Market Responses to AI Statements in Creative Domains

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Abstract

Generative artificial intelligence (AI) can raise entrepreneurial productivity, yet market response also depends on how products are evaluated, particularly in creative domains where human craft is central. Prior work emphasizes AI's internal benefits but offers limited evidence on how market evaluations of products change when entrepreneurs make visible statements about AI use. As platforms increasingly require AI-use disclosures, understanding the market consequences of such positioning becomes critical. We examine this using Kickstarter's AI-disclosure policy, analyzing 42,745 crowdfunding campaigns of products launched after its introduction. We compare projects that disclose AI use, projects that adopt anti-AI narratives, and projects that remain silent about AI. Relative to silent projects, AI-disclosing campaigns attract 33% fewer backers and are 11.9 percentage points less likely to reach their funding goals, whereas anti-AI narratives are associated with 29% more backers and a 3.9 percentage points higher success rate. Among AI-disclosing projects, framing AI as assisting rather than replacing human work substantially reduces the penalty. The results show that visible statements about AI use serve as consequential elements of market positioning in creative domains, creating tensions between transparency and market performance.

Keywords: artificial intelligence, entrepreneurship, market response, skill substitution

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INTRODUCTION

Generative artificial intelligence (AI) tools now perform at or near human levels across a broad range of domains, and in some tasks even exceed human performance in areas traditionally reserved for human expertise (Bubeck et al., 2023; Csaszar, Ketkar, & Kim, 2024). Recent empirical studies show that these tools can augment human performance in product development ideation (Boussioux, Lane, Zhang, Jacimovic, & Lakhani, 2024) and generating and evaluating early stage business plans (Csaszar et al., 2024), and can deliver sizable productivity gains (Dell'Acqua et al., 2023). These gains are accelerating organizational adoption (Singla et al., 2025) and raising the possibility that generative AI can substitute for some forms of human work (Brynjolfsson, Li, & Raymond, 2023; Noy & Zhang, 2023). For entrepreneurs, the incentives to adopt AI tools are especially strong because many operate under severe resource constraints and any private returns from productivity gains directly accrue to them.

Inherent in this proliferation of generative AI use is an assumption that productivity gains will translate into net positive performance outcomes. Productivity gains, however, do not occur in isolation. Entrepreneurs operate in markets where backers, customers, and investors form judgments about production processes, particularly in creative markets where human craft is central (Ganzin et al., 2024). At the same time, AI use has attracted substantial backlash, which heightens scrutiny of how creative works are produced (Di Placido, 2024; Gorelick, 2026; Rogers, 2025). Existing management research offers a nuanced account of how AI tools affect *internal* productivity and ideation for organizations (Csaszar et al., 2024; Dell'Acqua et al., 2023), but it has relatively little to say about how *external* markets evaluate products when AI use becomes visible. This gap matters increasingly as leading online platforms require AI-use disclosures to promote transparency.[1] Yet it remains unclear how markets respond when AI use becomes observable through these disclosures.

[1] Some notable examples include Kickstarter's August 2023 policy requiring creators to disclose whether and how they used AI tools, Amazon Kindle Direct Publishing's September 2023 requirement that self-publishers declare whether content is AI-generated, Valve Steam's January 2024 requirement that game developers disclose AI use, and Etsy's July 2024 seller guidelines requiring disclosure when listings include AI-generated content.

On the one hand, disclosing AI use could benefit entrepreneurs. When AI tools are understood to enhance productivity and output quality (Csaszar et al., 2024; Noy & Zhang, 2023), disclosure may signal that entrepreneurs are capable of leveraging new technologies effectively to reduce production costs and building trust through transparency. On the other hand, disclosure may trigger negative market inferences in creative domains where production method matters for authenticity and perceived value (Ganzin et al., 2024; Wolfe, Blaseg, Patel, & Chan, 2024). If markets penalize visible AI use in creative domains, particularly in creative domains where AI is perceived as substituting for valued human craft, then demand-side costs could offset productivity benefits and disclosure intended to build trust may instead reduce market support.

Entrepreneurship research further underscores this ambiguity by highlighting that market evaluation depends on how products are framed by entrepreneurial narratives (Lounsbury & Glynn, 2001; Navis & Glynn, 2011). When a new technology makes a product's category placement uncertain, framing shapes what a market thinks a product is and how they assess its value (Anthony, Nelson, & Tripsas, 2016). Applying these insights to AI use, entrepreneurs face strategic choices in how they publicly account for AI involvement in production. If entrepreneurs believe that markets will evaluate their products more positively when they are perceived as human-made, they may adopt anti-AI narratives that explicitly emphasize non-use of AI tools or express opposition to AI in creative work. These narratives position the product as preserving valued human contribution rather than substituting AI for craft.

Given these countervailing forces, the net effect of disclosing AI use on entrepreneurial outcomes remains theoretically ambiguous. We still know little about how markets respond to different forms of AI use in creative production. Accordingly, we address two key questions in this paper: How do AI statements, disclosures or narratives about whether and how AI was used in the product's creation, shape market response to creative products? How do market responses to AI-use disclosures vary when entrepreneurs frame AI as assisting human work versus replacing it?

To answer these questions, we take an exploratory, question-driven approach (Eisenhardt, Graebner, & Sonenshein, 2016). Rather than theorizing formal hypotheses, we draw on plausible theoretical perspectives from the emerging AI literature and established entrepreneurship literatures to guide our questions and empirical design. This approach, increasingly common in management research (Krakowski, Luger, & Raisch, 2023; Moeen & Agarwal, 2017; Novelli & Spina, 2024; Sætre & Van de Ven, 2021), is well suited to nascent domains that lack settled theory. We adopt it because the net effect of disclosing generative AI use in entrepreneurship remains theoretically ambiguous, with existing theory supporting plausible arguments for multiple potential outcomes.

Empirically, we study these questions using a large-scale archival analysis of Kickstarter's platform-wide AI-use disclosure policy introduced on August 29, 2023. The policy prompts creators launching new projects to indicate whether and how they use AI tools through a standardized "Use of AI" section on the project page, while leaving creators free to discuss AI in their narrative story. In this setting, market evaluation is directly observable through demand-side response, captured by backers' funding decisions and participation. Using archival data on Kickstarter projects spanning the policy's introduction, we distinguish three mutually exclusive AI statements: campaigns that disclose generative AI use via the standardized "Use of AI" section; campaigns that remain silent about AI in both the disclosure section and the project story; and campaigns that, while not disclosing AI use via the interface, emphasize "no AI" or articulate anti-AI narratives in the story. We examine how these observable statements relate to campaign success and number of backers, and whether the disclosure association differs when creators explicitly frame AI as assisting rather than replacing human work.

Our results reveal a consistent pattern. Relative to otherwise similar campaigns that are silent about AI, projects that disclose using generative AI tools are substantially less likely to succeed and attract fewer backers, whereas projects that adopt anti-AI narratives enjoy higher success rates and more backers. These patterns largely persist when we compare propensity-score matched sets of projects. Finally, among AI-disclosing projects, disclosures that explicitly frame AI as assisting rather than replacing human work are associated with a smaller disclosure penalty, suggesting that how creators employ the use of narratives in framing the human–AI division of labor shapes market response.

This paper makes three contributions. First, we extend research on generative AI in management by shifting the focus from internal productivity to external market evaluations. Much of the literature emphasizes internal effects of AI use, including the performance effects of human–AI collaboration (Allen, Heshmati, Lenox, McDonald, & Perez, 2025; Csaszar et al., 2024; Dell'Acqua et al., 2023). We show that visible AI statements are strongly associated with crowdfunding outcomes: disclosure is penalized relative to silence, while anti-AI narratives are rewarded. Second, we contribute to entrepreneurship research by identifying AI-related statements as a new class of narrative signals that shape early-stage resource acquisition outcomes (Agrawal, Catalini, & Goldfarb, 2015; Kuppuswamy & Bayus, 2018; Mollick, 2014). Third, we show that market response depends not only on whether AI use is disclosed, but also on how creators frame the human–AI division of labor: disclosures that portray AI as assisting rather than replacing human work are associated with a smaller disclosure penalty.

THE DOUBLE-EDGED SWORD OF GENERATIVE AI USE IN ENTREPRENEURSHIP

In this section, we develop the theoretical logic linking generative AI use to entrepreneurial outcomes by outlining two competing forces. On the one hand, generative AI can boost entrepreneurial productivity by accelerating ideation, iteration, and execution in resource-constrained settings. On the other hand, when AI use becomes visible, it can trigger negative market inferences about authenticity, effort, and fit with category expectations, potentially reducing support even when output quality is high. Because markets often cannot observe production processes directly, we focus on externally visible AI statements embedded in disclosures and narratives.

Positive productivity boosts from generative AI

Generative AI tools have reached performance levels that often rival human experts across many domains and, in some instances, surpass them on tasks long viewed as the preserve of specialized human judgment. Early studies document strong capabilities in coding, scientific reasoning, and other complex knowledge tasks (Bubeck et al., 2023). Field and lab evidence further indicates that these tools can deliver sizable productivity and quality gains in non-entrepreneurial work settings. When adopted, consultants are significantly more productive and generate higher quality results (Dell'Acqua et al., 2023), customer-support agents resolve more issues per hour (Brynjolfsson et al., 2023), and mid-level professionals complete writing tasks faster with higher-rated output (Noy & Zhang, 2023). Together, this evidence portrays generative AI as a general-purpose cognitive aid that supports demanding knowledge work.

Building on these capabilities, recent work in management and innovation shows that generative AI can also augment productivity in activities central to strategy and entrepreneurship. AI tools increase the volume and quality of product-development ideas and support creative problem solving, including the generation and selection of novel, high-quality concepts (Boussioux et al., 2024; Doshi, Bell, Mirzayev, & Vanneste, 2025; Lane et al., 2024). They also help entrepreneurs and investors draft and refine early-stage business plans and evaluate strategic alternatives (Csaszar et al., 2024). These findings have led scholars to treat generative AI as a powerful complement to human cognition, with the potential to reshape how organizations and entrepreneurs structure knowledge-intensive work. From this perspective, visible use of generative AI could be neutral or even beneficial for market evaluations. If markets primarily care about the quality, reliability, or novelty of the output, and if they believe that AI tools help entrepreneurs produce better work, then disclosing AI use may leave evaluations unchanged or even enhance perceptions of competence and professionalism (Logg, Minson, & Moore, 2019; Longoni & Cian, 2022).

