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Determinants of Reward Crowdfunding Success for Technology Projects: The Moderating Role of Platform Age

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Abstract

Purpose: Moving beyond the average effects identified in prior literature, this study investigates the differential drivers of technology crowdfunding success and how platform maturity reshapes the competitive landscape. Specifically, it examines whether strategies ensuring basic viability can secure top-tier success and how key drivers evolve as a platform ages.

Design/methodology/approach: The study analyzes 600 technology projects from Kickstarter (2009-2023) using a complementary analytical approach. Generalized Least Squares regression and subsample analysis establish baseline relationships and test the moderating role of platform age. Quantile regression then uncovers how the influence of key determinants shifts across the entire conditional distribution of campaign success.

Findings: The results confirm the significance of fundamental determinants, with subsample analysis showing their influence is contingent on a project's final outcome. A key finding is that platform age positively moderates the relationship between media richness and success. Quantile regression further reveals a performance-level hierarchy, showing that influential criteria evolve from establishing baseline viability for lower-performing campaigns to signaling superior credibility and comprehensive development for top performers.

Originality/value: This study advances decision sciences by demonstrating context-dependent crowdfunding strategies and employing quantile regression to reveal a hierarchical decision model, with platform age as a key moderator. In contrast to earlier studies that overlook decision heterogeneity, this research proposes an original quantile regression approach that incorporates platform age as a moderator, enabling a differentiated analysis of reward-based crowdfunding success across performance levels. It identifies the key determinants of success in reward-based crowdfunding, offering a decision-oriented framework to understand how creators' strategic choices and backers' responses jointly drive funding outcomes.

Practical implications: For decision sciences in practice, the findings prescribe distinct contingent strategies for creators based on performance targets and platform maturity. They further advocate for platform administrators to develop level-specific decision support systems, moving beyond one-size-fits-all analytics to improve strategic outcomes.

Keywords: Reward-crowdfunding, Technology projects, Crowdfunding success, GLS regression, Quantile regression.

JEL-Classifications: C51, G24, M13, O33.

1 Introduction

While traditional bank financing remains vulnerable to economic volatility, the emergence of alternative funding mechanisms, particularly reward-based crowdfunding, has enabled entrepreneurs to secure capital while simultaneously validating market demand. As an innovative application of crowdsourcing, crowdfunding has profoundly reshaped capital acquisition for startups and small-to-medium enterprises (SMEs) (Schwienbacher & Larralde, 2012). This shift has prompted rigorous academic scrutiny, with scholars systematically comparing crowdfunding to conventional avenues like venture capital, angel investment, and bank loans (Böckel et al., 2021; Drover et al., 2017; Köhn, 2018; Mohammadi & Sakhteh, 2023). Technology startups, though statistically rare, are recognized as pivotal drivers of economic advancement due to their scalability and disruptive potential (Audretsch et al., 2006; Autio et al., 2014; Ngek & van Aardt Smit, 2013). Unlike institutional financing, crowdfunding democratizes access to capital by leveraging digital platforms to aggregate micro-investments from distributed networks. Mollick (2014) formalizes this paradigm as "the *efforts by entrepreneurial individuals and groups, cultural, social, and for-profit, to fund their ventures by drawing on relatively small contributions from a relatively large number of individuals using the internet, without standard financial intermediaries*."

Crowdfunding encompasses several distinct models, including equity-based, crowdlending, donation-based, and reward-based approaches (Belleflamme et al., 2014). This study focuses specifically on reward-based crowdfunding, where backers receive tangible products (e.g., prototypes) or intangible rewards (e.g., acknowledgments) in exchange for their financial support (Gerber et al., 2012; Mollick, 2014).

Grounded in signaling theory (Spence, 1978), reward-based campaigns function not only as fundraising instruments but also as market-validation mechanisms, enabling creators to transmit quality signals through campaign design and reward structures (Courtney et al., 2017). As the most prevalent crowdfunding model, it uniquely combines capital formation with co-creation opportunities and pre-launch marketing (Brown et al., 2017; Xu et al., 2014), a dual role consistent with the resource-based view of entrepreneurial ventures (Barney & Arikan, 2005).

Academic research on reward-based crowdfunding has evolved along two primary trajectories. The first seeks to conceptualize crowdfunding (Belleflamme et al., 2014; Kraus et al., 2016). The second investigates key determinants of success, employing theoretical perspectives such as information asymmetry (Akerlof, 1978), social exchange (Blau, 1964), and signaling theory (Spence, 1978) to analyze their impact. These studies emphasize four interrelated dimensions. These studies emphasize four interrelated dimensions. These include project characteristics that mitigate backers' perceived risks through quality signals (Courtney et al., 2017; Mollick, 2014), creator credibility that alleviates information asymmetries (Ahlers et al., 2015), social capital mobilization that fosters trust-based exchanges (Colombo et al., 2015), and platform-specific dynamics that influence funding outcomes (Thürridl & Kamleitner, 2016). Building on this foundation, our study examines how technological

distinctiveness interacts with these determinants in reward-based technology campaigns, offering new insights into backer decision making under conditions of uncertainty.

