From Choice to Mandate: Artificial Intelligence Disclosure as a Pseudo-Certification Scheme

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Abstract

Research Summary: The rapid adoption of AI has raised transparency concerns. Digital platforms have increasingly responded by mandating disclosure of AI use. Drawing on disclosure and certification theories, we suggest mandatory AI disclosure functions as a pseudo-certification mechanism, reducing information asymmetry and enhancing credibility. Analyzing 28,428 Kickstarter projects, we use conditional difference-in-differences focused on the period surrounding the platform's 2023 mandatory AI disclosure policy. Our analyses provide causal evidence that mandatory disclosure increases funding success probability by 13 percentage points for AI-disclosing projects. We explore moderating effects of project type and creator demographics. Our findings shed light on how platform governance shapes resource acquisition through verified transparency mechanisms.

Managerial Summary: Digital platforms increasingly mandate AI disclosure, but entrepreneurs question whether these policies help or hurt their ventures. We examined Kickstarter's August 2023 policy requiring creators to disclose AI use. We found mandatory disclosure significantly boosted funding success for AI-using projects by 13 percentage points after the policy. This suggests platform verification reduces information gaps between creators and backers, making enforced transparency a strategic advantage. Platform-mandated disclosure enhances the credibility of AI claims and directs funding toward verified projects. For AI entrepreneurs, our findings indicate that structured disclosure policies —initially seen as regulatory burdens— can effectively validate technological claims and facilitate resource acquisition.

Keywords: Artificial Intelligence; Certification; Crowdfunding; Digitalization; Disclosure

1. INTRODUCTION

Artificial intelligence (AI) emerges as a powerful driver for both technological and financial innovation, presenting significant opportunities for enterprises (Bain & Company, 2024; Bartram et al., 2019). Simultaneously, AI adoption intensifies the tension between leveraging innovation and ensuring transparency within entrepreneurial ecosystems. In response, digital platforms — critical arenas for venture resource acquisition and market entry — increasingly implement AI disclosure policies. Major platforms like Amazon, Meta, and YouTube have introduced such rules, often distinguishing between AI-generated content and AI-integrated products. While business practitioners emphasize such transparency as vital for informed decisions and trust (Renieris et al, 2024), academic research offers limited insight into the actual consequences of mandatory disclosure mandates. This leaves open the critical question of whether such policies facilitate or impede entrepreneurial success.

Platform governance is important for strategic entrepreneurship. Rules like AI disclosure mandates directly shape the competitive landscape, influencing how entrepreneurs formulate strategies, convey venture information, and acquire resources. How platforms regulate emerging technologies impacts resource allocation to new ventures and the co-evolution of financial and technological innovation within digital ecosystems (Nambisan et al., 2019; Yoo et al., 2012).

Existing literature has emphasized a general skepticism towards AI technologies. Studies highlight concerns about AI's reliability and ethicality (Hasan et al., 2021; Luo et al., 2019), and an "algorithm aversion" where individuals prefer human judgment over algorithmic decisions (Dietvorst et al., 2015). This skepticism often translates into reduced trust in AI-integrated products or services (Glikson & Williams Woolley, 2020), suggesting that disclosing AI use should deter potential crowdfunding backers, particularly in platforms with less sophisticated investors (Yu & Xiao, 2023).

We challenge this perspective by proposing that enforced, mandatory AI disclosure functions strategically as a pseudo-certification mechanism (Gross et al, 2005; Mogyoros, 2021, 2023). This platform-mediated process leverages platform authority and verification to enhance the credibility of entrepreneurs' AI claims. Particularly valuable when technical information is complex and audiences diverse (cf. Fishman & Hagerty, 2003), this mechanism reduces information asymmetry. By compelling even simplified disclosure across the board, potentially increasing overall market information despite its coarseness (cf. Asseyer & Weksler, 2024; Harbaugh & Rasmusen, 2018), it transforms disclosure from potential liability into an asset marker of technological sophistication.

Kickstarter, a major reward-based crowdfunding platform where entrepreneurs pre-sell innovations, provides a relevant setting. In August 2023, Kickstarter transitioned from voluntary to mandatory AI disclosure, requiring creators to detail AI use with active moderation and enforcement. This policy shift offers a natural experiment to analyze how moving from optional to mandatory, verified disclosure impacts project-level funding outcomes, specifically focusing on the success rate (reaching the funding goal) and total funds pledged.

To test our pseudo-certification argument empirically, we leverage Kickstarter's policy implementation as a quasi-natural experiment, drawing data from 28,428 projects spanning December 2022 to April 2024. Our strategy, focuses on isolating the policy's strategic impact by comparing project-level funding outcomes for ventures disclosing AI use versus those not disclosing, concentrating on the periods immediately surrounding the policy's effective date. This targeted comparison reveals a significant transformation: while AI disclosure showed positive but inconsistent associations with funding outcomes pre-policy, mandatory enforcement substantially strengthened and broadened its positive impact across both funding success rates and amounts. Our conditional difference-in-differences analysis across three distinct timeframes confirms these effects while revealing their temporal dynamics. This suggests the policy not only amplified the disclosure's informational value but also reshaped market dynamics, lending strong support to our pseudo-certification framework.

Our study contributes to strategic entrepreneurship literature in several ways. First, we examine how platform governance through mandatory AI disclosure shapes entrepreneurial resource acquisition (Nambisan et al., 2019; Yoo et al., 2012). Second, we extend established disclosure (Grossman, 1981; Verrecchia, 1983) and certification (Booth & Smith, 1986; Lizzeri, 1999; Stahl & Strausz, 2017; Viscusi, 1978) models to the context of AI, demonstrating how platform-enforced transparency can function as effective pseudo-certification (Gross et al, 2005; Mogyoros, 2021, 2023), particularly valuable when technology is complex and information asymmetry high (cf. Fishman & Hagerty, 2003). Third, we add to the research on crowdfunding success factors (Ahlers et al., 2015; Chan & Parhankangas, 2017) by showing how technological disclosure affects backer behavior and funding outcomes. Finally, we respond to calls for empirical assessment of transformative technologies (Acemoglu & Lensman, 2024) with evidence on how disclosure policies shape market responses to AI. Our findings offer insights for platform managers developing disclosure policies and entrepreneurs meeting transparency expectations in technological ventures.

2. BACKGROUND AND HYPOTHESES

2.1 Disclosure

Information asymmetry is a common issue in crowdfunding markets, where backers make investment decisions with limited knowledge about project quality, creator capabilities, and technologies involved (Agrawal et al., 2014). This issue is particularly significant in reward-based crowdfunding where backers function simultaneously as both consumers and investors — "prosumers" (Belleflamme et al., 2015) — increasing the importance of effective disclosure mechanisms.

The disclosure literature presents two traditional contrasting views: one where firms truthfully disclose information when they choose to disclose (Grossman, 1981; Viscusi, 1978), and another where sellers cannot credibly convey private information to buyers (Akerlof, 1970). However, crowdfunding platforms operate in a middle ground where disclosure credibility varies considerably (Lizzeri, 1999; Marinovic & Sridhar, 2015).

In voluntary disclosure environments, project creators strategically reveal information (Albano & Lizzeri, 2001), typically emphasizing positive aspects while minimizing potential drawbacks (Verrecchia, 1983). This selective disclosure is exacerbated by strategic framing (Foss & Weber, 2016), particularly regarding complex technological elements like AI integration. Creators have incentives to disclose only when information is sufficiently favorable, leading to adverse selection problems that are especially evident in crowdfunding where participants tend to have less financial and technical sophistication than those in traditional financial markets (Yu & Xiao, 2023).

Fishman & Hagerty (2003) challenge the assumption that sellers would voluntarily disclose all verifiable information by modeling markets with both informed and uninformed customers. When a significant portion of customers lacks the technical expertise to interpret disclosed information — while still observing that disclosure occurred — voluntary disclosure may not materialize. Their theoretical model suggests that mandatory disclosure is most valuable in markets where product information is relatively difficult to understand — a condition that applies to technical innovations like AI in crowdfunding contexts.

Empirical evidence supports these theoretical perspectives, with Mathios (2000) demonstrating that mandatory nutrition labeling led to sales declines for previously non-disclosing high-fat products. This suggests mandatory disclosure can effectively influence consumer choices even in markets with existing low-cost disclosure mechanisms.

In the crowdfunding context, Strausz (2017) highlights how platforms change the relationship between creators and backers by allowing entrepreneurs to contract with future consumers before investments are made. This creates an information environment where disclosure serves both to signal product quality and to reduce demand uncertainty. Under these conditions, mandatory disclosure policies can help reduce moral hazard concerns by limiting creators' ability to misrepresent technological capabilities.

2.2 Certification

Traditional certification involves third parties who verify quality or attributes when information asymmetry exists between buyers and sellers (Biglaiser, 1993; Booth & Smith, 1986; Lizzeri, 1999; Stahl & Strausz, 2017). This process typically includes explicit fees paid to independent agencies, as seen with underwriters signaling firm quality in IPOs (Beatty & Ritter, 1986;

Megginson & Weiss, 1991) or venture capitalists conducting due diligence before investment (Brav & Gompers, 1997).

Recent research has identified "pseudo-certification," where entities that are not independent third-party certifiers — such as platforms, producers themselves, or other stakeholders — take on certification roles (Gross et al, 2005; Mogyoros, 2021, 2023). Expert intermediaries help reduce uncertainty about product characteristics through certification processes, significantly affecting market outcomes (Bapna, 2019). Our concept of pseudo-certification partially resembles these traditional models, but with the platform functioning as both enforcer and certifier rather than relying on independent third parties.

Crowdfunding markets feature substantial information asymmetry since creators naturally know more about their early-stage projects than potential backers do (Agrawal et al., 2014), creating uncertainty about creator credibility and intentions (Connelly et al., 2011). We propose that crowdfunding platforms can function as "pseudo-certifiers" in this environment. By mandating AI disclosure, vetting project submissions, and enforcing compliance, the platform performs functions similar to traditional certifiers, validating information transparency for potential backers.

Platforms themselves often function as certification mechanisms in early-stage fundraising (Drover et al., 2017). Through its moderation team's review process, Kickstarter creates credibility by verifying disclosed AI use before and after project publication, effectively warranting the accuracy of this information to potential backers despite not being an independent third party. This process is tailored to their specific context rather than following broadly established certification standards. Similar pseudo-certification occurs in trademark contexts when brand owners use trademarks to convey product characteristics without independent oversight (Mogyoros, 2021, 2023), and in software markets where customers evaluate components using vendor-provided information (Gross et al, 2005). Kickstarter's AI disclosure policy creates a comparable structure—with platform-specific validation mechanisms that reduce information asymmetry while providing informational cues for project evaluation.

While Kickstarter's AI disclosure policy lacks the explicit fees of traditional certification, it creates implicit costs for AI-disclosing creators, such as increased risk of imitation and potential penalties for non-compliance. This aligns with Harbaugh & Rasmusen's (2018) findings in certification markets that coarse information disclosure mechanisms can paradoxically increase overall market information. In their model, simplifying information (through coarse grading) encourages broader participation from middle-quality participants who might otherwise opt out of detailed disclosure systems. Similarly, Kickstarter's relatively straightforward AI disclosure requirement — which asks for presence rather than technical specifics — may achieve greater market transparency than a more precise technical verification system would. This approach parallels Asseyer & Weksler's (2024) findings that coarser certification schemes attain higher market coverage through increased participation. The net effect is potentially more valuable information reaching backers despite the simplified format, as the participation benefits outweigh the granularity costs.

