

From Hype to Hesitation: Negative Effects of AI Incidents in Crowdfunding

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Abstract:

This study investigates the impact of AI incidents on the crowdfunding performance of AI-related projects. We find that AI incidents negatively influence the funding success of AI-related projects on Kickstarter. The underlying mechanisms suggest that crowdfunding investors are risk averse and reduce their pledged amounts and participation following AI incidents. Further analysis indicates that high goal amounts exacerbate the negative effects of AI incidents, but experienced creators effectively mitigate these effects by building credibility and trust with investors. Additionally, we find that AI incidents influence not only investor behavior but also creator decision-making, as evidenced by an increase in campaign cancellations post-incident. These results highlight the interplay between external AI shocks, investor sentiment, and strategic adjustments by creators, offering valuable implications for entrepreneurs, platform managers, and policymakers navigating AI-related crowdfunding dynamics.

Keywords: AI Incidents; Crowdfunding; Risk Aversion; Entrepreneurial Finance; Investor Behavior

JEL Code: G41, G23, O33, L26

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“Technology is a useful servant but a dangerous master.”

—by Christian Lous Lange (Norwegian historian)

1 Introduction

Artificial intelligence (AI) has seen rapid development and extensive application across various industries, including finance, healthcare, and autonomous systems. In the financial sector, AI has been applied to algorithm trading, portfolio optimization, sentiment analysis, fraud detection and risk management, forecasting and planning, and customer service. Current literature emphasizes that AI enhance efficiency and accuracy, helping firms stay competitive and improve decision-making in fast-paced financial environments (Kumar and Ravi, 2016; West and Bhattacharya, 2016; Sigrist and Hirnschall, 2019; Goodell et al., 2021; Braun et al., 2023). However, the usage of AI also introduces various risks and concerns such as model overfitting, algorithmic bias, lack of transparency, cybersecurity threats, ethical concerns, and data privacy issues.

While prior research has focused on the benefits of AI in finance, relatively little attention has been drawn to the risks associated with AI failures like AI incidents. According to the AI Incident Database (AIID), an AI incident is defined as an alleged harm or near harm event to people, property, or the environment where an AI system is implicated. Types of harm include physical injury or safety risks, psychological harm, financial loss, damage to property, reputational harm, disruption to social or political systems, and violations of civil liberties. Theoretical perspectives diverge on the impact of AI incidents, leading to competing predictions about their effects on investment behavior. On one hand, risk aversion theory (Markowitz, 1952) and signaling theory (Spence, 1973) suggest that AI incidents may heighten investor skepticism, leading to reduced investment in AI-related projects. On the other hand, prospect theory (Kahneman and Tversky,

1979) and investor optimism (Wang, 2001) propose that some investors may view AI-related risks as opportunities, potentially increasing investment in AI crowdfunding campaigns. This theoretical conflict underscores the need for empirical examination to understand how decentralized investors react to AI-related crises.

Existing research on AI risks in finance has primarily examined traditional markets. Specifically, Danielsson et al. (2022) identify AI risks that destabilize the financial system by creating new tail risks and amplifying existing issues due to procyclicality, unknown-unknowns, the need for trust, and optimization against the system. Durongkadej et al. (2024) investigate the impact of AI incidents on banks and financial companies and find a short-term loss of 21.04% on banks market valuation after AI incidents and the negative impact can spread out to the financial industry with a three-day loss of 0.13%. Our study extends this line of research to decentralized investment environments such as crowdfunding and investigates the impact of AI incidents on crowdfunding activities of AI-related projects.

To examine the impact of AI incidents on crowdfunding performance of AI-related projects, we employ both standard and dynamic Difference-in Difference Method (DID) analysis. Our study utilizes a comprehensive dataset of crowdfunding campaigns from 2011 to 2023 collected from Kickstarter.com, which is among the largest crowdfunding platforms worldwide. This dataset includes detailed project attributes, funding outcomes, and creator demographics, which allows us to systematically analyze the effects of AI incidents on project success while controlling a wide range of observable characteristics.

To ensure AI incidents are external, we leverage the AIID, which documents instances of real-world harm or near-harm caused by artificial intelligence systems (McGregor, 2021). AIID is an incident collection constructed by an industrial/non-profit cooperative and adopted by scholars to

study various AI incident relevant topics like its impact on cryptocurrency return, AI ethics, and AI governance (Knight et al., 2025; Rodrigues et al. 2023; Shams et al. 2025; Waltersdorfer and Sabou, 2025; Wang et al., 2025). AIID provides detailed records of each incident, including the date, description, location, and the company involved. As of the end of 2023, it tracks over 750 incidents covering a broad range of issues, from biased algorithms in hiring to failures of autonomous vehicles and breaches of data privacy. Furthermore, these AI incidents are identified through independent media sources, ensuring that their timing is exogenous to individual crowdfunding platforms or projects. To mitigate confounding effects, we focus on the first AI incident in each U.S. state, thereby limiting the influence of overlapping events.

Our results indicate that AI incidents have a negative impact on the crowdfunding success of AI-related projects. This effect remains statistically significant when controlling for project-specific characteristics including funding goal, campaign length, staff pick status, and creator demographics (gender, race, and prior campaign experience). Furthermore, our findings are robust to propensity score matching (PSM), which controls for selection biases and ensures comparability between affected and unaffected projects.

Beyond overall success rates, we explore the underlying mechanisms driving this effect. We find that AI incidents reduce pledged amounts and the number of backers for AI-related projects, supporting the hypothesis that investors are risk-averse and react negatively to AI-related uncertainties. In addition, we conduct a heterogeneous analysis and observe that AI-related projects with higher funding goals are particularly vulnerable in the aftermath of AI incidents. This finding aligns with previous research on investment under uncertainty, suggesting that higher capital requirements amplify risk perception and deter backers (Mollick, 2014; Burtch et al., 2016). We also reveal that repeated creators with prior experience help to establish credibility and trust

with investors, effectively mitigating the negative impact of AI incidents on the successful rate of AI related projects. Consequently, these findings emphasize the significance of creator experience on crowdfunding platforms, especially in situations where project uncertainty is high.

Moreover, AI incidents affect not only investors' behavior but also creators' decision-making. By analyzing the cancellation rate of projects, we find that creators of AI-related projects are more likely to cancel their campaigns following an AI incident, which suggests that in response to increased uncertainty and perceived funding challenges, creators adjust their expectations and terminate projects early to conserve resources and reallocate their efforts to more promising opportunities. These results highlight the dynamic interplay between external shocks, investor sentiment, and creator strategy in the crowdfunding platforms.

As one of the first studies to reveal the linkage between AI incidents and crowd investment decisions, we contribute to the literature in three folds. First, our study complements to the growing but limited literature about AI risks in finance (Danielsson et al., 2022; Durongkadej et al., 2024). Existing studies such as Durongkadej et al. (2024) focus on institutional settings including banks or corporations and find negative effects on stock market return, bankruptcy risk and operational cash flow. By focusing on crowdfunding, we broaden the lens to examine how decentralized investors react to AI incidents, contributing to forward-looking implications for entrepreneurs, platform managers, and policy makers. The lessons drawn here are likely become even more relevant as AI continues to expand into consumer and entrepreneurial domains.

Second, crowdfunding represents a risk-sensitive environment that enables direct observation of real-time investor sentiment, distinct from institutional or professional finance. Prior review studies (Ashta & Herrmann, 2021; Allen et al., 2021) emphasize that crowdfunding lies at the intersection of entrepreneurial finance, social interaction, and digital platforms, where retail

investor participation and information asymmetry jointly shape investment behavior. Unlike institutional investors, crowdfunding backers are typically non-professionals whose decisions rely heavily on trust, reputation, and social influence rather than formal due diligence (Belleflamme et al., 2014; Allison et al., 2015). Platforms such as Kickstarter facilitate rapid information diffusion and transparency, allowing external shocks such as AI incidents to swiftly affect investor sentiment and funding outcomes. Creators must also signal credibility and manage perceived risk in a highly visible and competitive environment, amplifying the behavioral and informational effects of such shocks. Our results show that crowdfunding investors are risk-averse and reduce participation after AI incidents, while experienced creators and higher campaign cancellations reveal adaptive responses rarely seen in traditional finance.

Third, we provide additional insights into the fast-growing literature on reward-based crowdfunding. Prior literature has identified several important factors of crowdfunding success, including gender (Gafni et al., 2021), race (Younkin and Kuppuswamy, 2018), staff pick (Dai and Zhang, 2019; Lin and Pursiainen, 2021), campaign length (Gafni et al., 2021), goal amount (Mollick, 2014; Burtch et al., 2016; Younkin and Kuppuswamy, 2018), and repeated creator (Westhead et al., 1998; Buttice et al., 2017). Our results suggest that AI-related projects tend to be less successful when the goal amounts are high, but repeated creators effectively mitigate the negative impact of AI incidents, especially in situations where project uncertainty is high.