The persistent challenge of crowdfunding success, defined by the all-or-nothing requirement to reach a funding goal, is particularly pronounced in the technology sector. According to Kickstarter data[1], the overall project success rate is 41.1%, while the rate for technology projects is markedly lower at 23.09%. This disparity underscores a critical research gap and necessitates a focused investigation into the determinants of success within this category. Technology projects represent a compelling domain for such inquiry due to their distinct attributes. Therefore, they operate under elevated uncertainty and risk, yet remain fundamental to economic growth and innovation. Consequently, understanding how to address their unique challenges, such as significant prototyping costs and extended delivery timelines, is of paramount importance. This study contends that enhancing the efficacy of technology reward crowdfunding requires targeted, context-specific insights.

Previous research has identified various success factors in reward-based crowdfunding, analyzing variables such as campaign duration, minimum contribution levels, social media usage, and update frequency (Courtney et al., 2017; Kraus et al., 2016; Mollick, 2014). However, the existing literature exhibits two significant limitations. First, it has largely overlooked the evolving nature of the crowdfunding environment itself, failing to investigate how a platform's maturity, such as its age, can fundamentally alter the effectiveness of campaign strategies. Second, prior studies typically treat success as a homogeneous outcome, relying on average effects that mask critical differences in the determinants driving fundamental viability versus exceptional overfunding.

This study's originality and contribution to Decision Sciences arise from a comprehensive methodological framework designed to reveal differentiated relationships that previous studies have missed. It makes three key advances. First, it introduces platform age as a novel contextual moderator, advancing the understanding of how evolving decision environments shape strategic effectiveness. Second, methodologically, it employs quantile regression to move beyond average effects and uncover a hierarchy of decision criteria used by backers across the entire performance distribution, providing a differentiated diagnostic tool. Third, it synthesizes these insights into a dynamic, contingent decision model that explains how the drivers of success shift based on performance targets and platform maturity. This model yields a refined theoretical framework for academics and delivers actionable, context-specific decision rules for practitioners, thereby bridging decision theory and strategic practice in digital marketplaces.

The remainder of this paper is structured as follows. Section 2 presents the theoretical background. Section 3 conducts the literature review and develops the hypotheses. Section 4 describes the sample and variables, while Section 5 outlines the methodology. Section 6 reports the empirical results from the GLS and quantile regression analyses. Section 7 discusses the findings, and Section 8 concludes the paper.

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[1] https://www.kickstarter.com/help/stats?ref=global-footer .

2 Theoretical Framework

The emergence of technology crowdfunding platforms has revolutionized entrepreneurial finance by democratizing access to capital (Brabham, 2008; Deng et al., 2016). To ground our analysis of this phenomenon, this section outlines five complementary theoretical frameworks that collectively explain its dynamics.

2.1 Social Exchange Theory

Social Exchange Theory, proposed by Blau (1964), provides a crucial framework for understanding backer participation, revealing how non-monetary rewards and community engagement create reciprocal value beyond financial returns. In reward crowdfunding, backers assess the creator's reliability, the project's quality, and the implied reciprocity of the exchange (Jiang et al., 2021). Continuous interactions, including updates, comments, and comprehensive FAQs, are critical to this process, as they enhance transparency, mitigate uncertainty, and strengthen the relationship between creators and backers. The theory posits that individuals engage in digital environments when they perceive a favorable balance between anticipated benefits and associated costs, as formalized in Equation 1.

$$Participation_i = B_i - C_i. \tag{1}$$

In this context, $Participation_i$ represents the willingness of backer i to contribute to a crowdfunding campaign. B_i denotes the expected benefits derived from the exchange, which encompass anticipated rewards, community recognition, and the satisfaction derived from supporting innovation. Conversely, C_i represents the perceived costs associated with participation, including financial contributions, uncertainty regarding project delivery, and information search costs. According to Social Exchange Theory, individuals are inclined to participate when expected benefits surpass perceived costs.

In the realm of reward-based crowdfunding, these perceived benefits and costs are shaped by observable campaign elements such as updates, comments, and frequently asked questions, which serve to mitigate uncertainty and enhance the perceived value of the exchange between creators and backers. This cost-benefit framework constitutes the fundamental mechanism of social exchange behavior according to Blau (1964).

