosure			−0.861***	−0.785**
			(0.299)	(0.306)
Risk disclosure with overcome statements			−0.165	−0.106
			(0.322)	(0.330)
Controls	No	Yes	No	Yes
Observations	245	245	245	245
Adjusted R^2	0.01	0.02	0.03	0.03
	Panel B: Music			
With risk disclosure	0.096	0.172		
	(0.274)	(0.27 2)		
Only risk disclosure			−0.034	0.068
			(0.322)	(0.311)
Risk disclosure with overcome statements			0.214	0.271
			(0.301)	(0.301)
Controls	No	Yes	No	Yes
Observations	273	273	273	273
Adjusted R^2	−0.00	0.08	−0.00	0.08

Notes. This table reports OLS regressions with robust standard errors. The baseline group is that with no risk information. As controls, we include both demographic information, such as gender, age, native language, and education, and crowdfunding familiarity (i.e., knowledge about platforms and experience in contributing to a crowdfunded project).

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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Table 7. Impact of Risk Disclosure on Crowdfunders' Pledge and Overall Evaluation

Dependent variable	(1) Low risk Pledge	(2) Low risk Pledge	(3) Low risk Pledge	(4) High risk Pledge	(5) High risk Pledge	(6) High risk Pledge
Disclosure quality	0.117	−0.085	−0.138	0.861***	0.718***	0.781***
	(0.298)	(0.240)	(0.243)	(0.313)	(0.258)	(0.239)
Attitude	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	141	141	141	144	144	144
Adjusted R^2	−0.006	0.349	0.387	0.044	0.352	0.455

Notes. This table reports OLS regressions with robust standard errors. As controls, we included both demographic information, such as gender, age, and ethnicity, and crowdfunding familiarity (i.e., knowledge about platforms and experience in contributing to a crowdfunded project).
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

categories possess distinct characteristics other than product complexity. Following prior research (Mukherjee and Hoyer 2001), we thus used different projects within the same category in experiment 2. We employed a 2 (project risk: low versus high) × 2 (credibility of disclosure: low versus high) between-participants design. (Online Appendix E provides more details about experiment 2.)

To manipulate disclosure content, we borrowed real Kickstarter disclosures for real technology projects. To be credible and informative, disclosures must provide relevant and sufficient information (Campbell et al. 2014). Accordingly, a more credible disclosure included specific, detailed information specifying potential risks related to delivery and hardware; a less credible disclosure has a short description without detailed information about the production or reward delivery.

We ran separate regression analyses for the low- versus high-risk project conditions using the credibility of risk disclosure as the independent variable and the willingness to fund as the dependent variable. Table 7 shows that, for the low-risk projects, disclosure content had no significant effect. In contrast, credible risk disclosure had a significant, positive effect on funding in the high-risk project condition, indicating that credible and informative risk disclosure indeed helps crowdfunding for risky projects. Our mediation test using a bootstrapping approach (Hayes 2017) confirms that perceived risk significantly mediates the relationship between risk disclosure credibility and willingness to fund, suggesting that more credible risk disclosure indeed reduces funders' perceived risk and, in turn, promotes funding.

Overall, our online experiments complement our empirical analysis by directly examining and showing that both risk disclosure and its content affect crowdfunding. Experiment 1 confirms that risk disclosure has negative impacts, especially for relatively high-risk projects, and that content also matters. Experiment 2 more precisely tested the influence of disclosure content by directly manipulating it and using projects within the same category. The results support our findings from the observational data, further revealing that credible, detailed information reduces risk perception and increases the likelihood of success.

7. Long-Term Effects of the Risk Disclosure Policy

We show that the risk disclosure policy worsens project outcomes, mainly for high-risk projects, indicating that it may have reduced information asymmetry between creators and funders. Next, we examine whether the policy has long-term positive effects for the platform. We first conducted a within-site comparison in Kickstarter over a two-year period to examine whether our main findings still hold. Then, we implemented a cross-site comparison, which further complements our empirical analysis at the platform level.

We used Kickstarter data for one year before and after the policy and applied the same matching technique. Table 8, panel A, presents results. The policy introduction and interaction effects were consistently and significantly negative, indicating that negative effects continued even after a year. To better understand whether the effects varied within the one-year period, we created quarterly dummies and interacted them with *project risk index high* (Online Table C13). Consistent with our main findings, the effects were significant and negative in every quarter and more strongly for high-risk projects.