2.3 AI Adoption, Narratives, and Perceptions

The global AI market has experienced rapid and steady growth over the past few years. Recent forecasts on the AI-related hardware and software market estimate 40%-55% growth annually, reaching $780-$990 billion by 2027 (Bain & Company, 2024). Widespread AI adoption remains in early stages, with economic impact only beginning to materialize. This market expansion, particularly in the generative AI (GenAI) sector, has simultaneously raised significant public concerns focused on issues of authenticity, transparency, and ethical implementation.

Research on AI tends to indicate that public perceptions of AI technologies are context dependent. Organizational studies highlights that AI integration depends significantly on workers' trust, revealing tension between initial excitement about innovation and underlying skepticism (Glikson & Williams Woolley, 2020). This tension becomes particularly pronounced in virtual and embedded AI settings, where trust typically begins high but gradually declines with continued exposure — a pattern especially relevant to crowdfunding contexts. In these environments, predominantly non-technical backers may recognize AI as an innovation marker without comprehending its technical aspects. As platforms function as pre-markets for prototypes with limited opportunity for direct product experience, backers must rely on disclosed information when forming judgments. This creates a strategic challenge for creators: balancing innovation claims (Chan & Parhankangas, 2017) while addressing potential "algorithm aversion" - the documented preference for human judgment over algorithmic decisions (Dietvorst et al., 2015).

A critical distinction emerges between projects that disclose AI as a technological feature versus those using AI to generate project descriptions. While backers may value AI as an innovation marker, empirical evidence indicates that algorithmically-generated content can trigger negative authenticity judgments (Jago et al., 2022), diminished perceptions of customization capability (Longoni et al., 2019), and amplified skepticism in communal-oriented platforms (von Walter et al., 2023). This creates a tension wherein backers may value AI as a technical innovation feature while expecting authentic human expertise in creator communications.

While not specific to crowdfunding, Guo et al. (2018) demonstrated how strategic language can influence competitive interactions. In crowdfunding, research on impression management shows strategic disclosure enhances authenticity perceptions (Bolinger et al., 2024). Shrestha et al. (2023) found backers assess technological viability while responding to presentation style and perceived authenticity. In our setting, given information asymmetry between creators and backers and pre-policy limited verification methods, project information accuracy is critical for funding decisions. The policy implementation creates an opportunity to understand how backers interpret cues about creators' technological sophistication, potentially distinguishing between those who merely use AI for project descriptions versus those incorporating AI as a substantive innovation component.

2.4 Introduction of Kickstarter's Policy

Kickstarter's strategic decision to implement an AI disclosure policy gains significance due to its status as the world's largest crowdfunding platform. The platform's scale — enabling over $8.66 billion for 276,000+ projects since 2009 — and market influence, highlighted by its recognition as one of Time's "100 Most Influential Companies of 2023," establish it as a critical environment for studying platform governance. Analyzing Kickstarter's policy is particularly relevant as it aligns with a broader trend of AI transparency initiatives across major digital platforms (e.g., Amazon, Meta, YouTube), reflecting strategic responses within the digital economy.

On August 29, 2023, Kickstarter implemented a mandatory AI disclosure policy with two key aspects. First, it allows AI integration in creative projects. Second, it requires creators to disclose how AI is used, clearly distinguishing between human and AI-generated elements. Creators must detail which elements are wholly original versus AI-generated, and projects developing AI technology must disclose information about databases and data sources used, including consent and credit practices.

Active enforcement supports the policy's implementation through a human moderation team that reviews AI disclosures during project submission. For approved projects, these disclosures become public information within a dedicated “Use of AI” section. Platform moderation continues post-launch to identify non-compliant submissions. Non-compliance carries significant risks: projects may face suspension, while misrepresentation can lead to restrictions on creators' future platform access. The policy applies only to submissions made after August 29, 2023, requiring creators to weigh potential benefits of disclosure against platform penalties and the heightened risk of imitation resulting from mandated transparency.

Platform governance challenges and creator relations dynamics motivated this initiative. CEO Everette Taylor framed the policy as supporting “creative work and the humans behind that work” following controversies that brought tensions between enabling AI innovation and protecting creator rights. Notable incidents included the removal of “Unstable Diffusion” (which had raised $56k) [1] and the AI-driven plagiarism attempt by “Illusionary Radiance” against Ali Fell's “A Trick of The Light” [2], illustrating the need to manage AI's disruptive potential.

Kickstarter demonstrates commitment through strict enforcement. In February 2024, the “Coast Runner” project was terminated after raising $542,123 in a few hours (goal: $24,999) for non-compliance with Kickstarter's AI policy. This action demonstrated prioritization of AI transparency over immediate project funding success, despite significant financial implications.

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[1] TechCrunch (High-tech and startup online media). https://techcrunch.com/2022/12/21/kickstarter-shut-down-the-campaign-for-ai-porn-group-unstable-diffusion-amid-changing-guidelines/ [accessed: May 12, 2025].
[2] BleedingCool (Entertainment online media). https://bleedingcool.com/comics/kickstarter-approves-then-removes-comic-stolen-with-a-i/ [accessed: May 12, 2025].

Stakeholder reactions reveal complexities. While many creators and backers support increased transparency, online discourse shows ongoing debates about AI's implications for creative industries. Some express concerns about AI threatening artists' livelihoods, while others view the technology as a valuable creative tool requiring careful integration.

Functionally, this mandatory AI disclosure policy operates as a 'pseudo-certification' mechanism within the Kickstarter ecosystem. The policy mitigates information asymmetry by establishing a standardized verification process. Although lacking traditional third-party independence, this system enhances the credibility of creators' AI claims and enables more informed funding decisions. Kickstarter's specific requirements, coupled with validation processes, create a framework with enforcement mechanisms analogous to traditional certification, adapted to the platform setting.

2.5 Hypotheses Development

Informational effect of AI disclosure under voluntary conditions

In crowdfunding markets, significant information asymmetry exists between creators and backers (Agrawal et al., 2014). This asymmetry is particularly pronounced regarding technological innovations like AI integration, where backers often lack the expertise to evaluate claims independently. Under these conditions, voluntary disclosure theory suggests that creators strategically reveal information to differentiate themselves in the marketplace (Verrecchia, 1983).

While some disclosure literature suggests that revealing certain types of information could negatively impact firms (Mathios, 2000), we argue that in crowdfunding, AI use disclosure represents a marker of technological innovation rather than a general quality indicator. Prior research demonstrates that technological innovation claims attract backers seeking novelty in crowdfunding contexts (Taeuscher & Rothe, 2021). Overall, AI disclosure serves as a marker of applied innovation, which particularly appeals to reward-based crowdfunding backers who typically favor practical, incremental improvements over radical innovations (Chan & Parhankangas, 2017). This aligns with Berg's (2022) observation that while creators may occasionally face radical innovations that fundamentally change their industries, most often the challenge is responding to constant incremental change in what is popular (Klepper, 1997). This addresses what Fishman & Hagerty (2003) identify as the dual audience challenge in disclosure environments — satisfying both technically informed and uninformed backers. For informed backers, AI disclosure provides substantive information about project capabilities; for uninformed backers, it functions as a simple innovation heuristic in crowdfunding's complex decision-making environment.

Reduced perceived risk from such innovation disclosure increases backers' willingness to support projects financially. The disclosure functions as part of what Steigenberger & Wilhelm (2018) term as "portfolio of signals," where AI disclosure serves as a substantive cue that, combined with other project elements, creates positive differentiation for AI-integrating projects. This enhances perceived technological legitimacy and innovation potential.

Voluntary AI disclosure can drive higher funding amounts through two additional channels. First, in contexts where backers function as "prosumers"—simultaneously consumers and investors (Belleflamme et al., 2015) — AI disclosure addresses dual information needs about both product innovation and market potential. By voluntarily disclosing AI integration, creators differentiate their projects within competitive crowdfunding marketplaces (Porter, 1985), potentially attracting technology enthusiasts with higher willingness to pay, who may contribute larger amounts.

Additionally, as reward-based crowdfunding functions as a pre-market test (Schwienbacher, 2018), higher funding amounts may reflect backers' assessment of market potential. AI disclosure can indicate enhanced scalability and future opportunities for backers evaluating long-term project viability, motivating larger contributions to secure early access to promising innovations.

Based on these arguments, we propose the following hypotheses:

Hypothesis (H1a). *Under voluntary disclosure, projects that disclose AI use increase their probability of funding success relative to non-disclosing projects.*

Hypothesis (H1b). *Under voluntary disclosure, projects that disclose AI use receive a higher average funding amount compared to non-disclosing projects.*

Amplification of informational effect: Pseudo certification under mandatory disclosure

Kickstarter's mandatory AI disclosure policy represents a fundamental shift in platform governance that transforms voluntary information disclosure into a standardized information verification system. This policy functions as what we term a "pseudo-certification" mechanism (Gross et al, 2005; Mogyoros, 2021, 2023), enhancing information credibility while lacking the complete independence of traditional third-party certification (Biglaiser, 1993; Booth & Smith, 1986; Lizzeri, 1999; Stahl & Strausz, 2017).

Traditional certification typically involves independent third parties verifying specific attributes. However, Kickstarter's policy creates a platform-specific validation mechanism where the platform itself serves as both enforcer and certifier. The human-reviewed enforcement system with penalties for non-compliance incentivize "cheap talk" reduction by imposing tangible costs on misleading claims (Almazan et al., 2008; Chakraborty & Harbaugh, 2007).

While some might expect that mandatory disclosure of technological elements could reduce project attractiveness by forcing revelation of potentially negative aspects (Verrecchia, 1983), we argue that the certification-like nature of the policy enhances AI disclosure's positive informational value through several mechanisms.

As a key benefit, the policy mitigates adverse selection problems by reinforcing positive perceptions through external verification (Bederson et al., 2018; Dranove & Jin, 2010; Seigner et al., 2022). By establishing the platform as a neutral verifying entity, the policy reduces backers' interpretation burden, allowing funding decisions with greater confidence in disclosed information—directly increasing projects' likelihood of reaching funding goals.

Moreover, the mandatory framework enhances credibility by enforcing comprehensive disclosure of both favorable and unfavorable information. This reduces strategic framing opportunities (Foss & Weber, 2016) that might otherwise allow creators to selectively emphasize positive aspects while minimizing drawbacks. The resulting transparency increases both funding probability and amounts.

Asseyer & Weksler (2024) suggests that less precise certification schemes can enhance market transparency by enabling more participants to become certified, contrasting with precise designs where high costs lead only a fraction of participants to seek certification. This aligns with our context where Kickstarter's policy, while less precise than traditional certification, may achieve greater transparency by requiring all AI-integrating projects to disclose. When credibly verified, this coarse but compliance-driven information becomes more valuable to backers, increasing funding to AI-disclosing projects compared to non-AI ones—widening the funding gap.

Fishman & Hagerty (2003) model of markets with informed and uninformed customers explains why mandatory disclosure is particularly valuable in markets with products that are difficult to understand — like AI-enhanced projects. Their framework demonstrates that mandatory disclosure creates asymmetric benefits: informed backers can make better decisions without adversely affecting uninformed ones. In the crowdfunding, technically sophisticated backers can effectively evaluate AI claims under the mandatory policy and potentially increase their funding amounts, while less technically oriented backers benefit from the platform's verification function without needing to understand technical specifics.

Through mandated review processes and enforcement, the platform's pseudo-certification role strengthens disclosure's informational value. This approach particularly benefits markets with less financially and technically sophisticated participants, common in reward-based crowdfunding (Yu & Xiao, 2023). By reducing information asymmetry through verified disclosure, the policy enables backers to identify genuinely innovative AI projects, directing larger funding to these ventures while potentially reducing support for non-AI projects or those with less substantive AI integration.