2.2 Information Asymmetry Theory

Information Asymmetry Theory, introduced by Akerlof (1978), highlights the inherent market inefficiencies in crowdfunding, where knowledge gaps between creators and backers can lead to suboptimal funding outcomes. This challenge is fundamental. Creators possess superior information about project quality, placing backers at a disadvantage. The theory posits that backers will respond adversely to inadequate information signals. Akerlof's (1978) seminal market for lemons model formalizes this information problem. In its simplest form, the buyer's lack of information leads them to value all goods at

the average quality. This can be expressed mathematically, where the buyer's willingness to pay (P) is a function of their perceived average quality (μ) of the projects in the market, as expressed in Equation 2:

$$P = \mu. \tag{2}$$

Given that the true quality (q) of a high-quality project is greater than the average ($q_{high} > \mu$), creators of such projects find the market price insufficient. Conversely, creators of low-quality projects ($q_{low} < \mu$) receive a premium. This dynamic can lead to a market failure where high-quality projects are driven out, a phenomenon known as adverse selection. In crowdfunding, this implies that without effective signals, backers will assume an average quality, potentially underfunding superior projects and overfunding inferior ones. Therefore, as Kim et al. (2017) demonstrate, successful campaigns actively mitigate this asymmetry through quantifiable elements such as the minimum pledge amount, funding goal, campaign duration, and comprehensive project details.

2.3 Signaling Theory

Signaling Theory, as formalized by Spence (1978), explains how project creators employ strategic quality indicators to establish credibility and overcome backers' uncertainty in reward crowdfunding. To mitigate the fundamental information asymmetry, creators transmit credible signals through diverse elements such as rich multimedia content, external links, prototype availability, and documented prior experience. Roma et al. (2021) reveal that observable indicators like images, videos, detailed descriptions, and social media links serve as critical proxies for unobservable project quality. The core mechanism of Signaling Theory is based on a cost structure that makes signaling effective. In Spence's job market model, a signal (s) is credible only if the cost of obtaining it is negatively correlated with the unobservable quality (q) of the individual. This relationship is formalized in Equation 3, which specifies two essential conditions: the cost (C) of acquiring a signal must increase with the signal's level (s), but this cost must be lower for individuals with higher ability (q):

$$\frac{\partial C(s,q)}{\partial s} > 0 \text{ and } \frac{\partial C(s,q)}{\partial q} < 0. \tag{3}$$

This condition states that the cost (C) of acquiring a signal increases with the signal's level (s), but this cost is lower for individuals with higher ability (q). A separating equilibrium occurs when high-quality individuals choose a signal level (S_{high}) that is too costly for low-quality individuals (S_{low}) to mimic.

Applying this logic to reward crowdfunding, and as Mollick (2014) argues, project creators employ strategic quality indicators, such as rich multimedia content, external links, and documented prior experience, as costly signals to separate themselves from lower-quality projects. These signals are credible precisely because they are harder and more costly for a low-quality project to fake.

2.4 Social Capital Theory

Social Capital Theory underscores the significance of social networks, digital reputation, and established relationships within collaborative environments. In the context of reward-based crowdfunding, social capital exerts influence through multiple mechanisms. Specifically, Peng and Zhang (2025) and Zheng et al. (2014) reveal that a creator possessing active social networks enhances visibility and attracts external contributors. Cai et al. (2021) and Liu et al. (2021) demonstrate that connections to social networks function as verifiable social proof, thereby enhancing the project's credibility. Butticè et al. (2017), Cai et al. (2021), and Skirnevskiy et al. (2017) show that regular interactions within comment sections facilitate the development of relational social capital, founded on trust and reciprocity. Technology campaigns, in particular, derive substantial benefits from this form of capital, given the complexity of projects that necessitate robust relational evidence. Furthermore, the literature indicates that social capital enhances project dissemination, accelerates the provision of initial support, and strengthens the intention to contribute. Cai et al. (2021), Colombo et al. (2015), and Liu et al. (2021) confirm that it serves as an indirect measure of reliability. Peng and Zhang (2025) and Skirnevskiy et al. (2017) indicate that external links, social interactions, and comments exemplify these mechanisms and play a crucial role in structuring observable social capital.