The remainder of the paper is organized as follows. Section 2 discusses related literature and develops the main hypotheses. Section 3 outlines the research design and sample construction. In Section 4, we present our empirical analyses. Finally, Section 5 concludes the paper.

2 Literature review and hypothesis development

2.1 Literature Review of Reward-based crowdfunding and entrepreneurial finance

Crowdfunding is recognized as one of the key FinTech innovations that has the potential to disrupt traditional financial intermediation by democratizing access to capital. Unlike traditional financing channels, reward-based crowdfunding platforms allow fundraisers to attract early customers and “pre-sell” their products. Backers, in return, receive non-financial rewards for their support, including discounted products, exclusive access, or public recognition as early adopters. This mechanism is consistent with signaling theory, in which a successful funding round sends positive signals to subsequent investors from conventional financing sources, notably venture capitalists and banks (Spence, 1973; Belleflamme et al., 2015). Cumming et al. (2020) further examined how different crowdfunding mechanisms shape such signals through the design of fundraising goals. Specifically, they investigated two models, “Keep-It-All” (KIA) and “All-Or-Nothing” (AON), via fundraising goals set by an entrepreneur. They find evidence supporting that AON increases entrepreneurial risk while signaling commitment, leading to higher crowdfunding pledges, larger goals, and separate equilibrium with higher-quality, more innovative, and more successful projects. Consequently, AON reward-based crowdfunding platform like Kickstarter plays a role in shaping public perceptions of new technologies.

Building on the importance of reward-based crowdfunding in fostering early-stage innovation, Kickstarter represents a suitable dataset for examining the dynamics of AI crowdfunding for several reasons. First, Kickstarter provides an ideal testing ground to assess how external AI incidents influence investor sentiment and the funding trajectories of AI-driven projects. By examining how backers respond, we can assess whether negative AI news serves as a crisis signal (Coombs, 2007) that discourages participation in crowdfunding campaigns. Second, Kickstarter

offers sufficient number of AI-related projects and relatively transparent and structured data on campaigns, which allows for an empirical examination of funding patterns, public perceptions, and the evolving success factors for AI crowdfunding. According to Kickstarter¹, more than 267,000 projects have been successfully funded since its launch in 2009, with over \$98 million pledged as of October 2024. Third, Kickstarter facilitates a cross-sectoral analysis of AI applications, spanning robotics, creative arts, healthcare, and finance, allowing us to study the broader implications of AI technology. Given the heterogeneous nature of AI innovations, our analysis of Kickstarter projects allows us to examine how various AI use cases, including both consumer-oriented applications and high-stakes technologies, are influenced by external incidents and declining investor trust (Goffman, 1963; Jancsics, 2024).

In addition, the role of crowdfunding in early-stage entrepreneurship has been extensively studied in prior literature. Kuppuswamy and Bayus (2017) examined backer behavior and found that crowdfunding contributions decline once a project reaches its funding goal, indicating that backers make decisions based on reference points in line with behavioral finance theories. Similarly, Mollick (2014) offers a description of the underlying dynamics of success and failure among crowdfunded ventures. Recent studies have explored the interplay between human tendencies and AI techniques in crowdfunding. For instance, Lin and Pursiainen (2021) identified a novel pattern, demonstrating how the round number heuristic can explain clustering behavior and predict campaign outcomes. Similarly, Korzynski et al. (2021) revealed that advanced AI-driven video analysis can substitute human coding, showcasing the potential of large-scale automated video analysis to generate valuable insights, even beyond the crowdfunding domain. Additionally, Gafni et al. (2021) analyzed the behavior of male and female entrepreneurs in raising

¹ The latest updated statistics are available on the Kickstarter website, <https://www.kickstarter.com/help/stats>

early-stage capital by using Kickstarter dataset and found that both genders have a tendency to fund entrepreneurs of their own gender.

As a result, these studies illustrate that reward-based crowdfunding is not merely a funding mechanism but also a market validation tool that shapes investor perceptions, consumer adoption, and the broader entrepreneurial finance landscape. Understanding how external AI incidents disrupt these dynamics is important for evaluating the persistence of AI-driven innovations in the face of public trust challenges.

2.2 Hypothesis Development

Several traditional financial theories suggest that AI incidents may result in reduced ledged amounts or fewer backers of AI projects. For example, risk aversion theory (Markowitz, 1952) suggests that investors tend to avoid projects they perceive as risky, even when the potential for high returns exists. AI incidents can amplify this aversion, as they highlight the unpredictability and failure risks of AI technologies, leading investors to refrain from investing in AI-related crowdfunding campaigns. Unlike traditional financial markets, crowdfunding lacks strict governance and reporting requirements, making it inherently riskier for investors, particularly in an environment of increasing AI-related concern. We expect a decline in crowdfunding participation as investors react to increased uncertainty and heightened risk perceptions, especially given the rapid spread of information through media today.

Furthermore, crowdfunding backers seek rewards and face high uncertainty about project success. The expected return would be material return (product/service received), social return (supporting innovation or creators), and monetary return (resale value or future perks). In the mean-variance utility function, $U = E(R_p) - \frac{1}{2}A\sigma_p^2$, where A represents the risk aversion

coefficient. If AI-related incidents amplify uncertainty and fear of failure, backers will demand higher compensation for risk, leading to an increase in A. Thus, a risk-averse investor will now perceive the same portfolio as less attractive unless returns compensate for the additional uncertainty. If backers believe that AI incidents increase the likelihood of project failures, the expected risk, $\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \sigma_{ij}$, of AI-related crowdfunding projects rises due to higher failure probabilities and increased uncertainty about AI-driven projects. If AI-related uncertainty increases correlations among projects (σ_{ij}), diversification benefits shrink, making AI-related crowdfunding projects less attractive. The efficient frontier is derived by solving:

$$\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \sigma_{ij}$$

Subject to:

$$E(R_p) = \sum_{i=1}^n w_i E(R_i)$$

If AI-related crowdfunding projects experience higher perceived risk (σ_p^2) without a proportionate increase in expected return ($E(R_p)$), they shift below the efficient frontier, which results in backers allocating less capital to AI-related crowdfunding projects and shift to safer spending in other projects not affected by AI incidents. If AI incidents increase failure risk f_i , then

$$E(R_i) = (1 - f_i)R_{success} + R_{failure}$$

where $R_{success}$ is the expected reward from a successful campaign, $R_{failure}$ is the loss if project fails which is approximately 0 in crowdfunding. The increase in f_i due to AI incidents will decrease the expected reward, making the risk-return tradeoff less favorable. Under this view, AI incidents deter AI-related crowdfunding activities.

H1a: There is a negative association between the occurrence of AI incidents and the success of AI-related projects in a reward-based crowdfunding platform

However, it is also possible that AI incidents do not negatively impact crowdfunding activities and may even stimulate investment under certain conditions. Based on the prospect theory (Kahneman, 1979), investors are more likely to hold on to losing investments longer than they should to avoid realizing a loss, and they might sell winning investments too early to lock in gains. Applying this to crowdfunding, some investors may actually seek out AI investments after an incident, perceiving them as high-risk but also high-reward opportunities. Prospect theory models value as a function of perceived gains and losses, where losses loom larger than equivalent gains:

$$V(x) = \begin{cases} (x - R)^\alpha & \text{if } x \geq R \text{ (Gains)} \\ -\lambda(R - x)^\beta & \text{if } x < R \text{ (Losses)} \end{cases}$$

where x is investment outcome; R is the expected reward; α and β are risk preference parameters between 0 and 1; λ is greater than 1 if people dislike losses more than they enjoy equivalent gains. After AI incidents, R shifts downward. Conservative backers will avoid AI projects because they see more downside. However, risk-seeking backers (with lower λ and higher α) may perceive a “discounted” opportunity, consider X still attractive due to potential high rewards, and increase participation in AI crowdfunding.

Additionally, some backers may have overconfidence bias (Wang, 2001) even if the problem of information asymmetry exists. Even in the wake of AI incidents, some backers may believe they have unique insights or strategies that will allow them to make correct investment decisions. This bias could lead to sustained or increased crowdfunding in AI-focused projects, particularly in crowdfunding environments, where backers are more likely to act on personal beliefs or insights

rather than relying on institutional guidance. Therefore, we generate a competing hypothesis to examine the association between AI incidents and AI-related crowdfunding activities.