Based on these considerations, we propose:

Hypothesis (H2a). *The mandatory AI disclosure policy will increase the funding success probability for AI-disclosing projects compared to the voluntary regime.*

Hypothesis (H2b). *The mandatory AI disclosure policy will widen the funding amount gap between AI-disclosing and non-disclosing projects.*

3. DATA AND VARIABLE OPERATIONALIZATION

3.1 Sample

To construct our dataset of Kickstarter projects, we sourced data from webrobots.io, a web crawling service extensively used in crowdfunding research (Cascino et al., 2019; Chang et al., 2023; Guo et al., 2018). We downloaded comprehensive CSV files covering the period from December 2022 through April 2024, providing a focused dataset surrounding Kickstarter's August 2023 AI disclosure policy implementation. The dataset contains creator information, backer counts, project descriptions, completion status (live, suspended, canceled, failed, successful), industrial categories (15) and subcategories (146), geographical locations (25 countries), funding goals, pledged amounts, currencies, and USD exchange rates. Additional metadata include Staff Picks designation, project URLs, launch dates, and deadlines.

We enhanced this primary dataset with several derived variables: (1) an AI synthetic Google Trends index, (2) creator gender, (3) creator ethnicity, (4) a binary indicator for AI disclosure, and (5) a moderator variable distinguishing between GenAI and traditional AI applications.

Our data preprocessing workflow consisted of four key steps. First, we automatized the merging procedure for all CSV files involved and resolved format inconsistencies. Second, we standardized all monetary values to USD and adjusted for inflation using the Consumer Price Index (CPI) from the Federal Reserve Bank of St. Louis, normalizing to 2023 values. Third, we generated supplementary time variables including creation-to-launch duration, campaign length, and a variable measuring weeks to policy within a year to control for seasonality. Fourth, we created our longitudinal repeated cross-section.

Following established practice in crowdfunding research (Cascino et al., 2019; Gafni et al., 2021; Mollick, 2014), we restricted the analysis to projects with definitive outcomes (successful or failed), excluding those with intermediate or indeterminate statuses (live, suspended, or canceled). These excluded observations were negligible and omitted to prevent bias from preliminary states or unserious funding attempts.

Our final sample involves 14,848 projects spanning from December 2022 through April 2024. We deliberately constrained our time window to this period to balance two methodological considerations. First, focusing on the immediate aftermath of the August 2023 policy implementation allows us to capture the initial market reaction to mandatory AI disclosure with minimal confounding factors. Second, this timeframe provides sufficient post-policy observations to establish credible causal connections without extending so far as to introduce potential confounds from evolving technology acceptance norms or industrywide standardization of AI disclosure practices. Longer observation periods would risk diluting the policy effect as AI disclosure requirements potentially become standard across other platforms, making the policy less distinctive as a treatment condition.

INSERT FIGURE 1 HERE

3.2 Variable Definition and Measurement

The focal variable in our analysis is AI disclosure in project descriptions. We create a binary indicator that equals one when a project discloses AI use and zero otherwise. To identify AI disclosures across the dataset, we developed a systematic text mining procedure using a dictionary of AI-related terminology extended from Rezazadegan et al.'s (2024) patent classification lexicon (Appendix A). We refined this dictionary to ensure comprehensive coverage of AI terminology relevant to crowdfunding. After applying this dictionary to identify AI-related keywords within project descriptions, we conducted manual verification on a selected subset of projects to address potential false negatives and enhance classification accuracy.

To differentiate between generative AI and traditional AI applications, we implemented a secondary classification methodology based on Feyzollahi & Rafizadeh (2025). Adapting their approach for identifying LLM use patterns in academic writing, we distinguish between projects using AI as a functional product component versus those using generative AI capabilities. This distinction addresses whether backers respond differently to AI as a technical innovation feature versus as a content generation tool—potentially revealing tensions between perceptions of technological sophistication and expectations of authentic human expertise.

To control for temporal variations in market sentiment toward AI technologies, we constructed a synthetic Google AI Trends index following Baker & Fradkin's (2017) methodology—an approach commonly used in economic research as a proxy for consumer confidence and market expectations (e.g. Da et al., 2015). We created a country-weighted index reflecting Kickstarter's changing geographical composition over time, weighting country-specific Google Trends values for "Artificial Intelligence" according to the proportion of projects originating from those countries. This approach ensures our index represents Kickstarter's geographic distribution rather than being dominated by trends from any single country. The resulting index serves as a key control variable, accounting for changing market interest in AI technologies that could independently influence both creators' disclosure decisions and backers' funding behaviors.

To examine demographic heterogeneity in AI disclosure effects, we estimated two key creator attributes. For ethnicity prediction, we used creators' names with established methodology (Xie, 2022), allowing us to examine whether non-majority ethnic status moderates the relationship between AI disclosure and funding outcomes—extending research on ethnicity effects in labor markets (Fryer & Levitt, 2004; Kang et al., 2016). For gender identification, we employed name-based classification (Pérez, 2016) to investigate gender as a potential moderator, building on research documenting gender differences in crowdfunding outcomes (Gafni et al., 2021; Greenberg & Mollick, 2017).

For project success measures, we employ two dependent variables: (1) a binary Success indicator that equals one if a project reached its funding target and zero otherwise, and (2) the natural logarithm of the amount pledged plus unit, addressing the right-skewed distribution of funding amounts. All variables and their definitions are provided in Appendix B.

4. EMPIRICAL DESIGN

4.1 Empirical Specification

To examine the impact of Kickstarter's mandatory AI disclosure policy on project outcomes, we leverage the policy change as a quasi-natural experiment, inspired by Cascino et al. (2019), who explored a change in Kickstarter's terms of use to study disclosure and consumer protection regulation. We focus on this policy introduction on August 29, 2023, as our pivotal event.

We restrict our analysis to 18 weeks before and after implementation, reducing confounding factors by focusing on the period where policy effects are most evident. Similar to Gaessler et al.

(2024), who narrow their analysis around patent invalidations, our chosen timeframe balances sufficient observations with isolating policy effects from long-term trends or seasonal variations.

Our main empirical specifications are:

(1) OLS Model: $\ln(Pledged_i + 1) = \beta_0 + \beta_1 AI\_Disclosure_i + \beta_2 X_i + \gamma_c + \delta_t + \varepsilon_i$

(2) Logit Model: $\Pr(Funded_i = 1|\mathrm{X}_i) = \Phi(\beta_0 + \beta_1 AI\_Disclosure_i + \beta_2 X_i + \gamma_c + \delta_t + \varepsilon_i)$

Where, the dependent variables are $\ln(Pledged_i + 1)$ the natural logarithm of the amount pledged to project i, plus a unit to address zero values, or an indicator variable equal to 1 if project i is successfully funded, and 0 otherwise $(Funded_i)$. $\Phi(.)$ denotes the cumulative distribution function of the standard logistic distribution. $AI\_Disclosure_i$ is an indicator variable equal to 1 if the project discloses AI use, and 0 otherwise. X_i is a vector of control variables including project characteristics (e.g., funding goal, campaign duration, blurb length), creator attributes (e.g., gender, ethnicity), and market conditions (e.g., Google Trends index for AI). γ_c represents subcategory fixed effects. δ_t denotes time fixed effects (week-year).

Subcategory fixed effects control for time-invariant factors potentially affecting project success and AI disclosure, while week-year fixed effects account for broader crowdfunding trends. We cluster standard errors at the project subcategory and week-year level. Our main coefficient of interest is β_1, capturing the effect of AI disclosure on outcomes.

We estimate these models using both OLS and logit specifications with entropy balancing weights (Hainmueller, 2012; Hainmueller & Xu, 2013). This technique matches control group covariate distributions to the treatment group across the first three moments (mean, variance, and skewness) of key variables such as funding goal, blurb length, campaign duration, and the Google

AI Trends index. Entropy balancing offers advantages over traditional matching methods (Heckman et al., 1998) by directly balancing on covariate moments. We perform this balancing separately for pre- and post-policy periods to account for compositional changes over time.

The OLS model provides interpretable coefficients for pledged amounts, while the logit model (with reported average marginal effects) is appropriate for the binary funding success outcome. By estimating models separately for pre- and post-policy periods with consistent sample equivalence between specifications, we can directly compare how the policy altered the relationship between AI disclosure and project outcomes.

To investigate heterogeneous effects, we introduce interaction terms. First, we examine whether backers distinguish between projects using AI as a functional component versus those using generative AI for descriptions, addressing theoretical considerations about different responses to AI as innovation versus content creation tool. Second, we focus on innovation-intensive creators developing technically complex and interactive products in domains characterized by rapidly changing standards and heightened market uncertainty (Berg, 2022). Third, we explore heterogeneity across creator demographics by interacting AI disclosure with indicators for female creators, creators of color, and their intersection, revealing potential disparities in the policy's impact. Fourth, we examine projects with high funding goals (exceeding the 90th percentile among unsuccessful pre-policy projects) to assess whether the policy's effects differ for ambitious projects.

4.2 Conditional Difference-in-Differences and Identification Strategy

Beyond the baseline specifications, we use a conditional difference-in-differences (CDiD) approach (Murtinu, 2021) to address time-variant unobservable factors. For this analysis, we precisely define our treatment and control groups: the treatment group consists specifically of projects disclosing AI use after the policy implementation, while our control group includes both non-AI projects and pre-policy AI-disclosing projects. This definition allows us to isolate the effect of mandatory disclosure rather than just AI use itself.

We estimate the following model:

$$\text{(3) CDiD Model: } y_i = \beta_0 + \beta_1(Treated_i x Post_t) + \beta_2 Treated_i + \beta_3 Post_t + \gamma X_i + \delta_t + \varepsilon_i$$

Where y_i indicates successful funding and X_i includes control variables such as funding goal, blurb length, creation-to-launch days, campaign duration, Google Trends index, staff pick status, creator location, and subcategory fixed effects. We include time fixed effects (δ_t) at the week level to account for temporal variations.

We examine three distinct timeframes: March–December 2023 to capture immediate effects, March 2023–March 2024 for medium-term impacts, and December 2022–April 2024 to assess longer-term trends. This multi-period design enables us to track the evolution of treatment effects over time. To estimate the policy impact, we implement both a traditional Two-Way Fixed Effects (TWFE) model and the more flexible estimator developed by Callaway & Sant'Anna (2021), which is robust to treatment effect heterogeneity and staggered adoption. The TWFE model is estimated as a linear probability model (LPM) with heteroskedasticity-robust standard errors. For the Callaway and Sant'Anna estimator, we compute robust standard errors for the influence functions and conduct inference using bootstrap resampling. The coefficient of interest, β_1, identifies the average treatment effect on the treated (ATT), capturing the differential impact of mandatory AI disclosure on project outcomes. As in Section 4.1, we apply entropy balancing weights (on the first three moments of continuous covariates) to ensure comparability between treated and control groups. For a discussion of the limitations of TWFE under treatment effect heterogeneity, see also Goodman-Bacon (2021).

A relevant assumption underlying our CDiD approach is that treatment and control groups would have followed parallel trends in the absence of intervention. We test this assumption twofold: through standard F-tests of pre-treatment differences and visually implementing a stacked event study design (e.g. Atal et al, 2024). As shown in Figure 2, estimated coefficients for pre-policy months are small and statistically indistinguishable from zero, confirming parallel trends, while post-policy coefficients reveal positive and increasing treatment effects.