These benefits are especially salient for entrepreneurs, who are typically resource constrained and for whom speed to market is vital. Generative AI can reduce the time and effort required to produce viable early-stage outputs, lowering the cost of experimentation and accelerating time to market. In early-stage settings, entrepreneurs must engage in rapid experimentation while facing meaningful costs and imitation risks (Contigiani, 2023; Ott & Eisenhardt, 2020), and they commonly struggle to meet product-delivery timelines (Peterson & Wu, 2021). Because markets cannot directly observe underlying work processes, they rely on cues embedded in pitch materials and narratives when forming evaluations (Contigiani & Young-Hyman, 2022; Wolfe et al., 2024).

Thus, in this context, when entrepreneurs highlight the use of generative AI, markets may infer greater efficiency and competence. On its own, however, existing work says little about how external markets respond when AI use becomes visible. Entrepreneurial outcomes such as funding and sales depend not only on the quality of the underlying work, but also on how backers, customers, and other evaluators assess the authenticity and legitimacy of what entrepreneurs do. To understand the net effect of AI tool adoption for entrepreneurs, we therefore need to also examine how AI-related information is incorporated into market evaluations of producers. These conditions make it plausible that AI-use disclosure can sometimes signal efficient execution and competence.

Potential negative effects of AI statements

AI statements—market-facing disclosures or narratives that frame whether and how generative AI was used in the product's creation—can alter market response by changing how a product is interpreted and evaluated through inferences about human contribution. Market evaluations of entrepreneurs often depend on whether entrepreneurs appear authentic and legitimate in the product's given category (Navis & Glynn, 2011; Pontikes, 2012). Work on authenticity shows that evaluators judge whether organizations are "what they claim to be," and that positive authenticity attributions can yield higher evaluations and willingness-to-pay premia (Lehman, O'Connor, Kovács, & Newman, 2019; Zuckerman, 1999). Work on product positioning similarly emphasizes that when a technology is novel or interpretively flexible, market response depends in part on what the product is taken to be and which evaluative standards apply (Anthony et al., 2016). In this context, AI statements operate as cues about the production process. Disclosing AI use highlights tool involvement in production and can shift perceived product meaning and authenticity. Conversely, explicitly emphasizing non-use can draw attention to production technique and invite evaluation on craft-based standards. In domains where category expectations emphasize distinctive human skill and craft (Ganzin et al., 2024), either type of statement can therefore shape market response even when observable output quality is high.

Effects on product perceptions in market evaluations

Entrepreneurs shape how markets interpret their projects through narratives about what the product is, why it matters, and how it is produced (Gioia, Patvardhan, Hamilton, & Corley, 2013; Lounsbury & Glynn, 2001; Martens, Jennings, & Jennings, 2007). How founders describe their purpose, capabilities, and distinctiveness influences market assessments of feasibility, appropriateness, and potential value, which in turn affects resource acquisition and growth (Deeds Pamphile & Ruttan, 2023; Martens et al., 2007). Entrepreneurs also influence these assessments through positioning by framing the product relative to category expectations that guide comparison and evaluation (Anthony et al., 2016; Pontikes, 2012). Because production technique can be central to authenticity, narratives that highlight how work is done can shape whether markets perceive the product as made in a category-appropriate way (Carroll & Wheaton, 2009; O'Connor, Carroll, & Kovács, 2017). AI statements are therefore consequential narrative elements because they can shift how a product is understood (Anthony et al., 2016) and whether the production process is perceived as consistent with valued skills (O'Connor et al., 2017). Importantly, this applies both when creators disclose AI use and when they explicitly distance themselves from AI by emphasizing non-use or opposition.

Complementary research in marketing shows that AI-use disclosure can reduce demand when markets value human work. Experimental studies of AI involvement in advertisement creation find that AI-use disclosure suppresses downstream evaluations, reducing purchase intentions (Grigsby, Michelsen, & Zamudio, 2025). Related evidence in premium and luxury contexts finds that AI-generated imagery can reduce perceived effort and trigger negative reactions unless the output is seen as exceptionally creative (Zhang & Hur, 2025). More generally, labels such as "*AI-generated*" or "*Made with AI*" operate as cues about production processes that shift how a product is interpreted in markets where process expectations are salient (Altay & Gilardi, 2024; Jago, 2019). By the same logic, explicit anti-AI statements can heighten attention to production technique and activate evaluative standards centered on human craft.

Taken together, these insights imply that AI statements are not neutral descriptions of technique. They cue interpretations about product meaning and authenticity. Disclosing generative AI can signal efficiency, but it can also suggest that core work was performed by a tool, which can be penalized in domains where human skill is central to value (Ganzin et al., 2024; Lehman et al., 2019; O'Connor et al., 2017). Anti-AI statements can instead signal commitment to human skill and category-appropriate production practices, but they may also be read as reluctance to adopt tools that improve efficiency. Accordingly, the consequences of AI statements are ambiguous and likely to vary with whether the implied role of AI is seen as compatible with the human skills that markets value.

AI–human skill substitutability and perceived human contribution

The preceding discussion emphasizes category-based evaluation: AI-use disclosures can shift perceived fit with category expectations and, in turn, market response. A closely related channel concerns perceived human contribution. Because creative categories encode expectations about valued human work and craft, disclosure can also shape whether markets interpret AI as complementing that work or substituting for it. When generative AI use becomes visible, markets update beliefs about how much of the focal task is performed by the entrepreneur versus by the tool. These inferences depend on how creators describe AI's role in the production process. Disclosures that frame AI as assisting human work position it as a complement and help preserve perceived human contribution. Disclosures that imply replacement, or that leave the division of labor unclear, are more likely to be read as substitution. Accordingly, market responses may reflect not only category fit but also what the disclosure implies about the human–AI division of labor.

Research on AI in organizations formalizes these contribution inferences by distinguishing between AI as a substitute for human labor and AI as a complement to human skill. In some applications, AI performs tasks that would otherwise require human labor, effectively substituting for human work. In others, AI supports human work by improving speed, consistency, or decision quality without displacing the human contribution (Raisch & Fomina, 2025; Raisch & Krakowski, 2021). As algorithms improve, they can take on a larger share of routine and even expert tasks, shifting how work is allocated and which human skills remain central (Kellogg, Valentine, & Christin, 2020). Evidence from labor markets similarly suggests that generative AI can substitute for some forms of work, such as basic programming, text drafting, and image generation, while complementing more complex tasks that still require human judgment and coordination (Demirci, Hannane, & Zhu, 2025; Eloundou, Manning, Mishkin, & Rock, 2024). These distinctions imply that substitution inferences should be strongest in settings where AI can produce the core output with limited incremental human input.

Consistent with this view, current generative AI models can produce convincing creative outputs quickly, which can make it difficult for markets to distinguish substantial human craft from tool-enabled generation (Ha et al., 2024). In such settings, explicit AI-use disclosure may lead markets to infer that the entrepreneur's contribution to the central creative work is thinner, that less human effort and craft were required, and that similar outcomes could be replicated by others with access to the same tool. This logic aligns with the effort heuristic, in which perceived effort serves as a cue for quality (Kruger, Wirtz, Van Boven, & Altermatt, 2004), and with the handmade effect, in which products believed to be handmade are valued more because they signal care, effort, and personal investment (Fuchs, Schreier, & van

Osselaer, 2015). Because markets apply similar intuitions to craft-based offerings (Ganzin et al., 2024), AI-use disclosure in creative markets may implicitly signal lower human effort and reduced reliance on scarce creative skill, thereby depressing evaluations even when the visible output is polished.

However, AI statements can differ in what they imply about the human–AI division of labor. When entrepreneurs explicitly frame AI as assisting rather than replacing human work, they may reduce perceived substitution by clarifying that human direction, judgment, and craft remain central. By contrast, AI statements that emphasize automation or replacement—or that do not clarify AI's role—may heighten inferences that AI performed much of the core work. This logic implies heterogeneity in market response to AI statements based on how creators frame AI's role.

These countervailing inferences make heterogeneous and even null effects plausible. AI-use disclosure can signal efficiency and competence, yet also raise concerns about diminished human contribution. Anti-AI narratives can strengthen perceptions that human work remains central, but may also invite inferences about foregone efficiency.

Research questions

In sum, this discussion suggests that AI-use disclosures can plausibly lower, leave unchanged, or raise market response depending on which mechanism dominates in a given domain. Productivity benefits can make entrepreneurs who disclose AI use appear competent and professional, while category expectations, authenticity concerns, and perceived skill substitution can signal low effort or misfit with the value of the craft.

These mechanisms point to two empirical questions.

RQ1: *How do AI statements, disclosures or narratives about whether and how AI was used in the product's creation, shape market responses to new products?*

RQ2: *How do market responses to AI-use disclosures vary when entrepreneurs frame AI as assisting human work versus replacing it?*

Because existing theoretical insights yield competing predictions to the research questions, we do not posit directional hypotheses. Instead, we adopt an exploratory approach and use large-scale archival data to examine market responses to AI statements in creative domains.

EMPIRICAL CONTEXT: AI-USE DISCLOSURES IN CROWDFUNDING

Crowdfunding platforms offer a particularly useful setting for examining how markets respond to visible AI statements. On reward-based platforms such as Kickstarter, dispersed backers must decide which creative projects to support based on incomplete information about quality, effort, and production methods. Because they cannot observe the production process directly, backers rely on cues embedded in project narratives, creator histories, social proof, and platform endorsements when forming judgments about which campaigns merit their support (Agrawal et al., 2015; Kuppuswamy & Bayus, 2018; Mollick, 2014). These informational frictions take on heightened importance in creative markets, where the process of making often matters as much as the final output and where audiences frequently value human craft and authenticity. Generative AI complicates these evaluations by blurring the line between human-made and machine-generated work, raising questions about effort, skill, and the nature of creative contribution. Together, these features—rich narrative content, pronounced information asymmetries, and normative concerns about craft—make crowdfunding a setting where AI statements are likely to be especially consequential for market outcomes.