H1b: *There is a positive association between the occurrence of AI incidents and the success of AI-related projects in a reward-based crowdfunding platform.*

AI incidents could exacerbate the problem of information asymmetry based on the agency theory (Jensen and Meckling, 1976). The startup or company raising funds always have more information about the project than the crowdfunding investors. After AI incidents, perceived risk (σ_p^2) increases. If backers cannot assess AI risks, they assume the worst-case scenario and the utility function becomes

$$U = E(R_p) - \frac{1}{2}(A + \Delta A)(\sigma_p^2 + \Delta\sigma^2)$$

where $\Delta A > 0$ and $\Delta\sigma^2 > 0$ because of increased risk aversion and perceived AI risk spike. This reduction in expected utility discourages backers from participating in AI-related crowdfunding projects. Agrawal et al. (2014) identify three primary risks in crowdfunding: creator incompetence, fraudulent behavior, and project uncertainty. Each of these risks can be amplified by information asymmetry. After AI incidents occur, potential investors may believe that they cannot accurately assess the risks posted in the project. In return, they would be hesitant to participate in AI related crowdfunding. This can create a trust gap between project creators and backers, leading to reduced pledged funding or fewer backers of AI projects, which is consistent with H1a.

In addition, AI-related projects with larger funding goals may be perceived as requiring more complex technology or facing greater challenges, further exacerbating information asymmetry. Investors may avoid such projects due to the difficulty in assessing their feasibility or credibility. On the contrary, experienced creators can reduce asymmetry. Investors may see experienced

creators as more reliable because they have a track record, reducing uncertainty and mitigating the negative impact of heightened risk aversion.

Meanwhile, AI incidents serve as negative investment signals, influencing investor sentiment even when an AI project is not directly linked to the incident. Signaling theory (Spence, 1973) suggests that investors interpret external events as signals of risk, and AI failures can diminish confidence in the broader AI ecosystem. Thus, fear outweighs actual risk, leading to overreaction and decrease in AI projects investing. Confidence loss can be modeled as a downward shift in expected utility,

$$U = E(R_p) - \frac{1}{2}(A + \lambda C)\sigma_p^2$$

where C measures signal credibility risk or lack of confidence, and λ is confidence sensitivity factor that measures how strongly backers react to AI incidents news. $A + \lambda C$ represents adjusted risk aversion, which increases when confidence in AI projects declines after AI incidents. Higher adjusted risk aversion lowers investor's expected utility and thus reduces participation in AI-related crowdfunding.

The literature has documented the important role of investors' confidence in financial markets. Duarte et al. (2012) found that trustworthiness is a key determinant in crowdfunding success, as investors tend to back projects with strong credibility. Moreover, Lui and Lamb (2018) show evidence that the misuse of AI such as data or algorithmic bias in banking can undermine consumers' trust and confidence. Given these findings, AI incidents may reduce investor enthusiasm as well as pose greater challenges for AI startups in securing financial backing through crowdfunding.

Furthermore, higher goal amounts may signal greater ambition or complexity, which investors often interpret as increasing perceived risk or uncertainty, especially in the context of emerging technologies like AI. Prior work supports the idea that crowdfunding backers use goal amount as a heuristic for project risk (Mollick, 2014; Allison et al., 2017). For example, Mollick (2014) suggests that higher goals partly heightened backer skepticism about feasibility and make projects with higher goals less likely to succeed. Similarly, Courtney et al (2017) find that high funding targets can deter participation by amplifying concerns over project viability. Therefore, we generate the second hypothesis to examine whether a large funding goal can signal a riskier project, making investors hesitant, especially after an AI incident when risk sensitivity is heightened.

***H2:** High goal amounts aggravate the negative impact on crowdfunding success of AI-related projects triggered by AI incidents.*

On the contrary, an experienced creator signals reliability and competence, reassuring investors and possibly counterbalancing the negative impact of AI-related uncertainty. Consistent with prior studies showing that repeated creators benefit from increased trust, credibility, and social capital (Mollick, 2014; Bi et al., 2017; Colombo et al., 2015), we use repeat creator status as a proxy for experience and generate the hypothesis below.

***H3:** Experienced/repeated creators mitigate the negative impact on crowdfunding success of AI-related projects triggered by AI incidents.*

3 Data and Research Design

3.1 AI Incidents Data

We explore AI incidents by external, third-party media news as a quasi-exogenous shock, the timing of which is arguably outside the control of either the platform or projects. Specifically, this

study utilizes the AI Incident Database (AIID)², which documents instances of real-world harm or near-harm incidents attributable to artificial intelligence systems. As of the end of 2023, it tracks over 750 incidents. Upon identifying an incident, AIID provides various aspects for each incident, such as date, detailed description, location and company involved.

As we view these incidents as an external shock to local crowdfunding platform participators, we limit our attentions to the first incident in each state to avoid other confounding effects. The detailed events we studied are listed in Appendix I. As shown in the table, the earliest event reported by AIID was taken place in New York, related to an algorithm biased in teachers' evaluation system.³

3.2 Kickstarter Data

In our study, we retrieved Kickstarter data from a web crawler platform called Web Robots⁴, which is a popular data source used by previous studies on Kickstarter projects (e.g., Song et al., 2019; Wolfe et al, 2021). This platform has been collecting data from all ongoing projects on Kickstarter periodically since March 2016⁵. The dataset contains a comprehensive list of information about each project, such as project ID, project name, project goal, project status, category, key dates, and many other important factors.

² <https://incidentdatabase.ai>

³ We also test whether subsequent AI incidents amplify the observed effects by including both the number of incidents and their interaction with the AI-related project indicator. The untabulated results show that the additional incidents do not significantly alter project outcomes, suggesting that investor reactions are primarily driven by the first exposure to AI-related risks.

⁴ <https://webrobots.io/kickstarter-datasets/>

⁵ For all projects finished before March 2016, the platform also collected the final status of the project.

3.3 Sample Construction

Our sample period of Kickstarter data is 2011-2023. We exclude all projects that are located outside of the United States. To mitigate any confounding effects, we also exclude all other projects that happened in the event year of the first AI incident in that state. For instance, we exclude all projects from New York State in 2012, the year in which the first documented AI incident occurred in that state. After merging with available AI incidents data from AIID, we get a final sample of 294,277 observations from 50 states.

We identified AI related projects based on the project name and introduction. Following the methodology outlined by Chen and Srinivasan (2024), we created an R code to automatically clean the text data and examine if a project contains AI related terms. For each project, we compared the project title and description with words and phrases in the dictionary from Chen and Srinivasan (2024). If a project contains matching terms, we coded it as an AI-related project⁶. Appendix III shows some example AI-related projects from our dataset.

The evolving landscape of AI-related crowdfunding activity is documented in Figures 1 and 2, which provide new empirical insights into both temporal and categorical patterns on Kickstarter between 2011 and 2023. Figure 1 presents platform-wide trends. Panel A displays the annual number of projects alongside the share of AI-related projects by count, while Panel B illustrates total funding raised and the corresponding proportion attributed to AI-related campaigns. Although the share of AI-related projects peaked around 2016, the variation across years is modest. More importantly, the funding share of AI-related campaigns has increased noticeably in recent years, suggesting a shift from early-stage experimentation toward fewer but larger and more mature

⁶ For robustness checking, we also examined our models with alternative AI dictionaries from previous research, and the findings are consistent (Enholt et al., 2022; Schoeberl et al., 2023).

projects. These patterns underscore the growing relevance and economic weight of AI-related ventures within the broader crowdfunding ecosystem.

[insert Figure 1]

Figure 2 shifts the focus to the distribution of AI-related activity across project categories. To improve interpretability, we concentrate on the top five categories with the highest AI engagement. Panel A shows the percentage of AI-related projects by count within each category over time, while Panel B plots the share of pledged amounts. The “Technology” category consistently accounts for the highest concentration of AI-related initiatives, with notable but more modest presence in categories such as “Photography,” “Art,” and “Journalism.” These findings highlight that the diffusion of AI-related innovation is not limited to technology-focused ventures but increasingly spans creative and media-oriented domains. This nuanced exploration adds depth to our understanding of how AI permeates distinct segments of the crowdfunding market and reinforces the importance of considering category-specific dynamics when evaluating investor behavior and funding performance.

[Insert Figure 2]

3.4 Research Design

Our main argument is that the appearance of AI incidents will negatively impact AI-related projects by decreasing the success rate. To formally assess the statistical and economic significance of the appearance of AI related incidents in local community, we adopt a standard Difference-in-Difference (DID) model by using the following specification:

$$\begin{aligned} \text{Successful}_i = & \alpha + \beta_1 * \text{After AI Incident}_i + \beta_2 * \text{AI Related Project}_i + \beta_3 \\ & * \text{After AI Incident}_i * \text{AI Related Project}_i + X_i\delta + \eta_i + \lambda_t + \mu_s + \varepsilon_i \quad (1) \end{aligned}$$

where i denotes crowdfunding project in Kickstarter platform. $Successful_i$ is the indicator variable to distinguish whether the project is successfully funded or not. $After\ AI\ Incident_i$ is an indicator variable that equals one if the project is initiated by the creator after the first AI incident recorded by AIID in creator's state, zero otherwise. Furthermore, $AI\ Related\ Project_i$ represents whether the project uses AI-related technology, which described in our prior section. Our variable of interest is the interaction between these two variables (β_3), which represents the effect of AI related crowdfunding project after a local AI incident. We also control a battery of characteristics, X_i that could affect the success rate of the project. Following previous research (Gafni et al., 2021; Lin and Pursiainen, 2021, 2022), we divide our controls into two broad groups. One is related to project characteristics, such as goal amount, campaign length and staff pick. For instance, staff pick captures the endorsement effect from Kickstarter, prior literature finds that the staff pick is positively related to the success rate of a project (Dai and Zhang, 2019; Lin and Pursiainen, 2021). The other set of controls is linked to a project owner's personality, including gender and race. Gafni et al. (2021) document that female project owners experienced a lower success rate than their male entrepreneurs on reward-based crowdfunding platforms. The detailed definition for each control can be found in our Appendix I. Standard errors are clustered at the state level.