INSERT FIGURE 2 HERE

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5. EMPIRICAL RESULTS

5.1 Descriptive Statistics

Our analysis includes 14,848 Kickstarter projects from December 2022 to April 2024. Table 1 details the sample distribution, illustrating Kickstarter's diverse project ecosystem during this timeframe.

The platform shows diversity across project categories, as detailed in Panel A. Games (14.82%), Publishing (12.22%), Film and Video (10.46%), Comics (11.55%), and Art (10.22%) represent the most common categories. This spread reflects Kickstarter's appeal to various creative and innovative ventures, supporting its role in funding early-stage projects that might struggle with traditional financing options.

Project size distribution, presented in Panel B, offers insights into how entrepreneurs use the platform. The majority (57.09%) of projects have funding goals under $5,000, indicating smaller ventures. However, 17.31% of projects seek $15,000 or more, showing the platform also serves more capital-intensive projects. This bimodal distribution highlights how Kickstarter meets diverse entrepreneurial needs across different scales of innovation.

INSERT TABLE 1 HERE

Table 2 compares project characteristics before and after the AI policy implementation on August 29, 2023. The percentage of AI-disclosed projects increased from 1.63% to 2.33% post-policy - a 42.94% relative increase. This shift suggests a change in either AI adoption or disclosure behavior following the policy implementation.

Comparing AI-disclosing projects with non-AI projects in the pre-policy period (Appendices C and D) reveals patterns consistent with our first hypothesis. Before the policy, AI-disclosing projects showed higher mean pledged amounts ($86,354) compared to non-AI projects ($23,147). This difference supports H1b's prediction about the positive informational effect of AI disclosure on funding amounts under voluntary disclosure conditions.

When examining success rates, we observe that pre-policy AI-disclosing projects had a 50.41% success rate compared to 75.59% for non-AI projects. While this initial comparison indicates an important difference, it's worth noting that AI projects typically set higher funding goals ($146,810 on average) compared to non-AI projects ($26,874), among other distinguishing characteristics. These structural differences suggest that raw comparisons alone may not fully capture the relationship between AI disclosure and project outcomes. Our subsequent analyses account for these compositional differences, allowing us to isolate the specific informational effect of AI disclosure from other project attributes that influence funding performance.

Post-policy implementation, we observe changes that align with our second hypothesis regarding the amplification effect of mandatory disclosure. Mean pledged amounts for AI-disclosing projects rose from $86,354 to $90,230, while non-AI projects saw an almost negligible decrease from $23,147 to $23,143. This widening gap provides preliminary support for H2b, which predicts that the mandatory policy would increase the funding amount difference between AI-disclosing and non-disclosing projects.

Success rates also show noteworthy changes post-policy. While non-AI projects experienced a slight decrease in success rates from 75.59% to 73.56%, AI-disclosing projects saw an increase from 50.41% to 56.82%. This trend suggests that the mandatory disclosure policy may have enhanced the success probability for AI-disclosing projects, consistent with H2a.

In the 18 weeks after policy implementation, the proportion of AI-disclosing projects increased by 42.94%, while overall project submissions declined by 23.78%. Furthermore, successful AI projects increased by 22.95%, while successful non-AI projects decreased by 26.36%. These trends provide preliminary evidence supporting both our hypotheses about the positive effect of AI disclosure and its strengthening under the mandatory policy regime.

The data also reveal demographic changes. Female representation in AI-disclosing projects increased from 5.79% to 12.12% following policy implementation, while remaining relatively stable at around 19% for non-AI projects. This differential change suggests that the policy may have affected creator demographics differently, a pattern we examine further in our analysis.

These descriptive statistics provide preliminary evidence supporting our hypotheses. The increased prevalence and success of AI-disclosing projects post-policy align with expectations of positive informational effects and the policy's role as a pseudo-certification mechanism.

INSERT TABLE 2 HERE

5.2 Disclosure and Project Performance

Table 3 presents findings on the relationship between AI disclosure and project performance before and after Kickstarter's policy implementation.

Pre-policy, under voluntary disclosure conditions, AI disclosure exhibited differential effects across our outcome measures. The logit model revealed a positive but statistically insignificant effect on project success probability (coefficient: 0.08, z-statistic: 0.29, p-value: 0.79). However, the OLS model demonstrated a significant positive effect on pledged amounts (coefficient: 0.63, t-statistic: 2.52, p-value: 0.01). These results provide support for H1b while offering no support for H1a. This pattern suggests that under voluntary disclosure, AI disclosure functioned primarily as an innovation marker that influenced funding amounts rather than funding goal achievement. Creators voluntarily disclosing AI use may have attracted technology-oriented backers who perceived AI as a cue of technological sophistication, leading to larger contributions, though this did not translate to a higher probability of reaching the project's funding goal. The coefficient for AI disclosure on success probability is close to zero (0.08) and non-significant (z-statistic: 0.29, p-value: 0.79), indicating no relationship between voluntary AI disclosure and funding success.

Post-policy, the effects of AI disclosure strengthened substantially across both outcome measures. AI disclosure exhibited a strong positive association with project success probability (coefficient: 2.03, z-statistic: 5.49, p-value: 0.00) and pledged amounts (coefficient: 0.95, t-statistic: 3.65, p-value: 0.00). These results provide support for both H2a and H2b, suggesting that the mandatory policy amplified the informational value of AI disclosure. The standardization of disclosure requirements through this platform's mechanism appears to have enhanced the credibility of AI-related information. This reduction in information asymmetry enabled backers to make more informed assessments, leading to increased support for projects disclosing AI use.

The control variables reveal consistent patterns across both time periods. Higher funding goals negatively associated with success probability both pre-policy (coefficient: -0.99, z-statistic: -9.00, p-value: 0.00) and post-policy (coefficient: -0.70, z-statistic: -7.78, p-value: 0.00) while showing a non-significant relationship with pledged amounts in both periods. This reflects the inherent challenge that ambitious funding targets present for project success, irrespective of AI disclosure status. Campaign duration exhibited positive effects on both success probability and pledged amounts across both periods, with post-policy coefficients of 0.58 (z-statistic: 5.27, p-value: 0.00) for success and 0.51 (t-statistic: 5.10, p-value: 0.00) for pledged amounts, highlighting the importance of allowing sufficient time for project discovery and backer engagement.

The 'Staff Pick' designation appear as a strong predictor of favorable outcomes across both periods, with large positive effects. Post-policy, it showed substantial impacts on both success probability (coefficient: 3.10, z-statistic: 10.00, p-value: 0.00) and pledged amounts (coefficient: 2.61, t-statistic: 10.88, p-value: 0.00). This effect shows the significance of platform endorsement as a credibility marker, complementing our findings regarding AI disclosure as a pseudo-certification mechanism.

These results provide evidence supporting our theoretical framework regarding the transformation of voluntary disclosure into a pseudo-certification mechanism through policy implementation. The mandatory AI disclosure policy appears to have functioned as a credibility-enhancing mechanism, reducing information asymmetry and enabling backers to more accurately assess the value of AI integration in crowdfunding projects.

INSERT TABLE 3 HERE

5.3 Heterogeneous Effects

Table 4 presents our analysis of heterogeneous effects, examining how AI disclosure effects vary across different project and creator characteristics. We investigate four distinct dimensions of heterogeneity: (1) GenAI versus traditional AI applications, (2) creator demographics (gender and ethnicity), (3) projects with particularly high funding goals, and (4) innovative creators in technology-intensive sectors.

GenAI moderates the relationship between AI disclosure and project outcomes in the pre-policy period. While AI disclosure itself shows a positive and significant effect on pledged amounts (coefficient: 0.61, t-statistic: 2.44, p-value: 0.02), projects using GenAI applications exhibit significantly lower funding amounts (coefficient: -0.82, t-statistic: -2.22, p-value: 0.03). This negative effect suggests that backers may have viewed GenAI projects skeptically, possibly perceiving them as lacking substantive technological innovation or authentic human creativity.

Under the voluntary disclosure regime, backers couldn't reliably distinguish whether project descriptions were generated by AI or humans, creating uncertainty about authenticity and creator capabilities. The interaction between AI disclosure and GenAI shows a complex pattern - it's positive but not significant for pledged amounts (coefficient: 0.98, t-statistic: 1.18, p-value: 0.24) while being negative and significant for success probability (coefficient: -2.96, z-statistic: -2.55, p-value: 0.01). This suggests that voluntarily disclosing GenAI use actually reduced the likelihood of reaching funding goals, despite potentially increasing the average funding amount. This negative effect on success probability highlights how voluntary disclosure without certification mechanisms may amplify rather than reduce information asymmetry problems, as backers may interpret voluntary disclosures about GenAI use with heightened skepticism in the absence of external verification.

Post-policy, the distinction between GenAI and other AI applications becomes less pronounced. The main effect of AI disclosure remains strong and significant for both success probability (coefficient: 2.05, z-statistic: 5.54, p-value: 0.00) and pledged amounts (coefficient: 0.97, t-statistic: 3.73, p-value: 0.00). The GenAI indicator shows a negative but non-significant effect (coefficient: -0.62, z-statistic: -0.86, p-value: 0.39 for success probability; coefficient: 0.36, t-statistic: 0.70, p-value: 0.48 for pledged amounts). The interaction between AI disclosure and GenAI could not be estimated in the post-policy period, suggesting that the mandatory disclosure requirements standardized how AI use is reported, eliminating the previous distinctions between AI application types.

Creator demographics reveal notable patterns. In the pre-policy period, female creators show a positive but non-significant effect on success probability (coefficient: 0.25, z-statistic: 0.83, p-value: 0.40) and pledged amounts (coefficient: 0.32, t-statistic: 1.45, p-value: 0.14). Gender does not emerge as a significant moderator of funding outcomes. However, people of color show a negative and significant effect on success probability (coefficient: -0.57, z-statistic: -3.00, p-value: 0.00) and a marginally significant negative effect on pledged amounts (coefficient: -0.29, t-statistic: -1.93, p-value: 0.06). Post-policy, the negative effect for people of color becomes significant for pledged amounts (coefficient: -0.44, t-statistic: -2.31, p-value: 0.02) while remaining non-significant for success probability. This suggests that racial disparities may be more pronounced than gender differences in this context.

The interaction between AI disclosure and female creator status is not significant in either period (coefficients: -1.511, z-statistic: -1.08 pre-policy; 0.272, z-statistic: 0.24 post-policy for success), suggesting no gender-specific effects of AI disclosure. Similarly, the interaction between AI disclosure and creator ethnicity is also non-significant. These findings indicate that while demographic factors may influence overall funding outcomes, they do not significantly moderate the relationship between AI disclosure and project success.

Examining projects with high funding goals (those exceeding the 90th percentile among unsuccessful pre-policy projects), we find negative main effects for risky goals in the pre-policy period, significant for pledged amounts (coefficient: -0.83, t-statistic: -2.30, p-value: 0.02) but not for success probability (coefficient: -0.43, z-statistic: -0.84, p-value: 0.40). This partially supports the notion that ambitious projects face funding challenges, but suggests that this effect manifests primarily in reduced funding amounts rather than lower success rates.

Post-policy, we observe a notable transformation in how ambitious projects are evaluated. While risky goals showed a significant negative effect on pledged amounts pre-policy (coefficient: -0.83, t-statistic: -2.30, p-value: 0.02), this penalty disappears post-policy (coefficient: -0.59, t-statistic: -1.44, p-value: 0.15). This pattern suggests that the mandatory disclosure policy may have created a more level playing field where ambitious projects face less inherent disadvantage, possibly because the standardized transparency about AI use helps mitigate concerns about project feasibility that might otherwise be triggered by high funding goals.