Kickstarter and the structure of creative crowdfunding

Kickstarter is a leading reward-based crowdfunding platform focused on creative projects. Creators launch campaigns in categories spanning games, comics, films, design objects, art, music, publishing, fashion, and crafts, seeking funding from geographically dispersed backers who pledge money in exchange for non-equity rewards. The platform operates under an all-or-nothing funding rule: pledged funds are collected only if the campaign reaches its stated goal by the deadline. This structure makes both campaign success and the number of backers particularly salient measures of market response, as they directly capture the extent to which audiences are willing to back a project with their own resources.

The platform's breadth across creative domains is valuable here because it allows us to observe how audiences respond to AI statements in contexts that vary in their perceived skill requirements, production norms, and expectations about technology's role in creative work. Informational frictions are endemic to this environment. Backers form beliefs about unobservable qualities—product merit, creator competence, production authenticity—based on limited signals: the project narrative, evidence of prior successes, early backer counts, and platform endorsements such as the "Projects We Love" badge (Agrawal et al., 2015; Kuppuswamy & Bayus, 2018; Mollick, 2014). Kickstarter's AI-use disclosure policy adds a new signal to this environment, one that makes visible whether and how creators employ generative AI tools and thereby invites backers to update their evaluations accordingly.

The AI-use disclosure policy and observable AI statements

On August 29, 2023, Kickstarter introduced a platform-wide policy requiring creators of newly launched projects to indicate whether they use AI tools. The policy operates through a structured disclosure interface: when creators report using AI, Kickstarter displays a dedicated "Use of AI" section beneath the project story that summarizes for potential backers which aspects of the project involved generative AI.[2] The policy does not prohibit AI use or penalize disclosure. Instead, it standardizes a channel through which creators can communicate about their use of these tools, prompting them to specify whether AI was employed for tasks such as generating images, drafting text, composing music, or writing code.

Compliance is imperfect, however. Enforcement relies primarily on community reporting and platform review rather than automated verification, which means creators retain considerable discretion over whether to disclose and how to discuss AI in their narratives. This has an important implication for interpretation: our measures capture observable AI statements—the claims about AI use or non-use that appear on the project page—rather than ground-truth AI usage in production. Some creators may use AI tools but choose not

[2]For an illustrative description and screenshots of Kickstarter's AI disclosure interface, see the contemporaneous news coverage at `https://finance.yahoo.com/news/kickstarter-requires-generative-ai-projects-160010149.html`.

to disclose, either because they believe nondisclosure will go undetected or because they anticipate that disclosure might harm their campaign. Others may claim non-use in ways we cannot independently verify. What matters for market evaluation is not the underlying production process but the information backers observe and incorporate into their funding decisions.

The disclosure interface, combined with creators' freedom to discuss AI in their narrative text, gives rise to three mutually exclusive categories of observable AI statements—market-facing disclosures or narratives that frame whether and how generative AI was used in the product's creation. First, some projects formally disclose AI use by displaying a "Use of AI" section that describes how generative AI was employed. Second, the majority of projects remain silent about AI: they neither display a "Use of AI" section nor mention AI in their story. These silent projects serve as our baseline and likely include both genuine non-users and undisclosed users who prefer not to draw attention to AI involvement. Third, a smaller subset explicitly adopts anti-AI narratives. These campaigns do not disclose AI use through the formal interface, but their stories contain statements emphasizing that AI tools were not used or expressing opposition to AI in creative work. Such narratives may reflect strategic positioning choices by creators who believe that emphasizing human craft will resonate more favorably with backers. We identify these narratives through sentence-level coding that looks for both explicit non-use statements—phrases such as "no AI was used" or "entirely human-made"—and negative evaluative statements about AI in creative contexts, such as "AI-generated content harms real artists" or "we refuse to use AI."

This three-way distinction allows us to examine not only how disclosure shapes market response but also how explicit anti-AI positioning functions as strategic narrative framing. We focus on projects that fall cleanly into one of these categories, excluding the small number that mention AI only in positive or neutral ways without formal disclosure. This ensures our silence baseline consists entirely of projects with no disclosure and no AI mention.

Sample construction and data structure

We construct the dataset from publicly available information on Kickstarter project pages, covering all projects created between August 29, 2021 and August 29, 2025. This four-year window is centered on the AI-use disclosure policy introduction, spanning two years before and two years after August 29, 2023. While we use the full sample to characterize how project composition and outcomes evolve around the policy's introduction, our primary analyses focus on the post-policy period when the disclosure interface becomes available. Because projects can be created well before their public launch, we restrict attention to those launched on or before August 29, 2025, ensuring that monthly aggregates are computed within a consistent observation window.

We apply two sample restrictions. First, we retain only campaigns that reached a definitive outcome—successfully funded or failed—dropping projects that remain live, suspended, or canceled. Second, we exclude all projects in the Technology parent category. Many Technology campaigns during this period are themselves AI tools or AI-enabled hardware, whereas our focus is on AI as an assistive tool in creative production rather than as the product itself. After these restrictions, the full sample contains 81,451 projects across the pre- and post-policy periods.

For our primary analyses, we further focus on the 42,745 projects created on or after August 29, 2023. This post-policy subsample is the relevant one for our research questions because the "Use of AI" disclosure section—and thus our observable AI statement categories—exists only for projects created after the policy introduction. Note that specific regression samples are smaller than 42,745 because we exclude projects that mention AI only in positive or neutral ways (without either disclosing AI use or adopting anti-AI narratives), as these do not fall cleanly into our three mutually exclusive AI statement categories.

Outcome variables, explanatory variables, and the role of framing

Our primary outcomes are campaign success and the number of backers, both of which capture market willingness to support a project. Campaign success is a binary indicator equal to one if the project reaches or exceeds its funding goal by the deadline. The number of backers counts distinct individuals who pledged to the campaign. Because the backer distribution is highly right-skewed, we model backers in logs, using $\log(Backers_i + 1)$ in regression analyses. These outcomes are related but capture different dimensions of market response: success reflects whether the project crosses the funding threshold, while backers reflect the breadth of audience support.

We also report descriptive statistics on pledged amounts and funding goals but do not treat these as primary outcomes. Funding goals are endogenously chosen by creators and reflect strategic considerations rather than pure market response, while pledged amounts scale mechanically with goals and are difficult to compare across projects that vary widely in scale and category.

The key explanatory variables are indicators for the observable AI statements described above. AI-use disclosure equals one if the project page displays a "Use of AI" section. Anti-AI narrative equals one if the project does not disclose AI use but the story contains statements either explicitly claiming non-use or expressing negative sentiment toward AI in creative work. The omitted category consists of projects in the silence baseline—those with no AI-use disclosure and no AI mention in the story.

To address our second research question, we further distinguish AI-disclosing projects by how they frame AI's role. Among projects that disclose, we identify those whose disclosure text explicitly frames AI as assisting rather than replacing human work. We construct this measure using a sentence-level large language model classifier applied to the disclosure text, coding statements that describe AI as supporting or augmenting human creativity. This yields an assist-framing indicator that equals one for disclosures emphasizing AI as a complement to human effort. Because disclosure text length may correlate with both framing and outcomes, we control for the log length of the disclosure in words, set to zero for silent projects and centered among disclosers.

Controls and empirical strategy

All regression models include a common set of controls and fixed effects. At the project level, we control for the log of the funding goal, the log of story length in words, and campaign duration. We also include two continuous measures of narrative orientation: the share of past- versus future-oriented action statements in the story, and the share of first-person references using "we" rather than "I." The former captures whether creators emphasize completed work or work yet to be done; the latter distinguishes team from individual framing. Additionally, we control for whether the project received a "Projects We Love" staff pick, which serves as a platform endorsement and may correlate with both AI statements and outcomes.

At the creator level, we control for the year the creator first joined Kickstarter and three measures of prior experience: the number of prior successful projects, total dollars raised on those successes, and total backers on prior successes, all log-transformed. All models include parent-category, country, and launch-month fixed effects to absorb cross-sectional heterogeneity and common time shocks.

To answer our first research question, we estimate a unified model treating AI statements as a multi-valued explanatory variable in the post-policy sample. For each project i created on or after August 29, 2023:

$$Y_i = \alpha + \beta_1\, \mathit{Disclosure}_i + \beta_2\, \mathit{AntiAI}_i + X_i'\gamma + \mu_{c(i)} + \lambda_{k(i)} + \delta_{t(i)} + \varepsilon_i, \tag{1}$$

where Y_i is either the success indicator or log backers, $\mathit{Disclosure}_i$ and AntiAI_i are the AI-statement indicators, X_i is the vector of controls, and $\mu_{c(i)}$, $\lambda_{k(i)}$, and $\delta_{t(i)}$ denote parent-category, country, and launch-month fixed effects. The coefficients β_1 and β_2 capture associations between disclosing AI use and adopting anti-AI narratives, respectively, relative to silence. For success, we estimate a linear probability model to facilitate high-dimensional fixed effects and interaction terms. For backers, we use ordinary least squares on $\log(\mathit{Backers}_i + 1)$. Standard errors are clustered by launch month.

To assess whether the disclosure association varies with how creators frame AI's role, we augment this model by adding an indicator for assist-framed disclosures, estimated on the subset of projects that either disclose AI use or fall in the silence baseline:

$$
\begin{aligned}
Y_i = \alpha &+ \beta_1\, \mathit{Disclosure}_i + \beta_2\, \mathit{AssistDisclosure}_i + \beta_3\, \log(\mathit{DisclosureWords}_i + 1) + X_i'\gamma \\
&+ \mu_{c(i)} + \lambda_{k(i)} + \delta_{t(i)} + \varepsilon_i.
\end{aligned}
\tag{2}
$$

Here, β_1 captures the association for AI disclosures without assist framing, while $\beta_1 + \beta_2$ gives the association for assist-framed disclosures. This specification allows us to examine whether explicitly framing AI as complementary to human work attenuates the disclosure penalty.

RESULTS

We begin by documenting broad patterns in platform activity and AI statement prevalence following the policy introduction. We then present estimates relating AI statements to campaign outcomes and examine how the disclosure association varies with framing. Finally, we assess robustness through alternative comparison sets and propensity-score matching.