3.5 Descriptive Statistics

Table 1 presents the summary statistics for our primary dependent, control variables, and other measures that we subsequently use in our analyses. The average success rate of campaigns is 49.4%, while 6.7% of campaigns are canceled. On average, the logarithm of backers is 3.1, indicating that campaigns typically attract around 22 backers. The average campaign length, measured as the natural logarithm, is 3.48, suggesting an approximate length of 33 days. Regarding

financial metrics, the average pledged amount is 6.44 in logarithmic terms, corresponding to approximately \$625.

Among control variables, the logarithm of the goal amount averages 8.5, translating to a typical goal of around \$4,918. Additionally, 10.3% of campaigns are labeled as "Staff Picks," and 1.3% of campaigns are classified as AI-related projects. Regarding creator demographics, we find comparable numbers as prior literature (Lin and Pursiainen, 2021), we have around 20% of projects are created by female and nearly 45% of projects are created by male individuals. In terms of racial composition, white project owners represent the largest group, accounting for roughly 30% of the total.

4 Empirical Results

4.1 AI Incident and the Success of AI-related Project

This section presents regression results for analyzing the appearance of AI Incident on the success rate of projects. Table 2 presents the results of estimating Equation 1. Column 1 reports the result of our baseline model, which only includes the indicator variables for AI-related projects and whether the project is initiated after the AI incident in corresponding state, and the interaction between these two variables. Additionally, column 1 also includes the gender, race, year-month, county category and number of prior campaign fixed effects.

The coefficient for the interaction term is negative (-0.027) significantly at the 5% level, indicating that AI incidents reduce the success rate of AI-related projects. Interestingly, we also observe a positive and significant main effect of the After AI Incident variable. This coefficient captures the average impact of AI incidents across all projects, including those unrelated to AI. One plausible interpretation is that high-profile AI incidents elevate public attention and media

coverage surrounding emerging technologies more broadly, which may inadvertently boost platform engagement or public curiosity toward innovation, even in non-AI domains. This aligns with prior research suggesting that technological controversies can serve as salient attention triggers, encouraging individuals to explore, discuss, and support new ideas or alternatives (D'Angelo et al., 2021; Juma, 2016; Boyd et al., 2013).

Column 2 further controls several confounding factors that may influence success rate, including a series of characteristics identified by prior researchers (Gafni et al., 2021; Lin and Pursiainen, 2021, 2022). Notice that the interaction term remains negative (-0.045) and is significant at a 1% level, indicating that AI incidents in the owner's state will decrease the success rate for those AI-related projects. We also find consistent results for our controls in column 2 to prior literature. Specifically, we observe that campaign length and goal amount are negatively associated with success rate, while the staff pick indicator is positively related to success⁷.

Furthermore, our evidence is based on the standard DID setting by treating the AI incident as an external shock to the participants on the crowdfunding platform. One concern is that the results presented in column 1 & 2 could be driven by unobservable differences between projects in AI incident affected states and projects in other states. If unobserved factors drive the results, we should observe the effect of AI incidents would influence the success rate of AI-related projects even before the implementation year. It's categorized as the parallel-trend assumption for standard DID setting. To verify the parallel-trend assumption and in the spirit of Bertrand and Mullainathan (2003), we examine whether the success rate of AI-related projects in the affected states was

⁷ We confirm that our findings remain robust when restricting the sample to non-withdrawn projects, suggesting that cancellations following AI incidents do not bias the results. The regression results are available from the authors upon request.

changed before the appearance of AI incident in affected states. To formally test this assumption, we run the following model specification similar to equation (1):

$$\begin{aligned}
Successful_i = & \alpha + \sum_{N=-3}^{+3} \beta_1^N * After\ AI\ Incident_i[N] + \beta_2 * AI\ Related\ Project_i \\
& + \sum_{N=-3}^{+3} \beta_3^N * After\ AI\ Incident_i[N] * AI\ Related\ Project_i + X_i\delta + \eta_i \\
& + \lambda_t + \mu_s + \varepsilon_i \quad (2)
\end{aligned}$$

where $\sum_{N=-3}^{+3} \beta_1^N * After\ AI\ Incident_i[N]$ stands for years around the appearance of AI incident and $After\ AI\ Incident_i[N]$ are indicator variables. For instance, $After\ AI\ Incident_i[-1]$ is an indicator variable that equals one if a firm-year observation is from one year before the appearance of AI incident in the affected state.

Column 3 of Table 2 reports the results from estimating Equation 2. As shown in the results, we do not find significant effects in the success rate associated with AI-related projects prior to the occurrence of AI incident in a specific state as outlined in Appendix II. Moreover, we observe a significant reduction in the success rate of AI-related projects following the appearance of AI-incident. This evidence suggests that the observed effects are unlikely to be driven by persistent local or project-specific characteristics that influenced the success rate of AI-related projects on Kickstarter platforms before the occurrence of the AI incident.

To address the concern that some investors may shift funding from AI-related to non-AI projects following AI incidents, we conduct a matched sample analysis using non-AI projects from different Kickstarter categories launched in the same year. Each AI-related project is matched to its closest non-AI counterpart based on observable characteristics such as funding goal, campaign duration, and creator history. This matching approach is intended to reduce the likelihood of investors overlap between the treatment and control groups. In the untabulated results, the

regression estimates from the matched sample remain statistically significant and consistent in direction with our main findings. The effect size is somewhat smaller, which is in line with the possibility that substitution effects in the unmatched sample may have led to an upward bias.

4.2 Matching Sample Analysis

In the baseline regression, we categorize all non-AI incident affected projects as the control sample. This makes the control sample size disproportionately large compared to the treatment sample. To improve the quality of the control group and strengthen causal inference, we adopt a propensity score matching (PSM) approach, a well-established method in empirical finance and accounting research (Rosenbaum and Rubin, 1983).

Our use of PSM is motivated by the goal of constructing a more appropriate counterfactual rather than relying solely on self-reported location information. Specifically, we match each project in the treatment group to a non-AI project launched in the same year with similar campaign features. This matching strategy aligns with recent work in the crowdfunding literature that emphasizes matching on campaign fundamentals to avoid selection bias, as seen in Cumming et al. (2023), who carefully matched fraudulent and non-fraudulent campaigns on key campaign-level attributes to isolate the impact of fraud-related risks.

By reducing observable differences between groups, our matched sample allows us to conduct a cleaner difference-in-differences analysis and test whether AI incidents have a meaningful effect on project outcomes.

[insert Table 3]

Panel A of Table 3 reports parameter estimates from the logit model used to estimate propensity scores for projects in the treatment and control groups. We use the predicted

probabilities in column (1) to perform the NNM matching. We obtained 3,791 pairs of matched projects. Furthermore, we also report in Panel B the univariate comparison of firm characteristics between the treatment and control projects. None of the differences are significant, implying that the characteristics of treatment and matched control groups are similar.

Panel C of Table 3 presents the DID regression results similar to Table 2 by using the matched group we constructed. The coefficient of the interaction term is still negative and significant across the two columns, which suggests that the occurrence of AI incident would reduce the success rate of AI-related projects relative to control projects. Finally, these results suggest that the observed effect of AI incident on AI-related reward based crowdfunding projects is unlikely to be driven by differences between treatment and control, which further strengthens our causal argument.

4.3 Mechanism Analysis

In this section, we investigate the mechanisms underlying our findings. In other words, why are investors unlikely to fund AI-related projects after AI incidents. As illustrated in the hypothesis development, investors are risk averse and are more likely to avoid investments they perceive as risky, even if potential returns are high (Markowitz, 1952). Following the appearance of an AI incident, AI-related projects were presumed to be more risky than other types of projects. As a result, investors would be less willing to invest in these projects. If the mechanism is through the changes in willingness in investing in AI-related projects, we should observe the changes in pledged amount and number of investors for AI-related projects after the appearance of AI incident in a specific state.