Innovative creators in technology-intensive sectors show distinctive patterns, though estimates should be interpreted cautiously given the smaller sample sizes (538 pre-policy, 457 post-policy). Pre-policy, AI disclosure exhibits a positive but non-significant effect on success probability (coefficient: 0.13, z-statistic: 0.19, p-value: 0.84) and a positive and significant effect on pledged amounts (coefficient: 0.88, t-statistic: 2.51, p-value: 0.01). Post-policy, this pattern changes: AI disclosure shows a positive and significant effect on success probability (coefficient: 1.69, z-statistic: 2.52, p-value: 0.01), while the effect on pledged amounts becomes non-significant (coefficient: 0.37, t-statistic: 1.00, p-value: 0.32). This suggests that the mandatory disclosure policy shifted how backers evaluate AI use in innovation-intensive contexts, potentially creating a legitimizing effect that enhances success probability rather than just funding amounts.

INSERT TABLE 4 HERE

5.4 Causal Evidence

Table 5 presents our conditional difference-in-differences analysis examining the causal effect of Kickstarter's mandatory AI disclosure policy on project success rates across three timeframes: March-December 2023, March 2023-March 2024, and December 2022-April 2024.

The results consistently show positive effects of the policy change on AI-disclosing projects' success rates. Panel A reveals that the Callaway Sant'Anna Difference-in-Differences estimator (CSDiD) indicates moderate but significant treatment effects, with DiD estimates of 0.13 (standard error: 0.07, p-value: 0.09) for the immediate period, 0.14 (standard error: 0.06, p-value: 0.03) for the medium-term, and 0.14 (standard error: 0.06, p-value: 0.02) for the longest timeframe. The TWFE estimates provide consistent support with stronger statistical significance: 0.13 (standard error: 0.03, p-value: 0.00), 0.08 (standard error: 0.03, p-value: 0.01), and 0.07 (standard error: 0.03, p-value: 0.01) respectively.

Panel B reveals a striking transformation in the relative performance of AI-disclosing projects. During the pre-policy period, the CSDiD estimates show essentially no disadvantage for AI-disclosing projects in shorter timeframes: 0.01 (standard error: 0.03, p-value: 0.86) for both the immediate and medium-term periods. The longest timeframe shows a modest negative effect of -0.03 (standard error: 0.02, p-value: 0.27), though not statistically significant. The TWFE estimates reveal more pronounced pre-policy disadvantages, particularly in longer timeframes, with significant negative effects of -0.06 (standard error: 0.03, p-value: 0.02) in both the medium-term and longest periods.

This pattern provides nuanced evidence about voluntary disclosure effects that complements our earlier findings. While Table 3 showed positive effects of voluntary AI disclosure on pledged amounts in the pre-policy period, the causal analysis here reveals a more complex temporal dynamic. The absence of significant pre-policy effects in shorter windows, combined with the emergence of negative effects in longer observation periods (particularly evident in the TWFE estimates), suggests that challenges faced by AI-disclosing projects under voluntary disclosure became more apparent over extended timeframes. This difference between our regression-based analysis and difference-in-differences approach indicates that voluntary disclosure regimes may create persistent disadvantages that are not immediately observable in shorter-term analyses, with both methodological approaches converging on evidence that voluntary disclosure created information asymmetry problems over time.

The post-policy transformation demonstrates consistent positive effects across all timeframes. The CSDiD estimates show positive effects of 0.12 (standard error: 0.07, p-value: 0.11) for the immediate period, 0.13 (standard error: 0.07, p-value: 0.05) for the medium-term, and 0.14 (standard error: 0.06, p-value: 0.04) for the longest timeframe. The TWFE estimates confirm this pattern with highly significant effects in the immediate period: 0.11 (standard error: 0.03, p-value: 0.00), though showing smaller magnitudes in longer timeframes: 0.01 (standard error: 0.01, p-value: 0.39) and 0.01 (standard error: 0.01, p-value: 0.28) respectively.

The stability of the CSDiD estimates across timeframes indicates that the mandatory disclosure policy created a durable advantage for AI-disclosing projects. This contrasts with the voluntary regime, where negative effects are more evident when examined over longer historical periods, suggesting the mandatory policy established a stable positive evaluation framework that persists across different observation windows.

These results provide robust causal support for our theoretical framework. The significant positive DiD estimates across all timeframes demonstrate that the mandatory AI disclosure policy transformed AI disclosure from a potentially ambiguous marker of technological innovation under voluntary conditions to a credible indicator of technological sophistication under the mandatory regime. This transformation persists even as markets adjust to new information environments, though with gradually decreasing magnitude over time—consistent with expectations of market adaptation to disclosure regimes.

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6. DISCUSSION OF IMPLICATIONS AND CONCLUSIONS

6.1 Contribution to Academic Literature

This study examines the integration of new, skeptically viewed technological innovations into an innovative financial market. In particular, we analyze a policy mandating AI disclosure in creative projects, using crowdfunding as a setting. With digital platforms like Meta, YouTube, Google and Kickstarter, addressing the use of AI in response to public concerns, studying the impact of mandatory disclosure policies becomes increasingly important. We document how the implementation of a platform-wide disclosure policy substantially changes the relationship between AI disclosure and project success, with different patterns emerging under voluntary versus mandatory disclosure regimes. Our findings contribute to four primary literature streams.

First, we address an important gap in innovation literature by investigating co-developments at the intersection of financial and technological innovation (Goldstein et al., 2019). By documenting how platform-level policy changes regarding AI disclosure affect resource allocation to early-stage ventures, we show the interdependencies between platform governance mechanisms and emerging technologies. This relationship extends understanding of how financial platforms and technological innovations interact in digital environments (Nambisan et al., 2019; Yoo et al., 2012), which has received limited attention in prior research.

Second, we contribute to the disclosure literature (Grossman, 1981; Verrecchia, 1983) and certification theory literature (Booth & Smith, 1986; Lizzeri, 1999; Stahl & Strausz, 2017; Viscusi, 1978) by providing empirical evidence on how platform-enforced mandatory disclosure functions as a pseudo-certification mechanism in markets with substantial information asymmetry. Our findings demonstrate how mandatory policies alter information revelation dynamics and offer empirical support for Fishman & Hagerty's (2003) theoretical model on the value of mandatory disclosure in markets with varying levels of consumer expertise. The increase in funding success rates we observed for AI-disclosing projects following policy implementation supports their prediction that mandatory disclosure particularly benefits markets where disclosed information is technically complex. Additionally, our findings provide empirical evidence consistent with Asseyer & Weksler's (2024) theoretical arguments that relatively coarse certification mechanisms can enhance market transparency by increasing participation rates, as shown by the increase in AI-disclosing projects post-policy implementation.

Third, we contribute to the crowdfunding literature by identifying AI disclosure as a significant success factor moderated by project characteristics and creator demographics. Building on research examining technological innovation cues in crowdfunding (Agrawal et al., 2014; Ahlers et al., 2015; Chan & Parhankangas, 2017), we demonstrate that AI disclosure functions as both a technological sophistication marker and a credibility cue when validated through platform enforcement. Our heterogeneity analysis revealed that GenAI projects faced significant disadvantages pre-policy (coefficient: -0.82, standard error: 0.37, p-value: 0.03) with voluntary disclosure actually reducing success probability (coefficient: -2.96, standard error: 1.16, p-value: 0.01). This aligns directly with our information asymmetry framework — without structured verification, voluntary disclosures about GenAI amplified rather than reduced market uncertainties. The post-policy disappearance of this negative effect confirms our pseudo-certification argument, as the platform's verification mechanism effectively normalized perceptions of different AI applications by standardizing disclosure credibility.

The analysis also shows that creator demographics affect funding outcomes, with creators of color showing lower success probability pre-policy (coefficient: -0.57, standard error: 0.19, p-value: 0.00) and lower pledged amounts post-policy (coefficient: -0.44, standard error: 0.19, p-value: 0.02), though these effects do not significantly interact with AI disclosure. This suggests that while demographic disparities exist in crowdfunding, they operate independently from the disclosure effects we observe. High-funding-goal projects and technology-intensive creators also show distinctive patterns, with mandatory disclosure creating a more level playing field across different project types while particularly benefiting technology-intensive projects with enhanced success probability.

Fourth, we provide empirical evidence on AI adoption and public perception in market contexts. While prior literature has documented public skepticism toward AI (Glikson & Williams Woolley, 2020; von Walter et al., 2023), our findings reveal that transparent, verified AI disclosure can positively influence market outcomes. This offers an important counterpoint to research on "algorithm aversion" (Dietvorst et al., 2015) and concerns about AI-generated content authenticity (Jago et al., 2022). By examining actual funding behaviors rather than stated preferences, we respond to calls for empirical assessment of transformative technologies like

GenAI (Acemoglu & Lensman, 2024) and provide evidence on how disclosure policies affect technological adoption in market settings (Strausz, 2017).

6.2 Conclusions, Implications for Practice and Policy Recommendations

Our quasi-experimental analysis reveals how platform governance changes affect entrepreneurial outcomes in innovative digital markets. This policy transformed voluntary information disclosure into a structured pseudo-certification mechanism with significant effects on entrepreneurial resource acquisition. In pre-policy voluntary conditions, entrepreneur AI disclosure exhibited limited associations with funding success probability but positive effects on funding amounts. Post-policy, AI-disclosing entrepreneurial projects experienced substantial increases in both success probability and funding amounts, while non-disclosing projects saw modest declines in success rates. These findings are particularly pronounced for high-aspiration ventures with substantial funding goals and digitally-focused creators, suggesting that structured disclosure policies can help entrepreneurs signal technological sophistication and attract resources.

Our conditional difference-in-differences analysis across three timeframes (immediate, medium-term, and longer-term) reveals consistent positive effects that remain statistically significant across all observation periods. The Callaway Sant'Anna estimates show stable treatment effects across timeframes. This temporal pattern suggests that the policy created a durable shift in how AI-disclosing projects are evaluated rather than merely a transitory response.

The effectiveness of this pseudo-certification mechanism lies in how it fundamentally restructures the information environment. Unlike traditional third-party certification that typically involves independent verification against standardized criteria, platform-based pseudo-certification uses the platform's moderation authority to validate disclosure claims while imposing real consequences for non-compliance. Our findings show that this mechanism addresses a critical strategic challenge in digital platform governance: how to reduce information asymmetry regarding technically complex innovations without imposing prohibitive verification costs. The amplification of AI disclosure effects post-policy suggests that this governance approach successfully balances the seemingly conflicting demands of verification credibility and implementation feasibility — a balance that has strategic significance.

For strategic management of digital platforms, our findings offer practical insights into the governance of emerging technologies. Many platforms have recently introduced AI disclosure policies in response to widespread skepticism about AI integration. Contrary to expectations that such disclosures might decrease success rates for AI-related ventures due to backer hesitancy, our results demonstrate that structured disclosure of AI integration with proper verification mechanisms can positively impact funding outcomes. This suggests that well-designed transparency policies can help manage the inherent tension between technological sophistication and consumer acceptance in reward-based crowdfunding. Platform managers might consider how information verification systems can create favorable conditions for technology adoption, particularly when technologies face public concerns about authenticity and appropriate use.