2.5 Level of Processing Theory

The Level of Processing Theory, articulated by Craik and Lockhart (1972), posits that the quality of cognitive processing is contingent upon the depth of information processed. This theoretical framework is pertinent to reward crowdfunding campaigns, where the application of this principle is evident in campaigns that offer rich, structured, and relevant content. Backers exhibit heightened attention towards projects that deliver accurate, consistent, and accessible information. The incorporation of detailed descriptions, clear visuals, and technical demonstrations facilitates deeper cognitive processing. Such processing enhances comprehension of the project and helps in retention. Campaigns that effectively engage this level of cognitive attention are subsequently remembered for longer durations by potential contributors. Furthermore, they are more likely to be shared, revisited, and supported. Consequently, the depth of processing engenders a cognitive advantage for projects that prioritize their presentation, thereby augmenting their likelihood of success within a competitive and saturated campaign environment.

Despite these theoretical frameworks and the expanded financing opportunities they help explain, technology crowdfunding campaign success remains inherently unpredictable due to complex interacting factors as proposed by Brabham (2008). The most widely adopted success metric, the funding ratio (calculated as amount raised relative to project goal), quantitatively captures this variability by measuring the level of financial support achieved (Mitra & Gilbert, 2014 ; Wang et al., 2017).

3 Literature Review and Hypothesis Development

Existing theoretical frameworks and empirical literature identify multiple factors influencing reward-based crowdfunding success, with ten key variables being particularly considered in our analysis

3.1 Duration

Multiple studies have established a link between campaign duration and success in crowdfunding. This research consistently indicates that a longer campaign duration is associated with reduced funding, diminished backer engagement, and a lower likelihood of success (Burtch et al., 2013; Kuppuswamy & Bayus, 2018; Mitra & Gilbert, 2014; Zheng et al., 2014).

> **Hypothesis 1 (H1):** *Campaign duration negatively affects the success of a technology crowdfunding campaign.*

3.2 Minimum

Research consistently underscores the critical role of the minimum pledge amount in determining crowdfunding outcomes. As evidenced by Makarova and Ulitina (2022), campaigns with lower minimum pledges achieve markedly higher success rates, which is attributable to increased backer participation and enhanced funding goal attainment.

> **Hypothesis 2 (H2):** *A lower minimum pledge amount increases the success rate of a crowdfunding campaign.*

3.3 Updates, FAQ, and Comments

The literature consistently affirms the critical role of project updates in crowdfunding success. Studies show that regular, informative updates build transparency and trust with backers (Xu et al., 2014), maintain campaign momentum and engagement (Wu et al., 2015), and ultimately lead to a higher number of backers and increased funds raised (Kuppuswamy & Bayus, 2018).

> **Hypothesis 3a (H3a):** *The number of updates has a positive effect on crowdfunding campaign success.*

A comprehensive FAQ section is another key determinant of success. By proactively addressing backers' questions and concerns, a well-crafted FAQ enhances project understanding and boosts supporter confidence (Xu et al., 2014).

> **Hypothesis 3b (H3b):** *The number of FAQ increases backer engagement, support, and campaign success.*

Furthermore, the number of comments serves as a vital indicator and driver of campaign performance. Comments foster community building and trust (Mollick, 2014), act as social proof that alleviates backer concerns (Courtney et al., 2017), and signal high levels of engagement that correlate with a greater likelihood of funding success (Petitjean, 2018).

> ***Hypothesis 3c (H3c):*** *The number of comments in a crowdfunding campaign has a positive effect on its success.*

3.4 Target amount

A campaign's target amount is negatively related to its success, as higher goals represent greater risk and are more difficult to achieve (Agrawal et al., 2011; Ahlers et al., 2015; Belleflamme et al., 2014; Burtch et al., 2013; Hobbs et al., 2016; Lagazio & Querci, 2018; Lelo De Larrea et al., 2019).

> ***Hypothesis 4 (H4):*** *The target amount negatively influences crowdfunding campaign success.*

3.5 Website

The success of a crowdfunding campaign often depends on its ability to communicate project credibility and value beyond the platform itself. An external website link can serve this function by providing a more comprehensive presentation of the project's objectives, value proposition, and team credentials (Lagazio & Querci, 2018).

> ***Hypothesis 5 (H5):*** *The presence of an external website link is positively associated with crowdfunding campaign success.*

3.6 Social media

Empirical research consistently demonstrates that social media engagement has a beneficial influence on crowdfunding outcomes, contributing to increased funding and campaign success (Alazazi et al., 2020; Belleflamme et al., 2014; Hong et al., 2018; Kraus et al., 2016; Mollick, 2014).

> ***Hypothesis 6 (H6):*** *The number of social media used has a positive impact on crowdfunding project success.*

3.7 Images

The number of images is a significant determinant of crowdfunding success. High-quality, pertinent images build backer confidence, attract more funding, and thereby increase the likelihood of campaign success (Kraus et al., 2016; Zhang et al., 2021; Zheng et al., 2014).