[insert Table 4]

Table 4 presents the results of this analysis, where the dependent variable in Equation 1 is replaced with pledged amount and the number of backers. The results indicate that both pledged amounts and the number of backers for AI-related projects are negatively affected, with coefficients that are statistically significant at the 1% level. These negative coefficients indicate that after the AI incident, AI-related projects experienced a decrease in both the total pledged amounts and the number of investors willing to back them. These findings support our argument that the changes in success funding rate of AI-related projects are mainly due to the changes in interest from investors. The results suggest that after an AI incident, investors may become more cautious about the perceived risks associated with AI technologies and shift their focus to more familiar project types, which is consistent with the risk aversion theory rather than the prospect theory. Overall, these insights contribute to a broader understanding of how market shocks influence the behavior of decentralized investors and the dynamics of crowdfunding ecosystems.

4.4 Heterogeneity Analysis

In this section, we conduct a heterogeneous analysis to investigate how the effects of AI incidents on project success rates vary across different types of projects. Specifically, we examine variations based on projects with high goal amounts and repeated creators to test H2 and H3.

As Kickstarter is an “All-or-Nothing” platform in which creators receive nothing unless the goal is achieved (Da Cruz, 2018). A high goal amount would associate with more uncertainty, high risk and negative signals. Prior literature also reveals a negative relation between the goal amount and projects success rate in crowdfunding platforms (Mollick, 2014; Burtch et al., 2016; Younkin and Kuppuswamy, 2018). Consequently, investors or backers on Kickstarter are likely to exhibit greater hesitation in supporting projects with high goal amounts that signal higher risk, particularly

when they become aware of the occurrence of an AI incident in the creator's state, which may further heighten perceived risks.

To examine whether higher goal amounts amplify the negative effect of AI incidents due to increased perceived risk, we introduce a triple interaction term by adding an indicator variable to identify whether the goal amount is categorized as high. For this analysis, we define high goal amounts as those in the top quartile of our sample. The result is presented in column 1 of Table 5.

[insert Table 5]

The results in Column 1 show that while higher goal amount with a coefficient of -0.039 are independently associated with lower funding success, the coefficient for the triple interaction term is negative (-0.047) and statistically significant at 5% level, indicating that after the occurrence of an AI incident, AI-related projects with higher goal amounts experience a greater reduction in their probability of successful funding by investors. Importantly, because high goal amount is already controlled for in the model, the significant triple interaction term does not be attributed solely to the structural difficulty of reaching a higher funding threshold. Instead, it supports our argument that higher goal amounts serve as perceptual signals of project risk or uncertainty, particularly in the context of AI incidents. These findings are consistent with the signaling theory and prior research showing that backers infer risk from campaign characteristics such as higher goal amount (Mollick, 2014; Courtney et al., 2017). Thus, the evidence supports the moderating role of perceived risk and provides a more nuanced understanding of how external shocks interact with project signals to shape investor behavior in the crowdfunding context. Rational investors, who tend to be risk-averse, are less likely to invest in such projects due to the increased uncertainty.

After looking at the project specific characteristics, we also investigate the creator's unique characteristics in differentiating the success of the crowdfunding projects. Repeated or serial creators may differ from inexperienced or first-time creators as they can learn from their earlier experiences (Westhead et al., 1998; Buttice et al., 2017). Gallagher and Salfen (2015) show that nearly one-third of all money pledged on the Kickstarter platform is secured by repeated creators. Prior literature also indicates that serial entrepreneurs would be more skilled and more socially connected, and such experience will increase the success rate of receiving funding from investors (Gompers et al., 2006; Zhang, 2011). Therefore, repeated creators can reduce information asymmetry through reducing uncertainty and mitigating the negative impact of heightened risk aversion.

To further investigate whether repeated creators experience different investor reactions, we construct a variable to distinguish between serial creators and first-time creators. Specifically, we create an indicator variable by counting the occurrences of unique creator IDs. If a creator's ID appears more than twice in the dataset, they are categorized as a repeated creator. Using a similar approach to the previous analysis, we introduce a triple interaction term that incorporates this repeated creator variable. The results are presented in Column 2 of Table 5.

The positive and significant coefficient for the triple interaction term supports our argument that repeated creators can reduce asymmetry and are more likely to secure funding from investors due to their prior experience and demonstrated skills. This prior experience helps establish credibility and trust with investors, effectively mitigating the negative impact of AI incidents on the success probability of AI-related projects. These results suggest that investors perceive repeated creators as more reliable, which offsets the heightened risk aversion triggered by external events such as AI incidents. These findings highlight the importance of creator experience in

crowdfunding platforms, particularly in contexts of high uncertainty of the projects. Repeated creators appear to benefit from their established track records, which allow them to signal themselves from first-time creators⁸.

Overall, the above analyses reveal significant variation in how AI incidents influence the success rates of AI-related projects across different types of projects, which supports H2 and H3 generated based on the theory of information asymmetry and signaling. The results suggest that investor behavior is shaped not only by external shocks but also by project-specific characteristics, such as funding targets and creator reputation, offering deeper insights into the complex interplay of factors in crowdfunding platforms.

4.5 Reactions from Creators

So far, we have primarily examined the reactions of investors or backers to projects after the AI incident. Another important perspective is to analyze the reaction of creators. As project creators, they have the discretion to decide whether to continue seeking funding for their projects before the campaign ends. This decision reflects the creator's expectations regarding the project's potential success and their willingness to invest further effort in the campaign.

To explore this, we examine whether the likelihood of creators canceling their projects changes following the occurrence of an AI incident. Specifically, we re-estimate equation 1 by replacing the dependent variable to indicate whether a project was canceled before the end of its campaign. The results are presented in Column 1 of Table 6.

⁸ We further examine whether investors respond differently to creators with prior AI-related campaign experience. The results show that prior AI experience does not attenuate the negative impact of AI incidents on funding outcomes; the coefficient is slightly negative and marginally significant at 10%. This suggests that investors place greater weight on general crowdfunding experience rather than domain-specific familiarity when evaluating projects after external shocks. Results are available from the authors upon request.

[insert Table 6]

The coefficient for the interaction term is positive and statistically significant at 1% level, indicating that creators of AI-related projects are more likely to cancel their campaigns following an AI incident. This suggests that creators of AI related projects are more likely to discontinue their projects after an AI incident happened in their state.

However, one potential concern with this analysis is whether the length of campaigns for AI-related projects differs significantly before and after the AI incident, as this could influence the likelihood of cancellation. To address this concern, we include a robustness check by analyzing the interaction effect on the campaign length. As shown in column 2 of Table 6, the interaction term is insignificant, suggesting that campaign lengths are comparable before and after the AI incident for AI related projects. This mitigates concerns about differences in campaign duration affecting the cancellation decision.

Overall, these findings highlight the role of creators in responding to external events. In the context of AI incidents, creators of AI-related projects appear to adjust their expectation by cancelling their project in advance to conserve resources and redirect their efforts toward more promising opportunities.

5 Conclusion

Our study sheds light on the multifaceted impact of AI incidents on crowdfunding activities for AI-related projects. The findings underscore the significant challenges induced by AI risks, as reflected in reduced success rates, pledged amounts, and backer engagement following such incidents. Such insights can help creators shape the launching strategy of their crowdfunding projects. Given that investor sentiment declines following AI-related failures, creators may benefit

from delaying campaign launches until public confidence stabilizes or proactively addressing AI risks in their project descriptions to reassure potential backers. Additionally, experienced creators who have successfully launched previous campaigns can leverage their reputation to mitigate the negative impact of AI incidents by emphasizing their expertise and credibility.

Furthermore, crowdfunding platform managers can implement measures to support AI-related projects in the wake of AI incidents. For instance, platforms may introduce verification badges or third-party endorsements to signal project credibility, reducing investor skepticism. Additionally, incorporating adaptive funding mechanisms, such as milestone-based disbursement of funds, could provide greater assurance to backers and help sustain investment levels even after AI failures make headlines.

Finally, policymakers and regulators can use these insights to assess the broader implications of AI incidents in decentralized financial markets. While much attention has been drawn to AI risks in traditional finance, our study highlights that the regulatory landscape for crowdfunding must also consider how AI failures shape investor behavior. Establishing AI transparency requirements or ethical AI certification programs may help restore confidence in AI-related crowdfunding projects.

As one of the first studies to examine the intersection of AI risks and reward-based crowdfunding, our research contributes to multiple academic discussions. By bridging the gap between AI risk, behavioral finance, and crowdfunding ecosystems, we provide a foundation for further exploration into how technological uncertainties influence decentralized investment landscapes. Moving forward, researchers can expand upon our study by examining how different types of AI incidents (e.g., ethical failures vs. technical malfunctions) create varying levels of

investor distrust or by conducting cross-platform comparisons to evaluate how AI risks are perceived in equity-based versus reward-based crowdfunding models.