For entrepreneurs and creators, our results suggest the value of transparent technological disclosure when backed by credible verification mechanisms. The differences we observe across project types and creator demographics indicate that disclosure strategies may yield different benefits depending on project characteristics. For instance, our analysis revealed that prior to the policy, projects using GenAI applications exhibited significantly lower funding amounts, and voluntarily disclosing such use actually amplified this disadvantage, reducing success probability further. This negative interaction disappeared under the mandatory disclosure regime, suggesting that platform verification transformed potentially harmful information asymmetry into beneficial transparency. Additionally, we found that creators of color faced lower success probabilities pre-policy and lower funding amounts post-policy, though these demographic effects did not significantly interact with AI disclosure. These findings suggest that standardized disclosure frameworks may help reduce certain information asymmetries in entrepreneurial resource allocation while providing greater certainty to backers evaluating technologically sophisticated projects, though additional mechanisms may be needed to address persistent demographic disparities.

Policy implications extend beyond crowdfunding to broader digital platform governance. Our findings show that mandatory disclosure policies can effectively address information asymmetry while potentially encouraging responsible technology integration. The positive market response suggests that transparency requirements need not create prohibitive compliance costs or stifle innovation when appropriately structured. Policymakers should note, however, heterogeneous effects when designing disclosure frameworks.

As with all research, our study has limitations that suggest directions for future work. Our analysis focuses exclusively on Kickstarter within a focused timeframe surrounding the policy implementation. This focus stems from methodological requirements crucial for the validity of our quasi-experimental design. While our data source contains raw data for both Kickstarter and Indiegogo, fundamental differences between these platforms impede a direct, meaningful comparison. Kickstarter's distinctive all-or-nothing funding model contrasts sharply with Indiegogo's mixed funding models. Attempting to compare outcomes across such different structures would introduce confounding factors, undermining causal identification — a challenge reflected in problematic benchmarking within prior literature. Therefore, focusing solely on

Kickstarter was methodologically necessary to isolate the policy effect within a consistent institutional context, though this choice constrains generalizability.

Further research could explore individual backer behavior through complementary methodologies such as surveys or interviews, addressing limitations in our project-level data. Obtaining backer-level data, for example, could allow for investigation into potential homophily biases, such as whether backers disproportionately support same-gender or same-ethnicity creators, and how disclosure information is processed across demographic groups. Additionally, studies could examine how structured disclosure policies influence consumer acceptance of AI-integrated products over time, particularly as AI technologies become more mainstream and disclosure norms evolve. The effects of AI disclosure in other digital contexts with different stakeholder relationships beyond the creator-backer dynamic of reward-based crowdfunding also represents a promising avenue for future investigation.

This study provides evidence on how platform governance structures can influence the integration of emerging technologies into financial markets. By documenting the transition from voluntary disclosure to mandatory pseudo-certification, we demonstrate how structured information verification mechanisms shape market responses to technological innovation. These findings add to our understanding of the strategic relationship between financial platforms, information asymmetry, and technological adoption in entrepreneurial settings.

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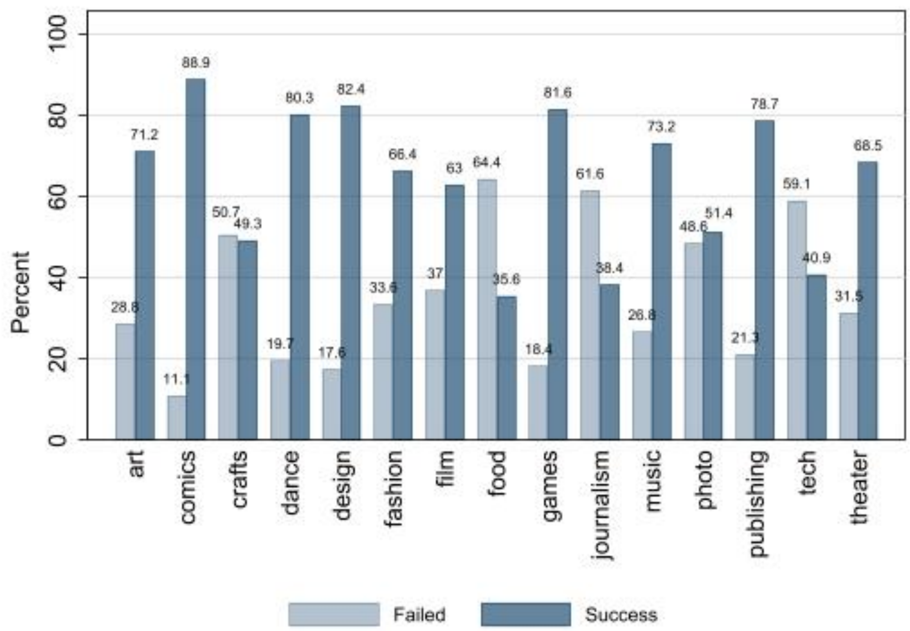
FIGURE 1: Historical cumulative count of states by category



The figure shows the distribution of states (failed/success) by industrial category for all the projects since the launch of the platform until the end of 2023.

FIGURE 2: Event study - differential effects of AI disclosure on project success

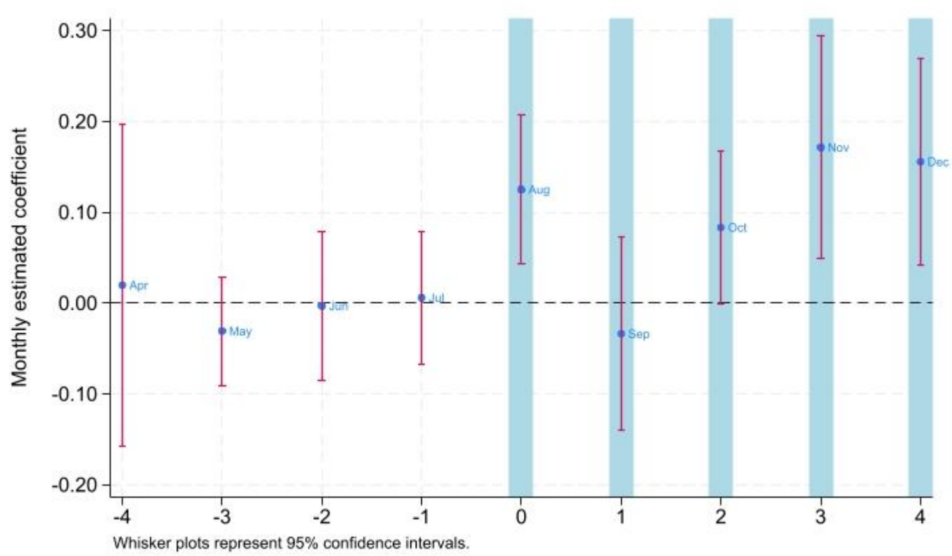


TABLE 1: Categories and goals

Panel A: Projects by category		
Category	Observations	Percentage
Film and video	1,553	10.46
Music	907	6.11
Publishing	1,814	12.22
Games	2,200	14.82
Art	1,518	10.22
Technology	1,474	9.93
Dance	46	0.31
Food	702	4.73
Fashion	597	4.02
Comics	1,715	11.55
Photography	254	1.71
Crafts	317	2.13
Design	1,474	9.13
Journalism	91	0.61
Theatre	186	1.25
Total	14,848	100.00
Panel B: Projects by size		
Size	Observations	Percentage
Goal < U.S. $5,000	8,477	57.09
U.S. $5,000 ≤ Goal < U.S. $10,000	2,503	16.86
U.S. $10,000 ≤ Goal < U.S. $15,000	1,298	8.74
Goal ≥ U.S. $15,000	2,570	17.31
Total	14,848	100.00

Table 1 illustrates the distribution across categories (Panel A) and project size defined by goals (Panel B). It uses an 18-week window.

TABLE 2 : Pre and post-policy summary statistics

Panel A: Full Sample						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	14,848	24,709	3,433	135,371	71	37,595
Goal	14,848	31,118	3,385	996,118	334	25,000
Backers	14,848	217	50	829	3	418
Blurb Length	14,848	16	16	6	7	23
Panel B: After AI Policy Implementation (+18 weeks)						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	5,673	24,716	3,386	142,679	65	36,790
Goal	5,673	38,543	3,291	1,369,476	368	25,000
Backers	5,673	205	45	810	3	383
Blurb Length	5,673	16	16	6	7	23
	Yes (%)	No (%)				
Discrete variables:						
US located	56.00	44.00				
Female	19.02	80.98				
People of Color (PoC)	73.54	26.46				
AI Disclosed	2.33	97.67				
Staff Pick	20.68	79.32				
Successful	73.17	26.83				
Panel C: Before AI Policy Implementation (-18 weeks)						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	7,443	24,175	3,511	128,069	82	37,377
Goal	7,443	28,824	3,500	737,768	310	25,000
Backers	7,443	223	54	757	3	443
Blurb Length	7,443	16	16	6	8	23
	Yes (%)	No (%)				
Discrete variables:						
US located	57.33	42.67				
Female	18.16	81.84				
People of Color (PoC)	73.32	26.68				
AI Disclosed	1.63	98.37				
Staff Pick	18.77	81.23				
Successful	75.18	24.82				

Table 2 presents descriptive statistics, showing results for the full sample, and for periods before and after the policy implementation (using an 18-week window). All variables used in the empirical analysis are defined in Appendix B.

TABLE 3: Disclosure and project performance

	Before AI Policy (-18 weeks)		After AI Policy (+18 weeks)	
	Logit(1)	OLS(2)	Logit(1)	OLS(2)
ln(pledged+1)		X		X
Success	X		X	
AI Disclosed	0.08	0.63**	2.03***	0.95***
	(0.29) [0.79]	(0.25) [0.01]	(0.37) [0.00]	(0.26) [0.00]
ln(Goal+1)	-0.99***	-0.07	-0.70***	0.06
	(0.11) [0.00]	(-0.06) [0.28]	(0.09) [0.00]	(0.07) [0.40]
ln(Duration+1)	0.55***	0.57***	0.58***	0.51***
	(0.08) [0.00]	(0.08) [0.00]	(0.11) [0.00]	(0.10) [0.00]
ln(Campaign Days+1)	-0.07	-0.21	-1.10***	-0.01
	(0.32) [0.83]	(0.24) [0.37]	(0.32) [0.00]	(0.32) [0.97]
Staff Pick	3.63***	3.03***	3.10***	2.61***
	(0.28) [0.00]	(0.23) [0.00]	(0.31) [0.00]	(0.24) [0.00]
US located	0.11	0.27	-0.01	0.05
	(0.28) [0.70]	(0.26) [0.29]	(0.27) [0.97]	(0.26) [0.86]
Demographic controls	Yes	Yes	Yes	Yes
Trends and characteristics controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	3,869	3,869	2,939	2,939
Pseudo-R^2	0.56		0.51	
Adjusted-R^2		0.57		0.48

Table 3 reports the results of separate regressions estimating the association between AI disclosure and project performance before and after the policy implementation. Columns 1 and 2 show results for the pre-policy period; columns 3 and 4 present results for the post-policy period. For each period, we estimate both a logistic regression (columns 1 and 3), where the dependent variable is Success (a binary indicator equal to 1 if the project reached its funding goal), and an OLS regression (columns 2 and 4), where the outcome is the log of pledged funding. All models are estimated using comparable samples within an ±18-week window around the policy implementation date (August 29, 2023). We apply entropy balancing separately for each period to reweight observations based on the first three moments (mean, variance, and skewness) of key continuous covariates: funding goal, blurb length, campaign duration, time from creation to launch, and Google Trends interest in AI. These weights are used in all models, and each pair of regressions (logit and OLS) is estimated on the same set of balanced observations. All specifications include the full set of control variables and fixed effects. The table reports heteroskedasticity-robust standard errors in parentheses, z-statistics for logistic regressions, and t-statistics for OLS regressions. P-values are reported in square brackets. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels (two-tailed), respectively. Definitions of all variables are provided in Appendix B.