Long-term influences might differ for technology versus nontechnology projects. That is, funders who are interested in technology are likely to be more sophisticated and have higher risk tolerance. Hence, they may have been clearly aware of potential risks even before the policy. Once they processed properly disclosed risk information, they might have more positive impressions. In contrast, funders of nontechnology projects may have lacked awareness of risks before the policy and been alarmed by an announcement of potential risks. Thus, we distinguished

Table 8. Long-Term Effect of Disclosure Policy

Variables	(1) *Ln(amount raised)*	(2) *Ln(amount raised)*	(3) *Campaign success*	(4) *Campaign success*
		Panel A: All projects		
Post disclosure	−0.507***	−0.304***	−0.050***	−0.024**
	(0.060)	(0.045)	(0.009)	(0.009)
Post disclosure × project risk index high		−0.645***		−0.084***
		(0.068)		(0.006)
		Panel B: Technology projects		
Post disclosure	−0.222**	−0.079*	−0.018**	0.007
	(0.026)	(0.025)	(0.003)	(0.008)
Post disclosure × project risk index high		−0.421**		−0.075*
		(0.072)		(0.020)
		Panel C: Nontechnology projects		
Post disclosure	−0.556***	−0.338***	−0.056***	−0.028**
	(0.055)	(0.041)	(0.008)	(0.009)
Post disclosure × project risk index high		−0.703***		−0.088***
		(0.069)		(0.005)
Project characteristics	Yes	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes
Month-of-year fixed effects	Yes	Yes	Yes	Yes
Observations	59,076	59,076	59,076	59,076
Adjusted R^2	0.299	0.305	0.236	0.238

Notes. This table reports linear regression estimates based on a new sample from multivariate distance NN matching estimates. For this, we used all the projects initiated within one year before and after the policy. For each column, we use the following project characteristics for matching: log of the goal amount, log of the number of videos, log of the total words, log of the median reward, project duration, foreign project, project complexity, log of the number of prior backing by a focal project creator, log of the number of projects created by a focal creator, and category dummies. Standard errors are clustered at the category level.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0$.

between inherently more risky technology products, such as 3-D printing, and less complex nontechnology products such as music and dance. Defining technology projects broadly, we included all projects in the technology, games, and design categories.

Results for technology projects are in Table 8, panel B; results for nontechnology projects are in Table 8, panel C. As expected, over a one-year period, the policy had a less negative effect for technology projects. Specifically, the quarterly analysis for technology projects (Online Table C14) shows that the policy's negative effects on funding dissipate in a year, especially for low-risk technology projects, for which the policy has no significant effects (Online Table C14, column (4)). For nontechnology projects, the negative effect persists for a year even for low-risk projects (Table 6, panel C, and Online Table C15). The findings indicate that risk disclosure generally has long-term negative outcomes, especially for high-risk projects. The long-term negative effects diminish for technology projects but remain for nontechnology projects. As argued, funders interested in technology projects were more sophisticated and aware of potential risks. They were less surprised by the salience of project risks over time, but funders interested in nontechnology projects might have been completely unaware of potential risks, so the risk disclosure served as negative publicity.

Next, to determine long-term effects at the platform level, we implemented another approach with a cross-site comparison, detailed in Online Appendix D. We constructed a synthetic control group based on Indiegogo.com, another leading crowdfunding market, and conducted a DID analysis. We chose Indiegogo as our control site because it is similar to Kickstarter in types of projects and popularity. The findings are highly consistent with those from the within-site comparison analysis. Online Table D1 shows negative coefficients for the interaction terms between *Kickstarter* and *post disclosure*, indicating that Kickstarter's new disclosure policy caused the number of pledges to decline over time. Online Table D2 further shows that the negative effect persisted for nontechnology projects but was short-lived for technology projects, particularly regarding shares of successful projects (Online Table D3). By drawing samples from different crowdfunding sites, we can examine whether the policy led to more projects (i.e., extensive margin). In Online Table D4, negative effects on new project initiation appeared only in the first quarter. Over time, Kickstarter attracted more technology projects after it adopted the policy.

8. Discussion and Conclusion

Online crowdfunding markets often lack quality assurance mechanisms and feature significant information asymmetry between project creators and funders. As a result, platform providers frequently endeavor to devise policies to ensure sound transactions and reduce associated risks, but they also need to understand how project creators and funders will respond. In this study, we investigate a policy change instigated to increase the salience of project risk at Kickstarter, a leading crowdfunding platform. Leveraging the policy change as an exogenous event, we adopt a DID empirical strategy with a matched sample to examine observable reactions from crowdfunders. We also conduct online experiments to examine pledge intentions.