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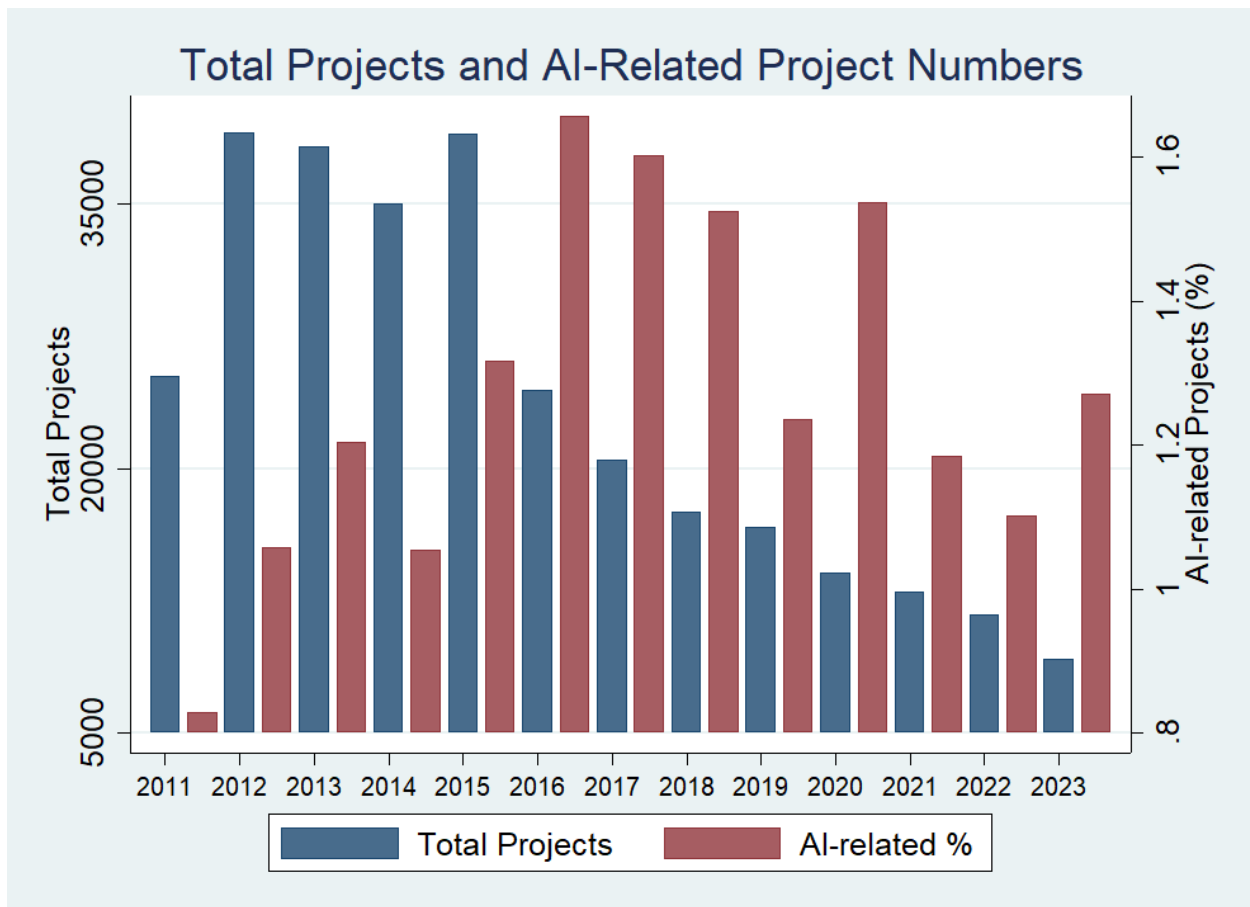
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Figure 1

Yearly Trend

This figure displays the percentage of AI-related projects for 2011-2023. Panel A shows the total number of projects launched on Kickstarter each year from 2011 to 2023, along with the proportion of AI-related projects by project count. Panel B presents the total annual funds raised on Kickstarter and the corresponding share allocated to AI-related projects.

Panel A



Panel B

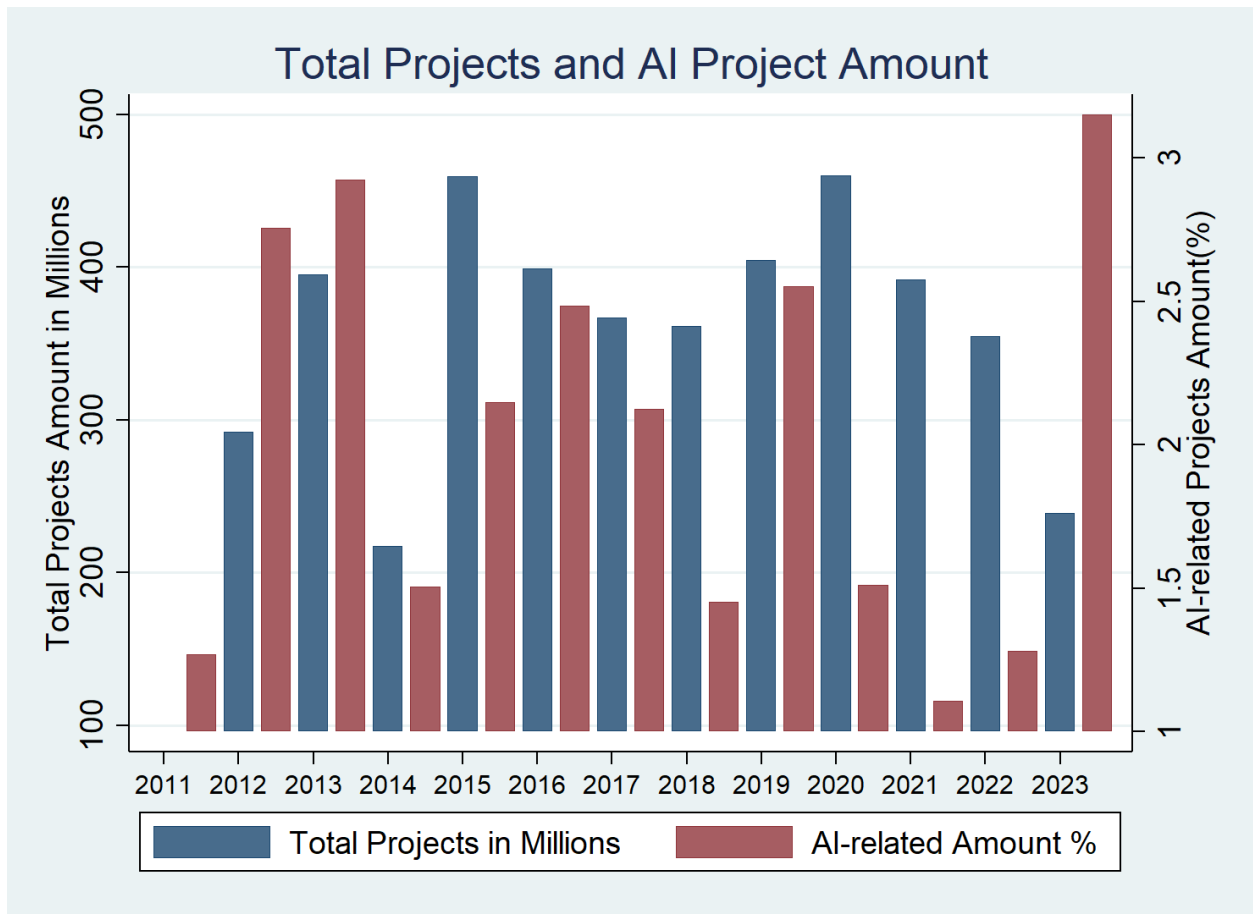
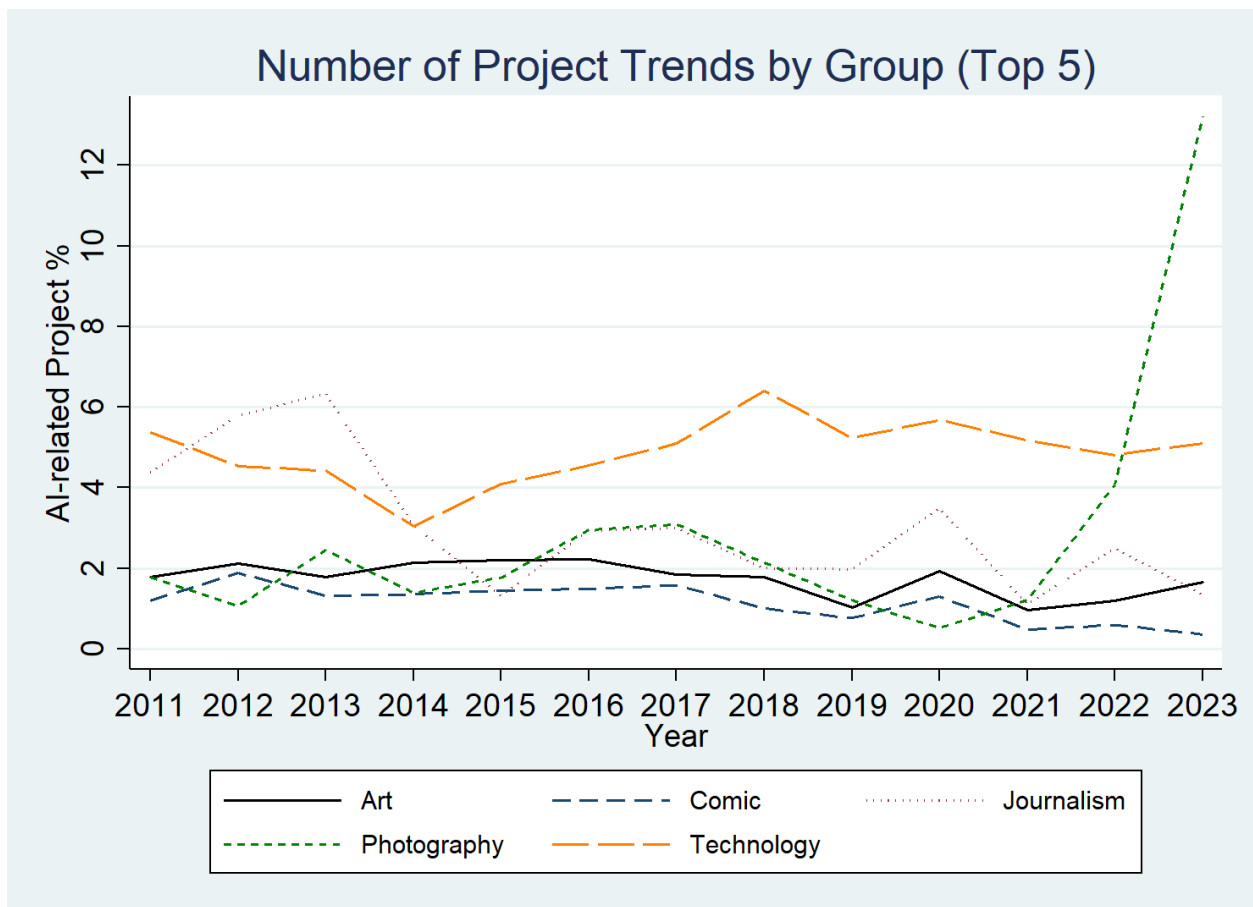