Descriptive patterns

Overall activity on Kickstarter increases following the AI-use disclosure policy, though average project-level performance declines somewhat. The number of projects rises from 38,706 in the two years before the policy to 42,745 in the two years after. At the same time, the aggregate success rate falls from about 77.9 percent to 73.0 percent. Mean pledged amounts decline from roughly \$21,000 to \$19,500, mean backer counts drop from 224 to 200, and mean funding goals fall from approximately \$71,100 to \$65,300. These shifts suggest the platform saw an influx of projects after the policy, though the composition may have changed in ways that affected average performance.

Among post-policy projects, observable AI statements remain relatively uncommon but increase over time. Approximately 7.1 percent formally disclose using AI, and about 7.1 percent mention AI somewhere in their stories. Of those mentioning AI, roughly 3.2 percent express negative sentiment toward AI in creative work, 3.8 percent include explicit non-use statements, and 3.6 percent meet our composite criterion for anti-AI narratives. Both disclosures and anti-AI narratives become more prevalent as time passes. The share disclosing AI use rises from roughly 3 to 6 percent in late 2023 to around 9 to 11 percent by mid-to-late 2025, while anti-AI narratives increase from about 1 to 2 percent to 4 to 6 percent over the same period. These trends suggest both forms of AI positioning are becoming more common as creators and backers gain experience with the policy.

Platform endorsement patterns also differ markedly by AI statement type. Projects with anti-AI narratives are substantially more likely to receive a "Projects We Love" staff pick (27.3 percent) compared to silent projects (18.5 percent), whereas AI-disclosing projects are much less likely to receive this endorsement (8.2 percent). While descriptive, these patterns suggest that both backers and platform gatekeepers respond differently to observable AI statements on project pages (see Appendix Table B1)

AI statements and market response

Table 2 and Figure 2 present the main results relating observable AI statements to campaign outcomes. The patterns are consistent, substantial, and statistically precise. Relative to projects that remain silent about AI, those that disclose using generative AI experience markedly lower success rates and attract fewer backers, while projects adopting anti-AI narratives enjoy higher performance on both dimensions.

[Place Table 2 here]

[Place Figure 2 here]

Consider first the estimates for campaign success. In the unified specification with the full battery of controls, fixed effects, and the staff-pick indicator, the coefficient on AI-use disclosure is approximately -0.119 ($p < 0.001$), implying that projects disclosing AI use are about 11.9 percentage points less likely to reach their funding goals than otherwise similar silent projects. This is a large effect: given that the average success rate in the post-policy sample is 73 percent, an 11.9 percentage-point reduction represents a meaningful decline in funding probability. In sharp contrast, projects adopting anti-AI narratives are associated with a 3.9 percentage-point higher success probability relative to silence (coefficient of 0.039, $p < 0.001$). These estimates suggest that making AI use visible carries a substantial penalty in terms of funding success, while explicitly positioning against AI confers a modest but meaningful advantage.

The patterns for backers are even more pronounced. The coefficient on AI-use disclosure is about -0.398 ($p < 0.001$), corresponding to roughly 33 percent fewer backers relative to silence. Anti-AI narratives again show the opposite pattern: the coefficient is approximately 0.256 ($p < 0.001$), corresponding to roughly 29 percent more backers. These results indicate that market response operates not only through the binary success margin but also through the breadth of support, with disclosures associated with substantially narrower audiences and anti-AI narratives with broader ones. Taken together, the unified estimates paint a clear picture: disclosing AI use is strongly associated with worse campaign performance, while adopting an anti-AI narrative is associated with better performance on both measures.

These associations are conditional on an extensive set of controls and fixed effects designed to account for observable differences in project scale, narrative characteristics, creator experience, category composition, geography, and temporal trends. The fact that the disclosure penalty and anti-AI premium remain large and significant after accounting for these factors suggests the associations are not simply artifacts of who chooses to disclose or adopt anti-AI positions. Of course, these are observational estimates, and we cannot rule out unobserved heterogeneity. The robustness checks we present later—particularly propensity-score matched comparisons—probe this concern by comparing observably similar projects.

How framing AI's role moderates the disclosure penalty

If the disclosure penalty arises partly because backers infer that AI has substituted for valued human work, then disclosures that clarify AI's complementary role might attenuate this penalty. Table 3 and Figure 3 examine this possibility by distinguishing between AI disclosures that frame AI as assisting rather than replacing human creativity and those that do not.

[Place Table 3 here]

[Place Figure 3 here]

The results suggest that framing matters, though it does not eliminate the penalty entirely. Among AI-disclosing projects, those without assist framing are associated with a 15.7 percentage-point lower success probability relative to silence ($p < 0.001$). Disclosures employing assist framing show a smaller penalty: the incremental coefficient for assist framing is positive and significant (0.063, $p < 0.001$), implying a net association of about -9.4 percentage points for assist-framed disclosures. In other words, assist framing reduces the success penalty by roughly 6.3 percentage points, though the association remains negative.

The patterns are similar for backers. Non-assist disclosures are associated with a coefficient of -0.600 on log backers ($p < 0.001$), corresponding to roughly 45 percent fewer backers relative to silence. Assist framing attenuates this penalty substantially: the incremental coefficient is 0.334 ($p < 0.001$), yielding a net association of -0.266 for assist-framed disclosures, or about 23 percent fewer backers. Assist framing thus reduces the backer penalty by approximately 22 percentage points in log terms, though again the association remains negative. Figure 3 visualizes these patterns, showing that while assist framing meaningfully reduces the disclosure penalty, it does not bring the association close to zero.

These framing results align with the theoretical logic developed earlier: when creators make explicit that AI serves a supporting role rather than substituting for core creative work, backers appear to respond more favorably, perhaps inferring that human judgment and skill remain central. At the same time, the persistence of a negative association even for assist-framed disclosures suggests that disclosure itself carries costs that framing alone cannot fully offset. One interpretation is that even when AI is portrayed as assisting, its mere involvement may trigger concerns about authenticity or effort that depress market support.

As an additional descriptive probe, Appendix Table B9 reports implied disclosure associations by disclosed AI modality—whether creators used AI for images, text, audio/video, or code. Because many projects disclose using AI for multiple modalities, these estimates evaluate the association of disclosing each modality at the within-modality-group average mix of other modality indicators. Penalties vary considerably. Image-related disclosures show the smallest penalties (about 8.0 percentage points for success and 21 percent fewer backers), while code-related disclosures show the largest (about 22.1 percentage points for success and 62 percent fewer backers). Text and audio disclosures fall in between. One speculative interpretation is that backers view code-related AI use as more likely to substitute for core project work, whereas image-related use may be more readily interpreted as a supporting tool. These patterns align with the broader finding that market responses depend on what AI use implies about human contribution, though we emphasize these modality-specific estimates are exploratory.

Robustness checks

The main results could be sensitive to how we construct comparison groups or to observable differences we have not fully accounted for. We therefore conduct two sets of robustness checks. The first examines whether findings hold when we restrict to narrowly defined comparison sets. The second uses propensity-score matching to compare treated and control projects that are observably similar.

Restricted comparison sets

The unified specification combines multiple project types, which could introduce ambiguity about what drives the associations. To ensure findings are not artifacts of these groupings, we re-estimate specifications within more restrictive subsamples that isolate each comparison.

Appendix Table B2 restricts the sample to projects that either disclose AI use or fall into the silence baseline, excluding anti-AI narratives. In this cleaner comparison, the disclosure penalty remains large and significant: the coefficient on AI-use disclosure is -0.118 ($p < 0.001$) for success and -0.392 ($p < 0.001$) for log backers, the latter corresponding to about 32 percent fewer backers. These estimates nearly match the unified specification, indicating the disclosure penalty is not driven by including anti-AI projects.

Appendix Table B3 takes the opposite approach, restricting to non-disclosers and comparing anti-AI narratives to silence while excluding projects mentioning AI only positively or neutrally. In this sample, anti-AI narratives remain associated with higher success (coefficient of 0.042, $p < 0.001$) and more backers (coefficient of 0.269 on log backers, $p < 0.001$, about 31 percent more). These estimates closely match the unified results, suggesting the anti-AI premium is robust to comparison group definition.

Together, these restricted-sample estimates provide reassurance that main findings are not sensitive to specific groupings. The disclosure penalty and anti-AI premium both persist in magnitude and significance when we narrow comparison sets to the most direct contrasts.

Propensity-score matched comparisons

While regression estimates control for rich observables, they could still reflect unobserved selection if projects and creators choosing to disclose or adopt anti-AI narratives differ systematically in ways we have not captured. To probe this more directly, we implement one-to-one propensity-score matching that compares treated and control projects within tightly defined strata.

For each contrast—AI-use disclosure versus silence, and anti-AI narratives versus silence—we restrict potential controls to the silence baseline and impose exact matching on parent category, country, and first-time creator status. We further require matched controls launched within one month of the treated project and that creator join years are within one year. Within these strata, we estimate propensity scores using a logistic regression with log funding goal, log story length, campaign duration, narrative-orientation measures, and log-transformed prior experience measures. We then perform one-to-one nearest-neighbor matching without replacement using a caliper of 0.2 times the standard deviation of the logit propensity score.

After matching, we estimate models with pair fixed effects.

For AI-use disclosure, the matched sample contains 2,051 treated projects and 2,051 controls. Appendix Tables B4 and B5 report balance diagnostics and results. The diagnostics indicate matching successfully reduces observable differences: standardized differences on all covariates are small, and groups are well-balanced. In within-pair regressions, AI-use disclosure remains negatively associated with both outcomes: the coefficient is -0.107 for success and -0.308 for log backers (about 26 percent fewer backers). These estimates are somewhat smaller than the full regression coefficients, which is unsurprising given matching restricts to a more comparable subset, but the qualitative inference is unchanged. Disclosure continues to be associated with substantially lower success and fewer backers even when comparing observably very similar projects.

For anti-AI narratives, the matched sample contains 1,125 treated and 1,125 controls. Appendix Tables B7 and B8 report diagnostics and results. The matched-sample estimates are positive but attenuated relative to full regressions. The coefficient for success is 0.015, not statistically distinguishable from zero, while the coefficient for log backers is 0.165 ($p < 0.05$), about 18 percent more backers. The backer advantage persists in matched comparison, though smaller than in regression estimates, while the success difference is less precisely estimated. One interpretation is that projects adopting anti-AI narratives are observably different in ways that matter for success, and once we match on observables, the residual association shrinks. Alternatively, reduced precision may simply reflect smaller sample size and loss of variation from restricting to closely matched pairs.