Our study shows that Kickstarter's new risk disclosure policy generally hurts project outcomes by reducing funding and success, especially for high-risk projects but less so for low-risk projects. Although the policy increases the salience of risk information, we show that creators can reduce negative effects by writing relevant, authentic content and avoiding tones that are too negative or too optimistic. We show that the negative effects persist for nontechnology projects, but gradually dissipate for technology projects.

Future research should further evaluate advantages and disadvantages of disclosure policies. Kickstarter platform owners and policymakers may not have intended or expected the policy to have an overall negative effect on project outcomes. Creators may have been unaware of how to properly disclose risks without driving funders away. Backers may have been too inexperienced to process suddenly disclosed information. On a positive side, the new policy reduces information asymmetry and potentially makes crowdfunding markets more sustainable by helping funders identify risks and make wiser contributions.

By finding that negative effects dissipate, especially for technology projects, we show that sophisticated funders learn to process risk disclosure information over time. Our empirical evidence, secondary data analyses, and online experiments show that crowdfunding markets may become more sustainable if creators properly evaluate their projects and disclose the risks authentically and consistently. Finally, crowdfunding platforms should know that the new policy caused the number of new projects to drop in the first quarter, but as time passed, innovative technology projects became more numerous. Overall, we encourage managers and policymakers to balance the pros and cons before enacting platform regulations. For risk disclosure policies, long-run benefits may overweigh short-term disadvantages.

Although reducing information asymmetry between creators and funders is essential for the sustainability of online crowdfunding, researchers fail to examine the details of quality assurance mechanisms in crowdfunding (Ahlers et al. 2015, Geva et al. 2019) except to show that creators' social networks and peer funders' contributions signal quality projects (Lin et al. 2013, Kim and Viswanathan 2019). We fill this gap in the crowdfunding literature.

We contribute to the entrepreneurial finance literature, which examines how investors respond to signals and cues from entrepreneurs seeking funding (Lin et al. 2013, Brooks et al. 2014, Bernstein et al. 2017, Greenberg and Mollick 2017, Bapna 2019). We show that the increased salience of project risk indeed leads to inferior funding outcomes and causes project creators even more difficulty in crowdfunding platforms, especially for high-risk projects. However, project creators could alleviate negative effects by properly preparing risk disclosure content.

Furthermore, the literature has generally relied on surveys, controlled experiments, and observational data to show that certain signals, cues, and conditions determine whether investment information is useful. We add to the literature by applying a text-based machine learning method to examine how topic relevance, authenticity, and emotional tone mitigate the negative consequences of risk disclosures, in alignment with crowdfunding literature using business analytics technologies (Gorbatai and Nelson 2015, Gao et al. 2022). Third, we complement information disclosure literature by examining risk disclosure on a crowdfunding platform. Corporate firms usually reveal as much information as possible because the traditional financial market is disdainful if they withhold information (Grossman 1981, Milgrom 1981). However, crowdfunders are usually less experienced and more sensitive to risk information. They are surprised when risk information suddenly appears and are unprepared to analyze it.

Our study has several practical implications for all who are involved in crowdfunding platforms. First, platform providers are advised to thoroughly consider unintended effects from new policies. Traditional financial market investors generally benefit by having more information (Dranove and Jin 2010), but mandatory disclosure policies compel less sophisticated online crowdfunders to review and consider project risks and challenges while amplifying uncertainties. Until funders can rationally judge risks, project outcomes are inevitably negative. Platforms might consider implementing disclosure requirements gradually or according to specific project types.

We show that project creators should closely attend to disclosure content and presentation. In particular, our text-mining analysis indicates that topic relevance, sentiment, and authenticity significantly influence funding decisions. Thus, to stimulate confidence and provide sufficient understanding of project risks, project creators should explain how they address the relevant challenges, using honest language and avoiding overly negative or overly optimistic tones.

Finally, our findings on reward-based crowdfunding suggest that funders interested in technology projects are sensitive to risk disclosure and able to process and interpret risk information in the long term. In contrast, equity-based crowdfunding attracts financially sophisticated professional investors who are financially incentivized to seek quality information, including risk, and should be better able to process disclosure messages. Moreover, technology projects are more connected with equity-based crowdfunding, so disclosure effects are even more significant. Indeed, equity-based crowdfunding start-ups are already required to disclose significant financial information (Agrawal et al. 2014).