Figure 2

Category Distribution

The figure shows the average AI-related projects across different categories . Panel A displays the percentage of AI-related projects within the top five Kickstarter categories over time. Panel B shows the corresponding share of total pledged funding received by AI-related projects in each of these categories.

Panel A



Panel B

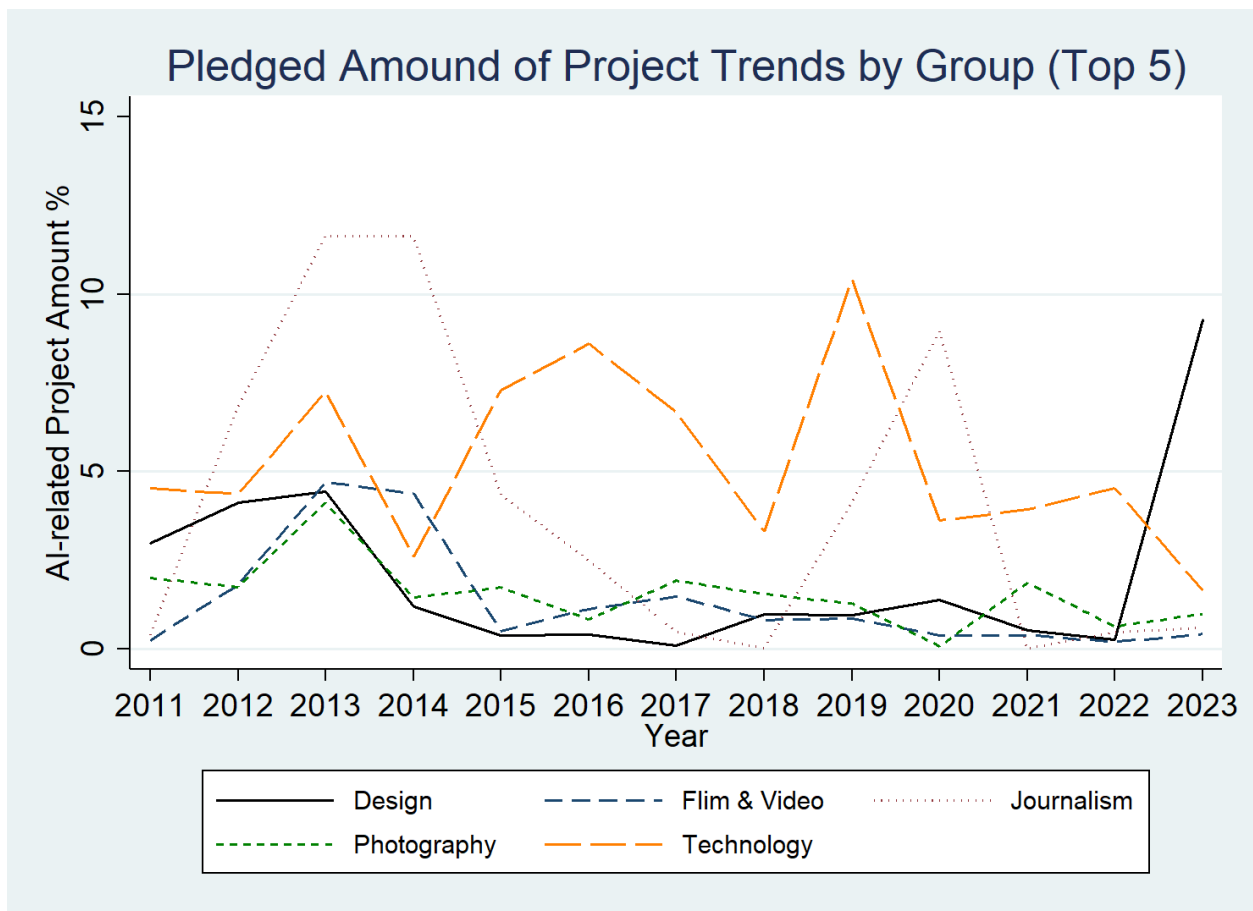


Table 1

Descriptive Statistics

This table presents summary statistics for all variables in our sample. The sample period is 2011-2023. Detailed definitions for each variable are provided in Appendix I. All continuous variables are winsorized at 1% and 99% levels.

	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
<u>Dependent Variable</u>						
Successful	294,277	0.494	0.500	0	0	1
Canceled	294,277	0.067	0.251	0	0	0
Ln (Backers)	294,277	3.100	1.916	1.386	3.178	4.477
Ln (Campaign Length)	294,277	3.476	0.361	3.434	3.434	3.584
Ln (Pledged Amount)	294,277	6.443	3.181	4.615	7.188	8.734
<u>Control Variables</u>						
Ln (Goal Amount)	294,277	8.500	1.580	7.601	8.517	9.616
Staff Pick	294,277	0.103	0.304	0	0	0
AI Related Project	294,277	0.013	0.111	0	0	0
After AI Incident	294,277	0.229	0.420	0	0	0
Female Creator	294,277	0.188	0.391	0	0	0
Male Creator	294,277	0.446	0.497	0	0	1
White Creator	294,277	0.285	0.451	0	0	1
Black Creator	294,277	0.017	0.128	0	0	0
Asian Creator	294,277	0.030	0.055	0	0	0
Hispanic Creator	294,277	0.014	0.037	0	0	0

Table 2

Main Regression Results

This table reports our main regression result by investigating the relation between success rate of AI related projects after the AI incident. Detailed definitions for each variable are provided in Appendix I. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) Successful	(2) Successful	(3) Successful
After AI Incident	0.027*** [3.243]	0.021*** [2.985]	
AI Related Project	0.004 [0.476]	0.015* [1.811]	0.022*** [9.716]
AI Related Project * After AI Incident	-0.026** [-2.158]	-0.046*** [-4.046]	
AI Incident [-3]			-0.052*** [-6.162]
AI Related Project * AI Incident [-3]			-0.009 [-0.952]
AI Incident [-2]			-0.038*** [-12.401]
AI Related Project * AI Incident [-2]			0.014 [0.741]
AI Incident [-1]			-0.017** [-2.107]
AI Related Project * AI Incident [-1]			-0.006 [-0.184]
AI Incident [+1]			-0.008 [-1.155]
AI Related Project * AI Incident [+1]			-0.029** [-2.398]
AI Incident [+2]			-0.002 [-0.330]
AI Related Project * AI Incident [+2]			-0.035*** [-3.895]
AI Incident [+3]			-0.017*** [-2.685]
AI Related Project * AI Incident [+3]			-0.065*** [-8.180]
Ln(Goal Amount)		-0.073*** [-72.591]	-0.073*** [-72.728]
Staff Pick		0.372*** [100.748]	0.375*** [93.656]
Gender Indicator	NO	YES	YES
Race Indicator	NO	YES	YES
Month FE	YES	YES	YES
County FE	YES	YES	YES
Category FE	YES	YES	YES
Campaign N FE	YES	YES	YES
Observations	294,277	294,277	294,277
Adjusted R-squared	0.282	0.364	0.362