Appendix Table B6 reports a matched-sample version of the assist-framing moderation. Point estimates continue to suggest assist framing reduces the disclosure penalty, with positive incremental coefficients, though these are estimated less precisely than in full models. The qualitative pattern—that assist framing attenuates but does not eliminate the penalty—remains consistent.

Taken together, robustness checks provide considerable support for main findings. Across restricted comparison sets isolating each conceptual contrast and matched-sample designs comparing observably similar projects, the disclosure penalty remains large, negative, and significant. The anti-AI premium is somewhat more sensitive: it persists in restricted-sample comparisons and matched-sample estimates for backers, but is smaller and less precisely estimated for success in the matched sample. Assist-framing moderation is qualitatively consistent across specifications, though incremental effects are less precisely estimated in matched samples. These patterns suggest that while observable selection may account for some associations, it does not explain them entirely. The fact that large penalties and premia remain even after carefully controlling for observables and matching on propensity scores increases our confidence that market responses are at least partly attributable to AI statements themselves rather than solely to unobserved heterogeneity.

DISCUSSION AND CONCLUSION

Contributions

Our exploratory analyses offer several insights that inform our theorizing about AI statements and market response. First, the consistent penalties associated with AI-use disclosure are difficult to reconcile with a purely instrumental view of generative AI as a productivity-enhancing tool. If markets cared only about efficient production, disclosing AI use should be neutral or beneficial. Instead, across the unified specification (Table 2; Figure 2) and the restricted-sample and matched comparisons (Appendix Tables B2–B5), AI-use disclosure is consistently associated with lower success and fewer backers relative to the silence baseline. Importantly, the penalty is not uniform across disclosed uses: Appendix Table B9 suggests that penalties are smallest when disclosures describe AI use for images and largest when disclosures involve modalities more directly tied to authorship and creative control (especially code, and also text and audio). This pattern is consistent with markets drawing inferences not only about efficiency, but also about authenticity, human contribution, and the perceived substitutability of AI for valued human work.

Second, the positive association between anti-AI narratives and campaign outcomes indicates that explicitly emphasizing non-use of AI (or expressing opposition to AI tools) can be rewarded relative to silence (Table 2; Appendix Table B3), even though these projects do not disclose AI use via the interface. Notably, this pattern is mirrored in platform endorsement: projects with anti-AI narratives are substantially more likely to receive a "Projects We Love" badge, whereas AI-disclosing projects are substantially less likely to receive one (Appendix Table B1). While these endorsement patterns are descriptive, they suggest that both backers and platform gatekeepers respond differently to observable AI statements on project pages.

Third, the heterogeneity across categories suggests that the market meaning of the same observable AI statement depends on domain-specific expectations about appropriate production practices. Category-specific estimates indicate that the association between AI-use disclosure and outcomes varies across parent categories, and that the association between anti-AI narratives and outcomes also varies across categories. This heterogeneity is consistent with the idea that evaluators apply different standards across creative domains, and that AI statements interact with category norms about craft, authenticity, and the acceptable role of automation in production.

Finally, the observational nature of the study means that we cannot fully isolate causal mechanisms or rule out all forms of unobserved heterogeneity. We therefore interpret the estimates as disciplined associations between observable AI statements and campaign outcomes, and view the moderation and modality analyses as descriptive probes that help characterize which types of statements are more strongly associated with market response. These findings motivate future experimental and qualitative research on how audiences and platforms interpret AI-related claims in entrepreneurial narratives.

Practical implications

Our findings point to an AI transparency dilemma in entrepreneurial markets. In the post-policy Kickstarter setting, projects that publicly disclose AI use perform worse than otherwise similar projects that remain silent, while projects that explicitly position themselves as "no

AI" or articulate anti-AI narratives perform better. This pattern implies that disclosure can be costly even when it is intended to build trust, and that creators face a real tradeoff between transparency and market support.

For entrepreneurs and managers, the core practical takeaway is that AI statements should be treated as part of the project's narrative positioning rather than as a purely compliance-oriented disclosure. Because markets respond to what the statement implies about authenticity and human contribution, disclosure language that clarifies the human–AI division of labor becomes consequential. Consistent with this logic, disclosures that explicitly frame AI as assisting rather than replacing human work face a smaller penalty than disclosures that do not provide that framing.

In practice, this suggests that when disclosure is required or strategically chosen, entrepreneurs can reduce downside risk by specifying where AI enters the workflow and by making the human role concrete, such as human direction, selection, revision, and final responsibility for the core creative output.

The results also suggest that the market does not treat all disclosed AI uses as equivalent. Disclosure penalties are smallest for image-related uses and largest when disclosures involve modalities more directly tied to authorship and creative control, especially code and also text and audio. This implies that creators should anticipate stronger skepticism when AI is disclosed in domains that audiences may associate with primary authorship. When creators operate in these domains, it becomes even more important to pair disclosure with a credible account of where human judgment and craft remain central.

More broadly, the patterns in this paper suggest the emergence of a new dimension of product positioning. Beyond positioning on visible product attributes, firms and creators increasingly position on AI association itself. In the post-policy environment, projects fall into three observable AI positions that audiences can readily interpret, namely AI-use disclosure, silence, and anti-AI narratives. These visible positions function as market-facing signals that shape evaluation. This implies that AI statements can become a durable axis of differentiation in creative markets, with some producers competing as explicitly AI-assisted and others competing as explicitly AI-free. The practical implication is that AI use is no longer only an internal production choice. It can be an external positioning choice that affects demand, who the product appeals to, and how evaluators apply craft-based standards. For platforms, this creates incentives for strategic silence and increases the stakes of how disclosure prompts are structured.

Finally, because platform gatekeepers appear to respond differently to these AI statements, platforms may be shaping outcomes through both disclosure design and endorsement decisions. Staff-pick rates are substantially higher for anti-AI narratives than for silence, and much lower for AI-disclosing projects. This descriptive pattern suggests that policy choices and curation practices can amplify market penalties or rewards associated with AI positioning. It also suggests that platforms seeking transparency should consider whether their own endorsement criteria unintentionally treat AI disclosure as a negative quality cue rather than as a neutral informational signal.

Limitations and directions for future research

This study is observational, so the estimates should be interpreted as disciplined associations between observable AI statements and campaign outcomes rather than as causal effects. Even with rich controls, fixed effects, restricted comparisons, and matched samples, unobserved heterogeneity may remain. This limitation opens several high-value opportunities for future research. First, experiments can isolate the mechanisms suggested here by holding constant product outputs while varying disclosure versus silence, and varying disclosure framing that clarifies whether AI assists versus replaces human work.

Such designs can directly test whether perceived authenticity, perceived effort, and perceived human contribution mediate market response, and whether these mechanisms differ systematically across categories. Second, our empirical constructs capture what backers can observe on the project page, not what creators actually do. Because compliance is imperfect, creators may under-report AI use, omit it entirely, or use AI while claiming non-use, and backers respond to these statements rather than to underlying production choices. This is an important boundary condition. Future work could combine disclosure-based measures with additional validation strategies to better approximate underlying AI use, and could study when misreporting is most likely. Relatedly, future research could examine the antecedents of disclosure choices, including how entrepreneurs weigh perceived market penalties against policy compliance and reputational concerns.

Third, the setting is creative crowdfunding, where informational frictions are pronounced and where narratives and authenticity concerns are plausibly salient. Future research should assess external validity by examining other entrepreneurial and product-market contexts where the balance between efficiency and craft differs. In parallel, longitudinal analyses can test whether the meaning of AI statements changes as AI use becomes more common and as category norms adapt. The increasing share of both AI-use disclosures and anti-AI narratives over time suggests that this meaning is evolving rather than fixed.

Taken together, the evidence in this paper suggests that visible AI statements already function as consequential signals in entrepreneurial markets. AI use has become not only a production technology but is now emerging as a salient positioning dimension.

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TABLES AND FIGURES

Table 1
Summary statistics and entry before and after the AI-disclosure policy

	Pre-policy	Post-policy	Post–Pre	t-stat
Entry and competition				
Projects (N)	38,706	42,745	4,039	
Unique creators (N)	29,955	31,154	1,199	
First-time creators (N)	21,152	21,195	43	
Projects per week (mean)	365.2	407.1	41.9***	3.724
Outcomes and project goals				
Success rate (fraction reaching goal)	.779	.730	-.049***	-16.251
Mean pledged per project (USD)	20,953	19,526	-1,427	-1.043
Mean backers per project	223.8	199.7	-24.1***	-3.173
Mean goal (USD)	71,124	65,269	-5,855	-.164
Total funding volume				
Total pledged to successful projects (USD)	798,210,541	820,999,186	22,788,645	
Total pledged to all projects (USD)	811,005,138	834,633,858	23,628,720	

Note: Sample consists of non-Technology Kickstarter projects with observed campaign outcomes (successful or failed). Projects are restricted to the analysis window August 29, 2021–August 29, 2025 (inclusive) based on project creation date. The pre/post split is defined by creation date at the policy introduction (post-policy: created on or after August 29, 2023). "Projects per week" is the mean number of newly created projects per week. Rows report period means, the Post–Pre difference, and Welch two-sample t-statistics allowing unequal variances. Pledged amounts and goals are in U.S. dollars. Total-dollar rows report sums across projects in each period (successful projects only or all projects). *, **, and *** indicate significance at 10%, 5%, and 1%.