TABLE 4 - Heterogeneous effects

	Before AI Policy (-18 weeks)								After AI Policy (+18 weeks)							
	GenAI		Female - PoC		Risky goals		Innovative		GenAI		Female - PoC		Risky goals		Innovative	
	Logit(1)	OLS(2)	Logit(3)	OLS(4)	Logit(5)	OLS(6)	Logit(7)	OLS(8)	Logit(1)	OLS(2)	Logit(3)	OLS(4)	Logit(5)	OLS(6)	Logit(7)	OLS(8)
ln(pledged+1)		X		X		X		X		X		X		X		X
Success	X		X		X		X		X		X		X		X	
AI Disc.	0.12	0.61**	0.04	1.57***	0.11	0.53**	0.13	0.88**	2.05***	0.97***	1.54**	0.29	2.07***	0.97***	1.69**	0.37
	(0.29)	(0.25)	(0.81)	(0.60)	(0.29)	(0.26)	(0.67)	(0.35)	(0.37)	(0.26)	(0.62)	(0.57)	(0.38)	(0.27)	(0.67)	(0.37)
	[0.67]	[0.02]	[0.96]	[0.01]	[0.71]	[0.04]	[0.84]	[0.01]	[0.00]	[0.00]	[0.01]	[0.61]	[0.00]	[0.00]	[0.01]	[0.32]
GenAI	0.04	-0.82**							-0.62	0.362						
	(0.53)	(0.37)							(0.72)	(0.52)						
	[0.94]	[0.03]							[0.39]	[0.48]						
AI Disc. x GenAI	-2.96**	0.98							0.00	0.00						
	(1.16)	(0.83)							(.) [.]	(.) [.]						
	[0.01]	[0.24]														
Female			0.25	0.32							-0.04	-0.20				
			(0.30)	(0.22)							(0.31)	(0.29)				
			[0.40]	[0.14]							[0.90]	[0.50]				
PoC			-0.57***	-0.29							-0.27	-0.44**				
			(0.19)	(0.15)							(0.22)	(0.19)				
			[0.00]	[0.06]							[0.22]	[0.02]				
AI Disc. x Fem.			-1.51	0.83							0.27	1.27				
			(1.39)	(0.94)							(1.11)	(1.24)				
			[0.28]	[0.38]							[0.81]	[0.31]				
AI Disc. x PoC			0.18	-1.05							0.89	0.66				
			(0.84)	(0.63)							(0.85)	(0.66)				
			[0.83]	[0.09]							[0.29]	[0.31]				
AI x Fem. x PoC			0.00	0.00							0.00	0.00				
			(.) [.]	(.) [.]							(.) [.]	(.) [.]				
Risky Goal					-0.43	-0.83**							0.68	-0.59		
					(0.51)	(0.36)							(0.51)	(0.41)		
					[0.40]	[0.02]							[0.19]	[0.15]		
AI x Risky Goal					0	0							0.25	-0.35		
					(.)	(.)							(1.29)	(1.04)		
					[.]	[.]							[0.85]	[0.74]		
Dem. controls	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Trends and charac. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,869	3,869	3,866	3,866	3,856	3,856	538	538	2,938	2,938	2,933	2,933	2,939	2,939	457	457
Pseudo-R²	0.57		0.56		0.536		0.73		0.51		0.50		0.511		0.63	
Adjusted-R²		0.57		0.58		0.588		0.44		0.48		0.49		0.511		0.48

Table 4 presents the results of the heterogeneity analysis. It reports the coefficients from pre- and post-policy estimations of logistic (columns 1, 3, 5 and 7) and OLS (columns 2, 4, 6 and 8) models. All models are reweighted using entropy balancing on the first three moments (mean, variance, and skewness) of all relevant continuous covariates. This balancing is performed separately for the pre- and post-policy periods to account for potential changes in the composition of projects over time. The resulting weights are used in all our regressions. All specifications include controls and time fixed effects. The table reports z-statistics for logistic regressions and t-statistics for OLS regressions, based on heteroskedasticity-robust standard errors (in parentheses). P-values are reported in square brackets. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels (two-tailed), respectively. Definitions of all variables are provided in Appendix B.

TABLE 5: Conditional difference-in-differences

CDiD (reweighted)	CSDiD	TWFE	CSDiD	TWFE	CSDiD	TWFE
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average treatment effect on the treated (ATT)						
DiD estimate (AI x Post)	0.13*	0.13***	0.14*	0.08***	0.14**	0.07***
	(0.07)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)
	[0.09]	[0.00]	[0.03]	[0.01]	[0.02]	[0.01]
Panel B: Average treatment effects by period						
AI projects (pre-period)	0.01	-0.01	0.01	-0.06**	-0.03	-0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
	[0.86]	[0.65]	[0.86]	[0.02]	[0.27]	[0.02]
AI projects (post-period)	0.12	0.11***	0.13**	0.01*	0.14**	0.01**
	(0.07)	(0.03)	(0.07)	(0.01)	(0.06)	(0.01)
	[0.11]	[0.00]	[0.05]	[0.39]	[0.04]	[0.28]
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Time, trends and characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes
Observations	16,019	16,019	21,909	21,909	28,428	28,428
Adjusted-R^2		0.65		0.65		0.65

Table 5 reports treatment effect estimates based on a Staggered Conditional Difference-in-Difference (CSDiD) approach, alongside a Two-Way Fixed Effects (TWFE) Linear Probability Model (LPM) for comparison. Both models are estimated using repeated cross-sections and entropy balancing. Columns (1) and (2) cover March to December 2023; columns (3) and (4) extend to January–March 2024; and columns (5) and (6) present estimates for the full period from December 2022 to April 2024. All analyses use August 29, 2023, as the policy implementation date. Entropy balancing is applied on the first three moments of continuous covariates separately for pre- and post-policy periods to ensure comparable treatment and control groups. Panel A reports the overall average treatment effect on the treated (ATT), while Panel B presents time-specific effects based on the group-time decomposition, estimated as average marginal effects. All specifications include relevant controls and fixed effects. Parallel trends assumptions are satisfied for all models. The table reports heteroskedastic-robust standard errors in parentheses. P-values appear in square brackets. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions are in Appendix B.

Appendix A

Table A1. List of AI-related keywords

AI Subdomains	Keywords
Ambient intelligence	'ambient intelligence'
Augmented/virtual/mixed reality	'augmented reality', 'virtual reality', 'mixed reality'
Autonomous vehicle	'collision avoidance', 'autonomous vehicle', 'autonomic computing', 'obstacle avoidance', 'pedestrian detection', 'trajectory tracking', 'simultaneous localization mapping', 'autonomous weapon', 'trajectory planning', 'unmanned aerial vehicle'
Bayesian learning	'bayesian learning', 'variational inference', 'markovian', 'naive bayes classifier', 'bayesian network', 'hidden markov model', 'multinomial naive bayes', 'gaussian process'
Bio-inspired methods	'swarm optimisation', 'computational intelligence', 'evolutionary algorithm', 'differential evolution algorithm', 'multi objective evolutionary algorithm', 'genetic algorithm', 'particle swarm optimisation', 'artificial bee colony algorithm', 'bee colony', 'gravitational search algorithm', 'ant colony optimisation', 'genetic programming', 'evolutionary computation', 'ant colony', 'memetic algorithm', 'firefly algorithm', 'swarm intelligence'
Brain-computer interface	'brain computer interface'
Clustering	'hierarchical clustering', 'single linkage clustering', 'cluster analysis', 'spectral clustering', 'k means'
Cognitive automation	'cognitive automation'
Cognitive modeling	'cognitive insight system', 'cognitive computing', 'cognitive modelling'
Complex networks	'community detection', 'link prediction'
Computational pathology	'computational pathology'
Computer vision (general)	'object recognition', 'emotion recognition', 'image processing', 'image recognition', 'computational pathology', 'machine vision', 'object detection', 'action recognition', 'face recognition', 'image retrieval', 'image segmentation', 'visual servoing', 'facial expression recognition', 'video segmenttation', 'activity recognition', 'gesture recognition', 'human activity recognition', 'image classification', 'human action recognition', 'computer vision'
Cyber physical system	'cyber physical system'
Decision tree	'regression tree', 'classification tree', 'decision tree'
Dialogue	'chatbot'
Distributed AI	'distributed artificial intelligence', 'mapreduce', 'multi agent system'
Ensemble learning	'stacked generalisation', 'lpboost', 'logitboost', 'random forest', 'gradient boosting', 'madaboost', 'ensemble learning', 'brownboost', 'bootstrap aggregation', 'totalboost', 'rankboost', 'gradient tree boosting', 'adaptive boosting', 'xgboost', 'adaboost'
Factorization Models	'non negative matrix factorisation', 'factorisation machine'
Feature learning	'feature selection', 'feature learning', 'feature engineering', 'feature extraction'
Fuzzy logic	'rough set', 'intuitionistic fuzzy set', 'fuzzy logic', 'fuzzy', 'fuzzy environment', 'takagi sugeno fuzzy systems', 'fuzzy set', 'fuzzy number', 'fuzzy system'
Gaussian mixture model	'gaussian mixture model'
Graphical models	'random field', 'bayesian network', 'graphical model'
High dimensional data	'high dimensional input', 'high dimensional feature', 'high dimensional model', 'high dimensional space', 'high dimensional system', 'spectral clustering', 'high dimensional data', 'autoencoder', 'self organising map self organising structure', 'dimensionality reduction'
Instance-based learning	'support vector regression', 'nearest neighbour algorithm', 'kernel learning', 'vector machine', 'support vector machine', 'instance based learning', 'factorisation machine'
Intelligence augmentation	'intelligence augmentation'
Intelligent classifier	'intelligent classifier'
Intelligent geometric computing	'intelligent geometric computing'
Intelligent infrastructure	'intelligent infrastructure'
Knowledge representation	'ontology engin', 'expert system', 'semantic network', 'knowledge graph', 'knowledge representation', 'semantic web'
Latent representation	'latent variable', 'latent representation'