Table 3

Matching Results

This table reports the results based on the propensity-score matched sample. The treatment group consists of projects where the owner is located in AI incident states, as defined in the Appendix II, while the control group consists of projects located in other states. Panel A presents parameter estimates from the logit model used to estimate the propensity scores. The dependent variable is one if the project belongs to the treatment group, and zero otherwise. Panel B reports univariate comparisons of project characteristics between the treatment and control sample. Panel C reports the results from the main regression by using the matched sample. Variable definitions are provided in the Appendix I. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Logit Regression Model

VARIABLES	(1) AI Project
Ln(Goal Amount)	0.087*** [6.303]
Female Creator	-0.384*** [-7.128]
Male Creator	-0.048 [-1.272]
White Creator	0.018 [0.525]
Black Creator	-0.094 [-0.626]
Hispanic Creator	-0.432 [-0.675]
Asian Creator	-0.158 [-0.536]
Staff Pick	0.186*** [2.777]
Year FE	YES
Category FE	YES
Observations	294,277
Pseudo R-squared	0.060

Panel B: Univariate Analysis for PSM Sample

	<u>AI Project = 0</u>	<u>AI Project = 1</u>		
	Mean	Mean	Diff	T-Stats
Ln (Goal Amount)	8.881	8.883	-0.002	0.15
Staff Pick	0.121	0.122	-0.001	0.49
Female Creator	0.122	0.120	0.002	0.50
Male Creator	0.469	0.472	-0.003	0.28
White Creator	0.273	0.280	-0.007	0.28
Black Creator	0.012	0.015	-0.003	1.32
Asian Creator	0.029	0.029	0.000	0.00
Hispanic Creator	0.005	0.006	-0.001	1.00
N	3,791	3,791		

Panel C: Regression Results for PSM

VARIABLES	(1) Successful	(2) Successful
After AI Incident	0.077** [2.337]	0.055** [2.061]
AI Related Project	0.031** [2.674]	0.026** [2.138]
AI Related Project * After AI Incident	-0.037** [-2.584]	-0.045*** [-3.088]
Ln (Goal Amount)		-0.072*** [-25.008]
Staff Pick		0.404*** [19.813]
Gender Indicator	YES	YES
Race Indicator	YES	YES
Month FE	YES	YES
County FE	YES	YES
Category FE	YES	YES
Campaign N FE	YES	YES
Observations	6,342	6,342
Adjusted R-squared	0.278	0.380

Table 4

Mechanism Analysis

This table reports our mechanism analysis. Column 1 tests the relation between AI incident and pledged amount from investors and column 2 tests the relation between number of backers and the AI incident. Detailed definitions for each variable are provided in Appendix I. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) Ln(Pledge Amount)	(2) Ln(Backers)
After AI Incident	0.189*** [9.637]	0.112*** [10.044]
AI Related Project	0.388*** [7.572]	0.175*** [6.025]
AI Related Project * After AI Incident	-0.373*** [-3.891]	-0.228*** [-4.196]
Ln(Goal Amount)	0.244*** [72.480]	0.121*** [63.455]
Staff Pick	2.558*** [154.637]	1.915*** [203.992]
Gender Indicator	YES	YES
Race Indicator	YES	YES
Month FE	YES	YES
County FE	YES	YES
Category FE	YES	YES
Campaign N FE	YES	YES
Observations	294,277	294,277
Adjusted R-squared	0.330	0.403

Table 5

Heterogeneity Analysis

This table reports our heterogeneity analysis. We define a high goal amount as the project's goal amount in the top quartile in our sample. In terms of repeated creators, we define it as the creators who have more than two projects in our database. Detailed definitions for each variable are provided in Appendix I. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) Successful	(2) Successful
After AI Incident	0.020*** [2.682]	0.022*** [3.973]
AI Related Project	-0.009 [-0.934]	0.021** [2.488]
AI Related Project * After AI Incident	-0.031*** [-2.754]	-0.055*** [-4.178]
High Goal Amount	-0.035*** [-4.150]	
High Goal Amount * After AI Incident	0.006 [0.390]	
High Goal Amount * AI Related Project	0.077*** [4.010]	
High Goal Amount * AI Related Project* After AI Incident	-0.049** [-2.620]	
Repeated Creator		0.112*** [14.539]
Repeated Creator * After AI Incident		-0.004 [-0.235]
Repeated Creator * AI Related Project		-0.068** [-2.612]
Repeated Creator * AI Related Project* After AI Incident		0.085** [2.333]
Ln(Goal Amount)		-0.074*** [-75.733]
Staff Pick	0.371*** [101.101]	0.375*** [101.594]
Gender Indicator	YES	YES
Race Indicator	YES	YES
Month FE	YES	YES
County FE	YES	YES
Category FE	YES	YES
Campaign N FE	YES	NO
Observations	294,277	294,277
Adjusted R-squared	0.364	0.362

Table 6

Reactions from Creators

This table reports the regression results analyzing creator reactions to AI incidents. The dependent variable in Column 1 is a binary indicator of whether a project was canceled by the creator before the end of the campaign. Column 2 uses the campaign length as the dependent variable to examine potential differences in campaign duration before and after the AI incident. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) Canceled	(2) Ln(Campaign Length)
After AI Incident	-0.009*** [-3.281]	0.013*** [3.102]
AI Related Project	-0.006 [-1.185]	0.005 [0.556]
AI Related Project * After AI Incident	0.017** [2.433]	-0.010 [-0.545]
Ln (Goal Amount)	0.014*** [28.104]	0.047*** [24.028]
Staff Pick	-0.058*** [-52.621]	0.020*** [8.139]
Gender Indicator	YES	YES
Race Indicator	YES	YES
Month FE	YES	YES
County FE	YES	YES
Category FE	YES	YES
Campaign N FE	YES	YES
Observations	294,277	294,277
Adjusted R-squared	0.040	0.069

Appendix I

Variable Definitions

Variable	Definition
Successful	An indicator variable equals one when the project is successfully funded.
Canceled	An indicator variable equals one when the project is canceled by the creator.
Ln (Backers)	Natural log of the number of backers for the project.
Ln (Campaign Length)	Natural log of the number of days between launch date and deadline for the project.
Ln (Pledged Amount)	Natural log of pledged amount for the project.
Ln (Goal Amount)	Natural log of goal amount for the project.
Staff Pick	An indicator variable equals one when project is picked by the staff from Kickstarter
AI Related Project	An indicator variable equals one when project is an AI-related project
After AI Incident	An indicator variable equals one when project is launched after the AI incident.
Female Creator	An indicator variable equals one if the creator is female.
Male Creator	An indicator variable equals one if the creator is male.
White Creator	An indicator variable equals one if the creator is White.
Black Creator	An indicator variable equals one if the creator is Black
Asian Creator	An indicator variable equals one if the creator is Asian
Hispanic Creator	An indicator variable equals one if the creator is Hispanic

Appendix II

AI Incident Date for Each State

This table reports the date for each state's first AI incident event.

State	Event Name	Event Date
New York	NY City School Teacher Evaluation Algorithm Contested	Feb 25,2012
California	Uber Autonomous Cars Running Red Lights	Aug 15,2014
Florida	Tesla on AutoPilot Killed Driver in Crash in Florida while Watching Movie	July 1,2015
Texas	Houston Schools Must Face Teacher Evaluation Lawsuit	May 8,2016
Nevada	Las Vegas Self-Driving Bus Involved in Accident	Nov 8,2017
Arizona	Uber AV Killed Pedestrian in Arizona	Mar 18,2018
New Jersey	Warehouse robot ruptures can of bear spray and injures workers	Dec 5,2018
Michigan	Detroit Police Wrongfully Arrested Black Man Due To Faulty FRT	Jan 30,2020

Appendix III

Example AI-related Projects

Project Name	Project Introduction	Category Name
Ozark Landscapes - Augmented Reality Time-Lapse Photo Book	Augmented Reality Time-Lapse Ozarks Landscape Photo Book, where still images will come to life when viewed with a smart phone or tablet	photography
SpaceVR: Step into Space	Giving everyone the opportunity to explore space by putting a virtual reality camera on the International Space Station!	technology/space exploration
Quarky: Learn AI. Make Bots. Have Fun!	Quarky: Learn AI. Make Bots. Have Fun!	technology/diy electronics
ROLLOVA! The World's First Compact Digital Rolling Ruler	Replacing traditional Measuring Tape Pocket-friendly gadget Measure curves and lines One roll at a time+D13609	design/product design
Drugs Digitized: Modern Developments in Internet Trafficking	Peer into other side through the eyes of dealers, customers, and law enforcement officers. An exploration of the internet black market	journalism
5 for 5e Gallery: support youth arts programming	We are creating opportunities for our youth to be image-makers, by adding digital media creation to our roster of summer programming.	art