Table 2
Outcomes by AI statement type: AI-use disclosure and anti-AI narratives vs silence

	Success (LPM)	Log(backers+1) (OLS)
AI-use disclosure vs silence	-.119*** (.006)	-.398*** (.031)
Anti-AI narrative vs silence	.039*** (.007)	.256*** (.030)
N	41,839	41,839
R^2	.375	.498
Adj. R^2	.374	.497

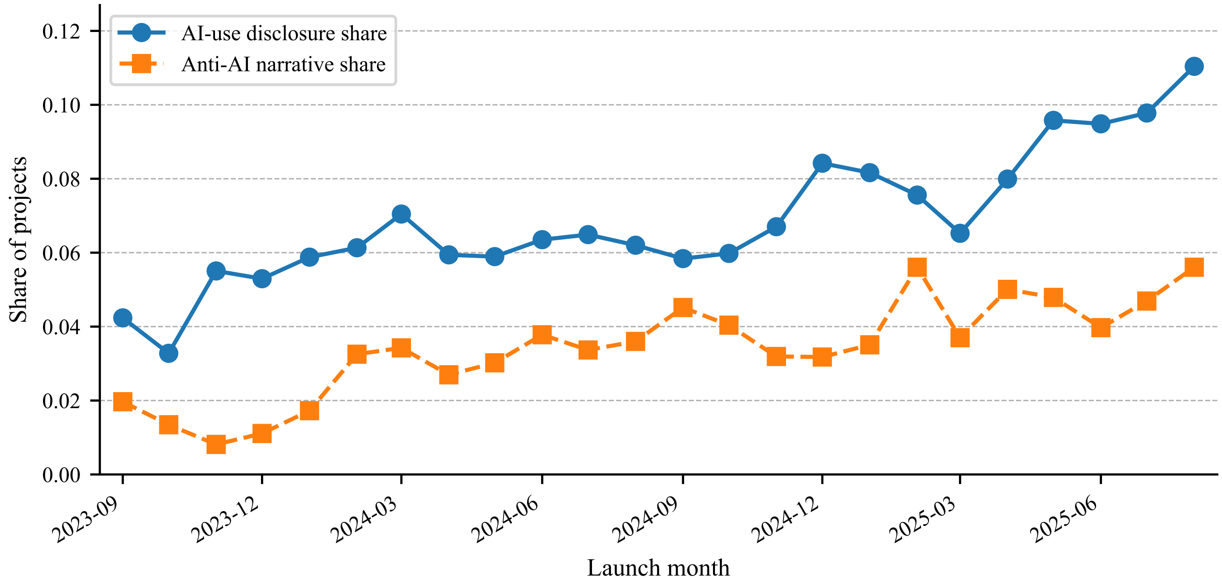
Note: Sample consists of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed) classified into three mutually exclusive AI statement types. "Silence" indicates no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. "AI-use disclosure" indicates the project displays a "Use of AI" section indicating AI use. "Anti-AI narrative" is defined among projects without a "Use of AI" section whose stories mention AI and either express negative sentiment toward AI or emphasize non-use. Projects that mention AI only positively or neutrally are excluded. Coefficients report effects of AI-use disclosure and anti-AI narratives relative to Silence. Success is estimated via a linear probability model (LPM); log(backers + 1) is estimated via ordinary least squares (OLS). All specifications include the staff-pick (Projects We Love) indicator, controls for log(goal), log(story length), past-action share, team framing share, campaign duration (days), creator join year, first-time creator status, and log measures of prior successful campaigns (projects, dollars, and backers), and fixed effects for parent category, country, and launch month. Standard errors are clustered by launch month. *, **, *** p<0.10, 0.05, 0.01.

Table 3
Does “AI assists, not replaces humans” framing mitigate the AI-disclosure penalty?

	Success (LPM)	Log(backers+1) (OLS)
AI-use disclosure (no “AI assists” framing)	-.157***	-.600***
	(.011)	(.052)
Increment for “AI assists” framing in disclosure	.063***	.334***
	(.017)	(.062)
AI-use disclosure with “AI assists” framing (sum)	-.094***	-.266***
	(.010)	(.039)
N	40,267	40,267
R^2	.375	.497
Adj. R^2	.374	.496

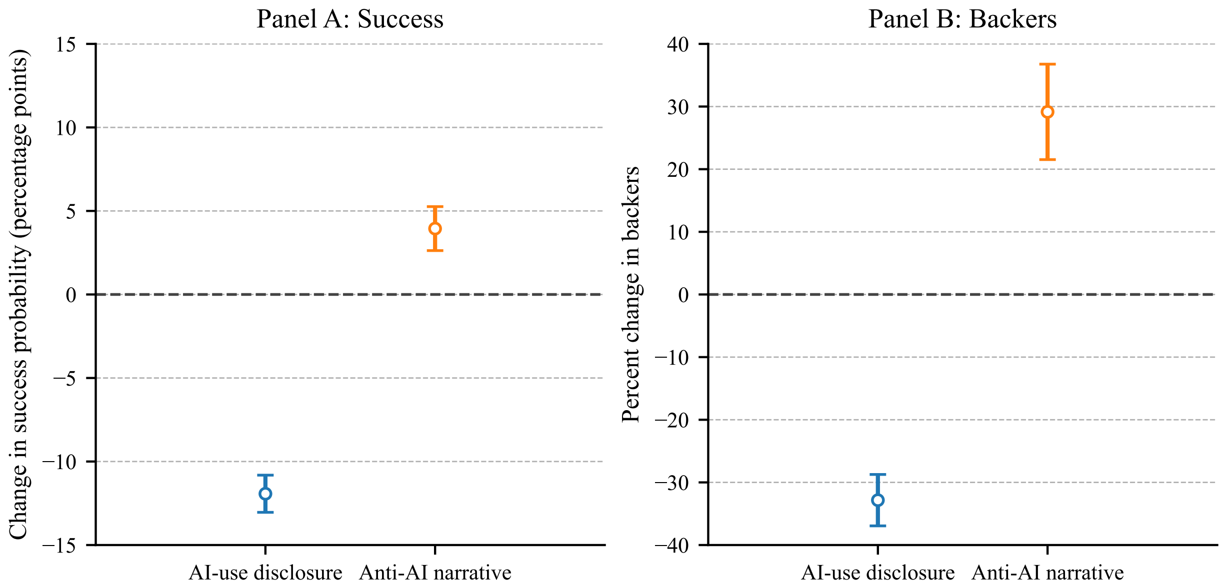
Note: Sample consists of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed) that either disclose AI use or are “Silence” projects; projects that mention AI in the story without disclosing AI use are excluded. “Silence” indicates no “Use of AI” section recorded (missing or “No AI disclosure found”) and no mention of AI in the project story. Among AI-disclosing projects, we identify disclosures whose text frames AI as assisting rather than replacing human work using large language model (LLM) coding; when LLM coverage is required, AI-disclosing observations are restricted to those with non-missing LLM coding. All specifications include the staff-pick (Projects We Love) indicator, controls for log(goal), log(story length), past-action share, team framing share, campaign duration (days), creator join year, first-time creator status, and log measures of prior successful campaigns (projects, dollars, and backers), and fixed effects for parent category, country, and launch month. Models also control for disclosure length via centered log(AI disclosure words + 1). Standard errors are clustered by launch month. *, **, *** p<0.10, 0.05, 0.01.

Figure 1
Monthly AI-use disclosure and anti-AI narrative shares



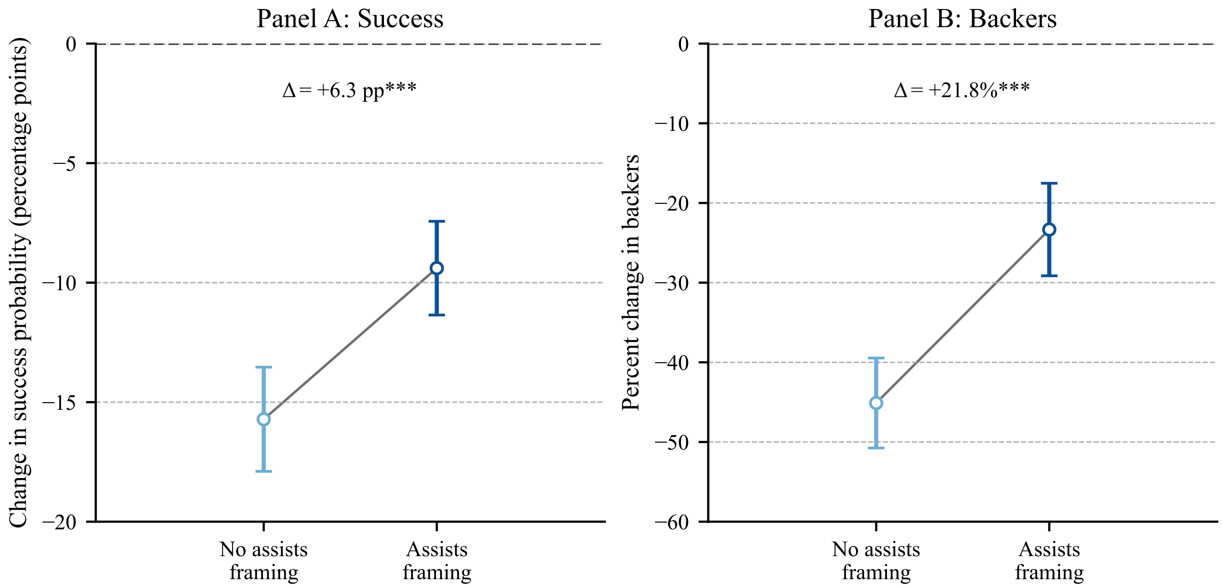
Note: Monthly shares by launch month for non-Technology projects created in the post-policy period (created on or after August 29, 2023) with observed outcomes (successful or failed). The plotted window is September 2023–August 2025. "AI-use disclosure share" is the fraction of projects that display a "Use of AI" section indicating AI use. "Anti-AI narrative share" is the fraction of projects without a "Use of AI" section whose stories mention AI and either express negative sentiment toward AI or emphasize non-use (including both simple non-use statements and statements that provide a reason for non-use).

Figure 2
Outcomes by AI statement type: AI-use disclosure and anti-AI narratives vs silence



Note: Effects of AI statement type relative to "Silence" in the post-policy period (created on or after August 29, 2023) for non-Technology projects with observed outcomes (successful or failed). Statement types are mutually exclusive. "Silence" indicates no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. "AI-use disclosure" indicates the project displays a "Use of AI" section indicating AI use. "Anti-AI narrative" is defined among projects without a "Use of AI" section whose stories mention AI and either express negative sentiment toward AI or emphasize non-use. Projects that mention AI only positively or neutrally are excluded. Each point shows an estimated effect with 95% confidence intervals. Panel A reports percentage-point changes in success from a linear probability model (LPM); Panel B reports percent changes in backers implied by ordinary least squares (OLS) estimates on log(backers + 1). All models include the staff-pick (Projects We Love) indicator, standard controls, and fixed effects; standard errors are clustered by launch month.