Logic programming	'inductive logic programming', 'relational learning', 'declarative programming', 'expert system', 'logic programming', 'statistical relational learning', 'description logic', 'neuro symbolic computing'
ML (general)	stochastic gradient', 'random forest', 'madaboost', 'data mining', 'nearest neighbour algorithm', 'totalboost', 'extreme machine learning', 'gaussian mixture model', 'decision tree', 'adaptive boosting', 'xgboost', 'hierarchical clustering', 'gradient boosting', 'brownboost', 'bootstrap aggregation', 'classification tree', 'regression tree', 'stacked generalisation', 'pattern recognition', 'cluster analysis', 'bayesian learning', 'dynamic time warping', 'kernel learning', 'gradient tree boosting', 'collaborative filtering', 'machine learning', 'single linkage clustering', 'lpboost', 'logitboost', 'ensemble learning', 'spectral clustering', 'k means', 'recommender system', 'instance based learning', 'factorisation machine', 'rankboost', 'similarity learning', 'adaboost'
Machine translation	'machine translation'
Meta learning	'meta learning'
Multi-objective optimization	'multi objective optimisation'
Multi-task learning	'multi task learning'
NLP (general)	'latent semantic analysis', 'topic model', 'natural language processing', 'sentiment analysis', 'natural language generation', 'latent dirichlet allocation', 'natural language understanding', 'text mining', 'machine translation'
Neural networks and DL	'backpropagation', 'neural turing', 'adversarial network', 'long short term memory', 'natural gradient', 'deep convolutional neural network', 'deep belief network', 'generative adversarial network', 'self organising map self organising structure', 'hebbian learning', 'neural turing machine', 'lstm', 'recurrent neural network', 'neural network', 'autoencoder', 'artificial neural network', 'multi layer perceptron', 'deep learning', 'convolutional neural network', 'deep neural network'
Neuromorphic computing	'neuromorphic computing'
Reinforcement learning	'q learning', 'learning automata', 'reinforcement learning', 'policy gradient methods', 'temporal difference learning'
Robotics	'multi sensor fusion', 'trajectory planning', 'legged robot', 'human robot interaction', 'industrial robot', 'quadruped robot', 'simultaneous localisation mapping', 'social robot', 'sensor data fusion', 'sensor fusion', 'wheeled mobile robot', 'service robot', 'biped robot', 'visual servoing', 'motion planning', 'robot', 'trajectory tracking', 'layered control system', 'trust region policy optimisation', 'humanoid robot'
Rule-based learning	'rule learning', 'rule based learning', 'association rule'
Scene understanding	'visual servoing', 'scene understanding'
Semi-supervised learning	'semi supervised learning'
Sentiment analysis	'sentiment analysis'
Signal separation	'blind signal separation', 'independent component analysis'
Similarity learning	'similarity learning'
Sparse representation	'dictionary learning', 'sparse representation'
Speech generation	'speech to text', 'speech synthesis', 'text to speech', 'speech generation'
Speech processing (general)	'speech recognition'
Speech recognition	'speech recognition'
Supervised learning	'supervised learning', 'factorisation machine', 'decision tree', 'regression tree', 'multi label classification'
Transfer learning	'transfer learning'
Unsupervised learning	'unsupervised learning'
Extension to Rezazadegan et al. (2024)	'AI', 'A.I.', 'artificial intelligent', 'artificial intelligence', 'generative AI', 'GenAI', 'Gen-AI', 'language model', 'large language model', 'LLM', 'ChatGPT', 'GPT-3', 'GPT-4', 'transformer model', 'predictive analytics', 'autonomous system', 'AI-driven', 'AI-powered', 'AI ethics', 'Explainable AI', 'Responsible AI', 'Ethical AI', 'Fairness in AI', 'Bias in AI', 'AI governance', 'AI regulation', 'AI transparency', 'AI accountability', 'AI auditability', 'AI interpretability', 'AI explainability', 'AI trustworthiness', 'AI reliability', 'AI safety', 'AI security', 'AI privacy', 'AI fairness', 'AI diversity', 'CNN', 'RNN', 'SVM', 'medical diagnosis', 'medical AI', 'robotic process automation', 'RPA', 'computer-aided design', 'self-driving car', 'TensorFlow', 'PyTorch', 'Keras', 'scikit-learn', 'spaCy', 'automation', 'gemini pro', 'langchain', 'ML algorithms', 'proprietary algorithms', 'big data', 'Power of AI', 'intelligent software', 'intelligent AI', 'embedding', 'AI powered', 'algorithmically', 'AI chat', 'smart app', 'smart automation', 'internet of things', 'cloud computing', 'IoT sensor', 'IoT kit', 'IoT using', 'IoT device', 'artificially intelligent', 'smart algorithm', 'smart algorithms'

Table A1 summarizes our chosen keywords. Building on Rezazadegan et al. (2024) we supplemented additional terms to align with our own research strategy. The table outlines the connection between AI subdomains and their corresponding keywords. The left column lists the subdomains, while the right column provides the associated keywords. We use these keyword-subdomain pairs to categorize and classify AI projects in crowdfunding platforms.

Appendix B

Table A2. Variable definitions

Continuous variables:	
ln(Pledged+1)	Natural logarithm of the amount pledged to a project, plus a unit (Source: Kickstarter).
ln(Goal+1)	Natural logarithm of a project's funding goal, plus a unit (Source: Kickstarter).
ln(Backers+1)	Natural logarithm of the number of project backers, plus a unit (Source: Kickstarter).
ln(Blurb Length+1)	Natural logarithm of the length of a project's blurb or short description in words, plus a unit (Source: Kickstarter).
ln(Duration+1)	Natural logarithm of the duration of a project's funding period in days, plus a unit (Source: Kickstarter).
ln(Campaign Days+1)	Natural logarithm of the number of days a campaign has been active, plus a unit (Source: Kickstarter)
ln(Synthetic Google AI trends + 1)	Natural logarithm of the synthetic Google trends index for AI-related searches, plus a unit (Source: Google Trends).
Indicator variables:	
US located	Indicator variable equal to 1 if the project creator is located in the United States, and 0 otherwise (Source: Kickstarter).
Female	Indicator variable equal to 1 if the name of a creator is inferred as female, and 0 otherwise (Source: gender-guesser).
People of Color (PoC)	Indicator variable equal to 1 if the project creator is estimated as a person of color, and 0 otherwise (Source: R rethnicity package).
Use of AI	Indicator variable equal to 1 if the project uses or incorporates AI technology, and 0 otherwise (Source: Text mining).
GenAI	Indicator variable equal to 1 if the project uses GenAI, and 0 otherwise (Source: Text mining).
Risky Goal	Indicator variable equal to 1 if the project exceeds the 90th percentile among unsuccessful pre-policy projects, and 0 otherwise (Source: Own estimation)
Successful	Indicator variable equal to 1 if the amount pledged by backers is equal or higher than a project's funding goal, and 0 otherwise (Source: Kickstarter).
Staff Pick	Indicator variable equal to 1 if a project is chosen as a "Staff Pick" by Kickstarter, and 0 otherwise (Source: Kickstarter).
Categorical variables:	
State	Categorical variable for the classification of a project progress (successful or failed).
Category	Categorical variable representing one of the 15 categories for a project.
Sub Category	Categorical variable representing one of the 146 subcategories for a project.

Table A2 provides the description for the variables in the dataset. Note: Following standard practices, for logarithmic transformations, we use ln(x + 1) to avoid undefined values when x = 0.

Appendix C

Table A3. Descriptive statistics for AI Disclosers

Panel A: Full Sample - AI Disclosing						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	305	76,462	2,832	438,343	6	92,410
Goal	305	72,033	7,000	821,194	388	63,470
Backers	305	230	26	989	2	392
Blurb Length	305	16	17	5	9	23
Successful	305	54.43%				
Panel B: After AI Policy Implementation (+18 weeks) - AI Disclosing						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	132	90,750	3,041	591,839	4	95,924
Goal	132	25,238	6,486	52,008	500	65,000
Backers	132	236	22	1,184	2	383
Blurb Length	132	16	17	5	7	23
	Yes (%)	No (%)				
Discrete variables:						
US located	43.18	56.82				
Female	12.12	87.88				
People of Color (PoC)	75.00	25.00				
Staff Pick	7.58	92.42				
Successful	56.82	43.18				
Panel C: Before AI Policy Implementation (-18 weeks) - AI Disclosing						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	121	86,354	3,361	319,035	13	117,244
Goal	121	146,810	10,000	1,302,155	600	63,470
Backers	121	243	25	883	2	403
Blurb Length	121	16	17	5	10	22
	Yes (%)	No (%)				
Discrete variables:						
US located	42.98	57.02				
Female	5.79	94.21				
People of Color (PoC)	84.30	15.70				
Staff Pick	9.92	90.08				
Successful	50.41	49.59				

Table A3 presents the main descriptive statistics for relevant variables in AI disclosing cases, showing results for the full sample size and for periods before and after the policy implementation (using an 18-week window). All variables used in the empirical analysis are defined in Appendix B.

Appendix D

Table A4. Descriptive statistics for Non-AI Disclosers

Panel A: Full Sample – Non-AI Disclosing						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	14,543	23,623	3,450	120,977	76	81,100
Goal	14,543	30,260	3,268	999,464	332	25,000
Backers	14,543	217	51	826	3	419
Blurb Length	14,543	16	16	6	7	23
Successful	14,543	74.76%				
Panel B: After AI Policy Implementation (+18 weeks) – Non-AI Disclosing						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	5,541	23,143	3,406	111,594	67	35,480
Goal	5,541	38,860	3,205	1,385,670	367	25,000
Backers	5,541	205	46	799	3	383
Blurb Length	5,541	16	16	6	7	23
	Yes (%)	No (%)				
Discrete variables:						
US located	56.31	43.69				
Female	19.18	80.82				
People of Color (PoC)	73.51	26.49				
Staff Pick	20.99	79.01				
Successful	73.56	26.44				
Panel C: Before AI Policy Implementation (-18 weeks) – Non-AI Disclosing						
	N	Mean	Median	SD	P10	P90
Continuous variables:						
Pledged	7,322	23,147	3,511	122,226	87	36,686
Goal	7,322	26,874	3,430	724,755	301	25,000
Backers	7,322	222	54	754	3	446
Blurb Length	7,322	16	16	6	8	23
	Yes (%)	No (%)				
Discrete variables:						
US located	57.57	42.43				
Female	18.37	81.63				
People of Color (PoC)	73.14	26.86				
Staff Pick	18.92	81.08				
Successful	75.59	24.41				

Table A4 presents the main descriptive statistics for relevant variables in Non-AI disclosing cases, showing results for the full sample size and for periods before and after the policy implementation (using an 18-week window). All variables used in the empirical analysis are defined in Appendix B.

Appendix E

Table A5. Correlation table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Successful	1									
(2) ln(Pledged+1)	0.64***	1								
(3) ln(Backers+1)	0.24***	0.64***	1							
(4) Use of AI	-0.07***	-0.02**	0.01	1						
(5) GenAI	-0.04***	-0.02***	-0.01	0.03***	1					
(6) ln(Goal+1)	-0.36***	0.15***	0.26***	0.06***	0.04***	1				
(7) ln(Blurb length+1)	0.07***	0.10***	0.04***	0.02***	0.01*	0.04***	1			
(8) ln(Duration+1)	0.29***	0.39***	0.19***	-0.01	-0.00	0.07***	0.09***	1		
(9) ln(Campaign days+1)	-0.27***	-0.08***	0.04***	0.03***	0.00	0.34***	0.00	-0.04***	1	
(10) ln(Google trends+1)	-0.00	0.02**	0.02**	0.01	0.01	0.02***	-0.00	0.02***	0.01*	1
(11) Staff pick	0.23***	0.39***	0.18***	-0.04***	-0.01	0.20***	0.09***	0.21***	-0.03***	0.02**
(12) US located	0.01	0.07***	0.21***	-0.04***	-0.01	0.11***	0.03***	0.04***	0.02**	-0.00
(13) Female	-0.00	-0.04***	0.04***	-0.03***	-0.00	-0.02***	-0.00	-0.04***	0.00	-0.00
(14) People of Color (PoC)	-0.02**	-0.01	-0.07***	0.02***	0.017**	-0.02***	-0.02**	-0.01	0.01*	0.02***
(15) Sub category	0.01	0.03***	-0.04***	0.02*	-0.00	-0.01	-0.00	-0.00	-0.05***	-0.00
(16) Category	-0.13***	-0.04***	0.02**	0.14***	0.02***	0.18***	0.04***	-0.02**	0.09***	0.00

	(11)	(12)	(13)	(14)	(15)	(16)
(11) Staff pick	1					
(12) US located	0.09***	1				
(13) Female	0.02***	0.04***	1			
(14) People of Color (PoC)	-0.04***	-0.12***	-0.11***	1		
(15) Sub category	-0.06***	-0.10***	-0.06***	0.06***	1	
(16) Category	0.02***	-0.05***	0.01	-0.01	0.06***	1