As with most empirical studies, our work bears limitations, which also inspires opportunities for future research. For instance, the observed divergence in trends of funding amount between high- and low-risk projects started even before the policy, which could imply funders might have already been aware of potential risks and acted accordingly in months closer to the actual policy introduction date. It could be a small proportion of funders starting to avoid investing in high-risk projects when a number of questions about accountability on Kickstarter emerged before the mandatory risk disclosure policy was formally introduced. We use multiple methodologies in our paper to account for this shortage and strengthen our findings. In future, researchers could conduct randomized field experiments on project risk disclosure and prevent a contaminated sample by sound experiment design. Using the low-risk projects as the control group is not ideal because low-risk projects are also influenced by the policy if small and compete with high-risk projects for funding. Whereas we believe that *project risk index* is a reliable and consistent project risk measure that reflects the inherent project risk meaningfully, we do not claim that our current approach is the best. Future research can aim to improve the measure of project risks.

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Endnotes

[1] See https://www.kickstarter.com/blog/kickstarter-is-not-a-store.

[2] Some projects failed to comply. The section is mandatory but has no minimum required length. As Figure 1 shows, few projects initiated before the policy included risk disclosures.

[3] The types of disclosed risks are more diverse in technology-intensive projects. We applied topic modeling to risk disclosure data from the music and technology categories. We found that the music category focused on one dominant topic, whereas the technology category focused on several distinct topics of greater or lesser importance.

[4] We created the measure of project complexity by topic modeling (Online Appendix B).

[5] Online Figure C3 reports significant weekday effects. Lower funding after the policy may have occurred because potential funders lost interest in funding and in Kickstarter around the time the policy was introduced. Thus, we collected the weekly search volume on Kickstarter using Google Trend and added it as a robustness check in a specification. Online Table C8 shows robustness for the main results.

[6] To control for unobserved project-level characteristics, we fitted an endogenous binary-variable model using etregress on Stata for Ln(total amount of pledges) and etpoisson for campaign success, and found that the negative effect of the risk disclosure policy still holds when we account for unobserved project-level characteristics.

[7] We used comments made one week after the campaign ended because comments made before that time may indicate backer excitement rather than delivery status.

[8] Using a proportional random sampling (i.e., stratified sampling) method, we selected 31 projects among the entire crowdfunding projects included in our sample.

[9] We confirmed that the parallel trend assumption holds in our DID models.

[10] In May 2012, "Pebble: E-Paper Watch for iPhone and Android" became the most-funded project in Kickstarter history at the time with $10 million in funding (https://www.kickstarter.com/projects/getpebble/pebble-e-paper-watch-for-iphone-and-android). People then began to wonder what would happen if a Kickstarter project failed to deliver as promised. An NPR podcast on September 3, 2012, reported on several Kickstarter projects that were hugely popular but failed to deliver promised rewards (https://www.npr.org/sections/alltechconsidered/2012/09/03/160505449/when-a-kickstarter-campaign-fails-does-anyone-get-their-money-back). In response to the story, Kickstarter clarified its position on accountability, refunds, and guarantees in a company blog post on September 5, 2012 (https://www.kickstarter.com/blog/accountability-on-kickstarter).

[11] When we used three months before the policy for the control group, we found no significant effect in panel A of Online Table C11. Using six months before the policy revealed a significant and negative effect in panel B, consistent with Figure 3.

[12] We used the similarity metric *KL divergence*, which measures how one probability differs from the other. Lower *KL* divergence indicates similarity between two probability distributions. For example, a *KL* divergence of zero means they are identical.

[13] *Topic consistency low* is equal to one if topic consistency is at the bottom 25%. We constructed *authenticity low* and *negative sentiment low* in the same way.

[14] We chose the two categories because our Amazon Mechanical Turk survey for measuring project complexity showed a huge variation within and across categories. Among the 13 categories in the sample, the technology category received the average highest ratings for complexity and for variations in project complexity, suggesting that the technology category is considered highly complex and risky. In contrast, the music category received the highest average ratings for low complexity and the second lowest ratings for variation, suggesting that the music category tends to have simpler, less risky projects. This is also consistent with prior research suggesting that product characteristics, such as technological complexity, increase consumers' perceived risk (e.g., Bettman 1973, Folkes 1988). Consumers are more likely to make rational, precise decisions about relatively complex products, such as computers and cars, and to make imprecise decisions about relatively simple products, such as brushes and curtains (Inbar et al. 2010). Thus, product categories can activate different information processing and different reactions to risk disclosure.

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