Figure 3
Does "AI assists, not replaces" framing in AI-use disclosure statements mitigate the disclosure penalty?



Note: Estimated association between AI-use disclosure and outcomes, and how it differs when disclosure text frames AI as assisting rather than replacing human work. Sample includes post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed) that either disclose AI use or are "Silence" projects; projects that mention AI in the story without disclosing AI use are excluded. "Silence" indicates no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. Among AI-disclosing projects, the "AI assists, not replaces" indicator is based on large language model (LLM) coding of disclosure text; when LLM coverage is required, AI-disclosing observations are restricted to those with non-missing LLM coding. Left points show the disclosure effect without assist framing; right points show the total effect with assist framing (sum of the disclosure coefficient and the assist-framing increment). Panel A reports percentage-point changes in success from a linear probability model (LPM); Panel B reports percent changes in backers implied by ordinary least squares (OLS) estimates on log(backers + 1). Horizontal bars show 95% confidence intervals. All models include the staff-pick (Projects We Love) indicator, standard controls, and fixed effects; standard errors are clustered by launch month.

APPENDIX A: CODING ANTI-AI NARRATIVES AND DISCLOSURE FRAMING

This appendix documents the procedures used to (i) construct the anti-AI narrative indicator $AntiAI_i$ from project stories and (ii) code whether AI-use disclosures frame AI as assisting rather than replacing human work.

A.1 Identifying stories that mention AI

We begin from post-policy project-level observations that contain, at a minimum, the project URL, a project identifier, and the project story text. We first clean URLs by removing query-string parameters and drop duplicate URLs. We then flag stories that mention AI using a case-insensitive regular expression that searches for references to AI or AI-based tools, including:

- the token "AI" or "A.I." as a standalone word;
- the phrase "Artificial Intelligence";
- references to large language models (LLMs), such as "LLM", "LLMs", or "large language model(s)";
- commonly used tools such as ChatGPT and GPT-based models; and
- named text-to-image systems such as Midjourney, Stable Diffusion, and DALL-E.

Stories whose text matches this pattern at least once are coded as $StoryMentionsAI_i = 1$; all other stories are coded as $StoryMentionsAI_i = 0$. Only stories with $StoryMentionsAI_i = 1$ are retained for sentence-level classification.

A.2 Sentence segmentation

For each project whose story mentions AI, we segment the story into sentences. We use spaCy's English language model (`en_core_web_sm`) with the `sentencizer` component to obtain sentence boundaries. Prior to segmentation, we collapse multiple whitespace characters into a single space. For each project i, we create a sentence-level dataset that contains one sentence per row, with a zero-based `sentence_number` and the sentence text. We filter out sentences that contain no alphabetical characters.

A.3 LLM-based classification of AI statements

We classify AI-related sentences using a locally run, 235 billion-parameter large language model (LLM). For each project, we present the model with the sentence-numbered story text and restrict attention to sentences that mention AI or AI-based tools. For these sentences, the LLM is asked to assign two types of labels:

- a stance label toward using AI in creative work for the project: *Positive*, *Negative*, or *Neutral*; and
- a non-use label indicating whether the sentence explicitly states that AI is not used for the project's creative content (a simple statement of non-use or non-use with a reason) or does not do so.

The prompts emphasize that the stance label should reflect the attitude toward using AI in the project's creative work (rather than overall sentiment), and that explicit non-use labels are reserved for clear statements that the project does not use AI, with a separate flag when a rationale is provided. We parse the model's output and map the resulting stance and non-use labels back to the sentence-level data. The sentence-level files with these labels are used solely as inputs to the project-level indicators described below.

A.4 Aggregation to project-level variables

We aggregate the sentence-level classifications to construct project-level indicators. We define:

- $StoryMentionsAI_i = 1$ if the project's story matches the AI-mention regular expression in Section A.1 at least once, and 0 otherwise.
- $AntiAI_i = 1$ if project i contains (a) any sentence labeled as *Negative* in the stance dimension, or (b) any sentence labeled as an explicit non-use of AI for the project's creative content (with or without a stated reason). All other projects receive $AntiAI_i =$ 0.

In the main text, we interpret $AntiAI_i$ as capturing projects whose stories emphasize that work is done without AI or express opposition to AI tools.

A.5 Coding "AI assists, not replaces" framing in AI-use disclosures

This section documents how we code whether an AI-use disclosure frames AI as assisting human work rather than replacing it. This measure is used as a moderator within the post-policy AI-disclosure sample.

A.5.1 Disclosure text and sample

Kickstarter's post-policy interface displays an "Use of AI" section on the project page when creators indicate AI use. For each AI-disclosing project, we collect the disclosure text shown in this section.

A.5.2 Cleaning disclosure text

Before classification, we clean the disclosure text to reduce noise introduced by the platform interface. Specifically, the disclosure field may contain boilerplate prompts and template sentences originating from the editor workflow (for example, questions such as "What parts of your project will use AI generated content?" and similar instructional text). We remove these template strings when present (including cases where they appear concatenated without clear spacing) and retain the remaining text as the cleaned disclosure statement.

A.5.3 LLM-based sentence-level labeling task for assistive framing

We classify cleaned disclosure statements using the aforementioned local LLM. For each disclosure, the LLM is prompted to output a binary label indicating whether the disclosure explicitly frames AI as assisting humans rather than replacing them.

The coding rule is:

- $AssistFrame_i = 1$ if the disclosure explicitly describes AI as a supportive tool used to assist human work—for example, AI is used for drafts, reference, ideation support, or routine production tasks *with human selection, revision, direction, or final production* *clearly retained by humans*. This includes disclosures that emphasize a "human-in-the-loop" workflow or state that humans remain responsible for the core creative output.

- $AssistFrame_i = 0$ otherwise. This includes disclosures that merely list AI tools or uses without describing the human–AI division of labor, disclosures that imply AI substitutes for core human creative work without emphasizing continued meaningful human contribution, and disclosures that are ambiguous.

To avoid over-interpreting ambiguous text, the LLM is instructed to code $AssistFrame_i = 0$ when assistive (rather than substitutive) framing is not clearly stated. In addition to the binary label, the model outputs a scalar confidence score on $[0, 1]$ reflecting its overall confidence in the disclosure-level classifications.

A.5.4 Project-level moderator used in the analyses

In the moderation analyses, we operationalize assistive framing as a disclosure-specific indicator that is defined only for AI-disclosing projects. Let $Disclosure_i$ denote the interface-level AI-use disclosure indicator. We construct:

$$AssistDisclosure_i \;=\; Disclosure_i \times AssistFrame_i,$$

so that $AssistDisclosure_i = 1$ for AI-disclosing projects whose disclosure text frames AI as assisting rather than replacing humans, and $AssistDisclosure_i = 0$ for all other projects (including projects in the silence baseline).

APPENDIX B: SUPPLEMENTAL TABLES AND FIGURES

Table B1
Platform Endorsement (Staff Picks) by AI Statement Type

Statement type	Staff-pick rate
Silence	.185
Anti-AI narrative	.273
AI-use disclosure	.082

Note: Staff-pick rates (receiving the "Projects We Love" badge) by AI statement type for post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed). "Silence" indicates no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. "AI-use disclosure" indicates the project displays a "Use of AI" section indicating AI use. "Anti-AI narrative" is defined among projects without a "Use of AI" section whose stories mention AI and either express negative sentiment toward AI or emphasize non-use. Projects that mention AI only positively or neutrally are not included in the "Anti-AI narrative" category.

Table B2
Effect of AI-Use Disclosure on Success and Backers

	Success (LPM)	Log(backers+1) (OLS)
AI-use disclosure	-.118*** (.006)	-.392*** (.031)
N	40,285	40,285
R^2	.375	.495
Adj. R^2	.374	.494

Note: Sample consists of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed). Treated projects disclose AI use by displaying a "Use of AI" section. Control projects are "Silence" projects with no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. Projects that mention AI in the story but do not disclose AI use (whether positively, neutrally, or negatively) are excluded from this contrast. Success is estimated via a linear probability model (LPM); log(backers + 1) is estimated via ordinary least squares (OLS). All specifications include the staff-pick (Projects We Love) indicator, controls for log(goal), log(story length), past-action share, team framing share, campaign duration (days), creator join year, first-time creator status, and log measures of prior successful campaigns (projects, dollars, and backers), and fixed effects for parent category, country, and launch month. Standard errors are clustered by launch month. *, **, *** p<0.10, 0.05, 0.01.

Table B3
Effect of Anti-AI Narratives on Success and Backers

	Success (LPM)	Log(backers+1) (OLS)
Anti-AI narrative	.042***	.269***
	(.007)	(.030)
N	38,819	38,819
R^2	.359	.500
Adj. R^2	.358	.499

Note: Sample consists of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed) and no "Use of AI" section recorded (missing or "No AI disclosure found"). Within this non-disclosing subsample, treated projects have "Anti-AI narratives": stories that mention AI and either express negative sentiment toward AI or state that no AI is used. Control projects are "Silence" projects with no "Use of AI" section recorded and no mention of AI in the project story. Projects that mention AI in the story only positively or neutrally are excluded. Success is estimated via a linear probability model (LPM); log(backers + 1) is estimated via ordinary least squares (OLS). All specifications include the staff-pick (Projects We Love) indicator, controls for log(goal), log(story length), past-action share, team framing share, campaign duration (days), creator join year, first-time creator status, and log measures of prior successful campaigns (projects, dollars, and backers), and fixed effects for parent category, country, and launch month. Standard errors are clustered by launch month. *, **, *** p<0.10, 0.05, 0.01.

Table B4
Covariate Balance in PSM Sample: AI-Use Disclosure vs Silence

Variable	Treated mean	Control mean	SMD	Match method
Number of observations	2,051	2,051	—	—
Log(goal)	7.831	7.791	.020	Nearest neighbor
Log(story length)	6.417	6.347	.072	Nearest neighbor
Past-action share (%)	.612	.600	.039	Nearest neighbor
Team framing share (%)	.570	.594	.062	Nearest neighbor
Creator join year	2021.970	2021.944	.007	Coarsened (±1 year)
First-time creator (%)	.584	.584	.000	Exact
Log(prior successful projects)	.784	.708	.088	Nearest neighbor
Log(prior success USD)	5.631	5.549	.017	Nearest neighbor
Log(prior success backers)	3.322	3.219	.034	Nearest neighbor
Launch month (index)			.005	Coarsened (±1 month)
Campaign duration (days)	32.175	31.780	.029	Nearest neighbor
Category (%):				
Games	43.2	43.2	.000	Exact
Publishing	21.4	21.4	.000	Exact
Film & Video	8.5	8.5	.000	Exact
All other	26.9	26.9	.000	Exact
Country (%):				
US	65.7	65.7	.000	Exact
GB	10.4	10.4	.000	Exact
CA	4.8	4.8	.000	Exact
All other	19.2	19.2	.000	Exact

Note: Treated units are post-policy projects (created on or after August 29, 2023) that project displays a "Use of AI" section indicating AI use. Control units are post-policy "Silence" projects (no "Use of AI" section and no mention of AI in the project story). Covariate balance for the propensity-score matched sample; means are computed in the matched sample only. For scalar covariates, the standardized mean difference (SMD) is the absolute value of $(\bar{X}_T - \bar{X}_C)/\sqrt{(s_T^2 + s_C^2)/2}$. For categorical variables (category, country, launch quarter), cells report percentages by level; for readability, the table reports the top 3 levels by frequency and an "All other" category. Launch month balance is summarized using the SMD of a numeric month index (year$\times$12 + month); means are suppressed for readability. "Exact" indicates variables requiring strict match; "Coarsened" indicates matching within restricted range (creator join year ±1 year, launch month ±1 month).

Table B5
Propensity-Score Matched Estimates: AI-Use Disclosure vs Silence

	Success (LPM)	Log(backers+1) (OLS)
AI-use disclosure (treated)	-.107***	-.308***
	(.017)	(.060)
N_{treated}	2,051	2,051
N_{control}	2,051	2,051
R^2	.676	.738

Note: Linear probability model (LPM) for success and ordinary least squares (OLS) for log(backers + 1) estimated on a 1:1 propensity-score matched sample of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed). Treated units disclose AI use (display a "Use of AI" section). Controls are "Silence" projects with no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. Projects with missing or empty story text are excluded to avoid misclassifying missing stories as Silence. Matching uses exact restrictions on parent category, country, and first-time creator status, and restricts matches to controls launched within ±1 month and creator join year within ±1 year. Propensity scores are estimated from log(goal), log(story length), campaign duration (days), past-action share, team framing share, and log measures of prior successful campaigns (projects, dollars, and backers). Within strata, 1:1 nearest-neighbor matching is performed without replacement using a 0.2 standard-deviation caliper on the logit propensity score. Outcome models include pair fixed effects and additional controls (including staff-pick, past-action share, team framing share, creator join year, and launch-month index), and control for disclosure length via centered log(AI disclosure words + 1). Standard errors are clustered by matched pair. *, **, *** p<0.10, 0.05, 0.01.

Table B6
Propensity-Score Matched Estimates: AI Disclosure vs Silence, Moderated by "AI assists, not replaces"

	Success (LPM)	Log(backers+1) (OLS)
AI-use disclosure (no focal framing)	-.159***	-.524***
	(.031)	(.111)
Increment for "AI assists, not replaces" framing	.076*	.291**
	(.040)	(.142)
AI-use disclosure with "AI assists, not replaces" framing (sum)	-.083***	-.233***
	(.022)	(.079)
N_{pairs}	2,037	2,037
N_{obs}	4,074	4,074
R^2	.683	.732
Adj. R^2	.363	.461

Note: Linear probability model (LPM) for success and ordinary least squares (OLS) for log(backers + 1) estimated on a 1:1 propensity-score matched sample of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed). Treated units are AI-disclosing projects (display a "Use of AI" section) and controls are "Silence" projects with no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story; projects with missing or empty story text are excluded. The focal framing indicator is based on large language model (LLM) coding of disclosure text; when LLM coverage is required, treated units are restricted to those with non-missing LLM coding. Matching uses exact restrictions on parent category, country, and first-time creator status, and restricts matches to controls launched within ±1 month and creator join year within ±1 year. Propensity scores are estimated using standard project and creator covariates; 1:1 nearest-neighbor matching is performed without replacement using a caliper on the logit propensity score. Outcome models include pair fixed effects and additional controls (including staff-pick, creator join year, launch-month index, story-orientation controls, and centered log(AI disclosure words + 1)). Standard errors are clustered by matched pair. *, **, *** p<0.10, 0.05, 0.01.

Table B7
Covariate Balance in PSM Sample: Anti-AI narrative vs Silence

Variable	Treated mean	Control mean	SMD	Match method
Number of observations	1,125	1,125	—	—
Log(goal)	7.610	7.477	.078	Nearest neighbor
Log(story length)	6.962	6.949	.019	Nearest neighbor
Past-action share (%)	.600	.597	.012	Nearest neighbor
Team framing share (%)	.511	.502	.023	Nearest neighbor
Creator join year	2019.796	2019.823	.006	Coarsened (±1 year)
First-time creator (%)	.365	.365	.000	Exact
Log(prior successful projects)	.959	1.030	.075	Nearest neighbor
Log(prior success USD)	6.806	7.112	.064	Nearest neighbor
Log(prior success backers)	4.083	4.306	.072	Nearest neighbor
Launch month (index)			.001	Coarsened (±1 month)
Campaign duration (days)	27.630	27.351	.027	Nearest neighbor
Category (%):				
Games	39.0	39.0	.000	Exact
Publishing	34.8	34.8	.000	Exact
Comics	10.9	10.9	.000	Exact
All other	15.2	15.2	.000	Exact
Country (%):				
US	73.5	73.5	.000	Exact
GB	11.1	11.1	.000	Exact
CA	4.8	4.8	.000	Exact
All other	10.6	10.6	.000	Exact

Note: Treated units are post-policy projects (created on or after August 29, 2023) without an AI Disclosure section whose stories contain anti-AI narratives (among projects without a "Use of AI" section, the story mentions AI and either expresses negative sentiment toward AI or emphasizes non-use). Control units are post-policy "Silence" projects (no "Use of AI" section and no mention of AI in the project story). Covariate balance for the propensity-score matched sample; means are computed in the matched sample only. For scalar covariates, the standardized mean difference (SMD) is the absolute value of $(\bar{X}_T - \bar{X}_C)/\sqrt{(s_T^2 + s_C^2)/2}$. For categorical variables (category, country, launch quarter), cells report percentages by level; for readability, the table reports the top 3 levels by frequency and an "All other" category. Launch month balance is summarized using the SMD of a numeric month index (year×12 + month); means are suppressed for readability. "Exact" indicates variables requiring strict match; "Coarsened" indicates matching within restricted range (creator join year ±1 year, launch month ±1 month).

Table B8
Propensity-Score Matched Estimates: Anti-AI Narratives vs Silence

	Success (LPM)	Log(backers+1) (OLS)
Anti-AI narrative (treated)	.015 (.016)	.165** (.066)
N_{treated}	1,125	1,125
N_{control}	1,125	1,125
R^2	.613	.739

Note: Linear probability model (LPM) for success and ordinary least squares (OLS) for log(backers + 1) estimated on a 1:1 propensity-score matched sample of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed). Treated units have "Anti-AI narratives": among projects without a "Use of AI" section recorded (missing or "No AI disclosure found"), stories that mention AI and either express negative sentiment toward AI or emphasize non-use. Controls are "Silence" projects with no "Use of AI" section recorded and no mention of AI in the project story. Projects mentioning AI only positively or neutrally are excluded. Projects with missing or empty story text are excluded to avoid misclassifying missing stories as Silence. Matching uses exact restrictions on parent category, country, and first-time creator status, and restricts matches to controls launched within ±1 month and creator join year within ±1 year. Propensity scores are estimated from log(goal), log(story length), campaign duration (days), past-action share, team framing share, and log measures of prior successful campaigns (projects, dollars, and backers). Within strata, 1:1 nearest-neighbor matching is performed without replacement using a 0.2 standard-deviation caliper on the logit propensity score. Outcome models include pair fixed effects and additional controls (including staff-pick, past-action share, team framing share, creator join year, and launch-month index). Standard errors are clustered by matched pair. *, **, *** p<0.10, 0.05, 0.01.

Table B9
Implied disclosure effect vs Silence, by disclosed AI modality

	Success (LPM)	Log(backers+1) (OLS)
AI-use disclosure: Images vs silence	-.081***	-.210***
	(.007)	(.033)
AI-use disclosure: Text vs silence	-.179***	-.659***
	(.012)	(.052)
AI-use disclosure: Audio vs silence	-.210***	-.750***
	(.031)	(.116)
AI-use disclosure: Video vs silence	-.161***	-.506***
	(.017)	(.080)
AI-use disclosure: Code vs silence	-.220***	-.964***
	(.026)	(.119)
N	40,267	40,267
R^2	.377	.498
Adj. R^2	.375	.497

Note: Sample consists of post-policy (created on or after August 29, 2023) non-Technology projects with observed outcomes (successful or failed) that either disclose AI use or are "Silence" projects; projects that mention AI in the story without disclosing AI use are excluded. "Silence" indicates no "Use of AI" section recorded (missing or "No AI disclosure found") and no mention of AI in the project story. Modality indicators (images, text, audio, video, code) are based on large language model (LLM) coding of disclosure text; when LLM coverage is required, AI-disclosing observations are restricted to those with non-missing LLM coding. Rows report implied effects of AI-use disclosure vs Silence for projects whose disclosures mention the given modality, evaluated at the within-modality-group average mix of the other modality indicators. Success is estimated via a linear probability model (LPM); log(backers + 1) is estimated via ordinary least squares (OLS). All specifications include the staff-pick (Projects We Love) indicator, centered log(AI disclosure words + 1), standard controls, and fixed effects for parent category, country, and launch month. Standard errors are clustered by launch month. *, **, *** p<0.10, 0.05, 0.01.