Hypothesis 7 (H7): *The number of images has a positive effect on the level of contributions and the overall success of a crowdfunding project.*

3.8 Video

The presence of campaign videos is a significant predictor of crowdfunding success. A higher number of videos enhances a campaign's perceived trustworthiness and provides a richer medium to demonstrate project quality, which in turn increases the likelihood of funding (Butticè et al., 2017; Courtney et al., 2017; Kraus et al., 2016; Mollick, 2014; Petitjean, 2018; Wheat et al., 2013).

Hypothesis 8 (H8): *The number of videos has a significant positive effect on crowdfunding campaign success.*

3.9 Platform age

The age of a crowdfunding platform shapes its ecosystem, influencing backer expectations and campaign strategies. As a platform matures, increased competition and established norms create a signaling environment that necessitates more robust visual strategies from creators to attract backers (Mollick, 2014). Grounded in signaling theory (Spence, 1978), we posit that creators on mature platforms will increasingly use rich media to reduce information asymmetry and stand out. Furthermore, the effectiveness of such media richness as a signal of project viability is expected to be moderated by platform age. Specifically, a rich media presentation is anticipated to have a stronger impact in a mature environment where backers are more experienced at evaluating quality (Butticè et al., 2017). This leads to the following hypothesis:

Hypothesis 9 (H9): *The relationship between media richness and funding success is positively moderated by platform age.*

4 Data Description and Variables

4.1 Data and Variables Descriptions

To investigate the determinants of reward crowdfunding success, we consider the data of 600 manually compiled technology projects in different countries across the world (Deng et al., 2022). All projects were extracted using standardized criteria to minimize selection bias. Only campaigns that had been completed at the time of extraction were included in the analysis. The sample encompasses multiple technology categories and a variety of geographic regions. These data were collected from the Kickstarter platform from the year of its launch in 2009 until March 2023 (Mora-Cruz & Palos-Sanchez, 2023). Kickstarter is utilized due to its status as the largest reward-based crowdfunding platform for technology projects. Its extensive scale, user-friendly interface design, and lengthy operational history facilitate researchers in examining project signals, creator actions, and the effects of platform maturity. The main criterion to select

a fairly long period is to examine the moderating role of the platform age on the relation between some independent variables and the reward crowdfunding success. Although the dataset comprises 600 manually coded projects, this sample size is in line with prior studies that rely on manual data collection to ensure high data quality and capture nuanced features that automated approaches often fail to identify (Laachach et al., 2025). Manual coding improves variable accuracy and reduces measurement error, thereby enhancing the validity of the empirical analysis (Colombo et al., 2015). Moreover, existing crowdfunding research frequently employs manually compiled samples of comparable size when detailed project-level characteristics are required (Kuppuswamy & Bayus, 2018; Laachach et al., 2025; Lagazio & Querci, 2018).

Our database was divided into 3 subsamples. Specifically, 200 Overfunding projects, 200 Successful projects, and 200 Unsuccessful projects. The projects were classified based on the ratio of the collected amount to the target goal amount. If the ratio was equal to 150 percent or more, the project was considered an Overfunding project; if the collected amount was equal to 100-150 percent of the target amount, the project was classified as a Successful project; otherwise, it was considered Unsuccessful. Based on the overall results of the different chosen technology projects, we considered that 150 percent was an acceptable threshold to distinguish between Overfunding and successful projects.

The dataset is pertinent for three primary reasons. Firstly, technology projects exhibit a higher degree of uncertainty in comparison to other categories. Secondly, they necessitate more robust signals to mitigate information asymmetry. Lastly, they produce greater variability in project quality indicators, such as images, videos, and technical descriptions. These attributes render the technology category particularly suitable for examining the influence of platform age and media richness on success outcomes.

4.2 Variables

The variables incorporated in the models represent the primary determinants identified in the existing literature, including project quality signals, creator engagement, social information, campaign design, and platform characteristics. These variables are evident in empirical studies on reward-based crowdfunding (Roma et al., 2017; Yeh et al., 2019; Zheng et al., 2014). The selected variables are listed in Table 1.

Table 1. Description of variables

Variable	Acronym	Description
Dependent variable: The crowdfunding project outcome	OCP	The ratio of the collected amount to the goal amount (Transformed in Log).
Independent variables		
Duration	DUR	The number of days during the funding period (Transformed in Log).
Minimal	MIN	The minimal pledge in US dollars established by the campaign creator (Transformed in Log).
Updates	UPD	The number of updates (Transformed in Log).
Frequently Asked Questions	FAQ	The number of Frequently Asked Questions (Transformed in Log).
Comments	COM	The number of comments (Transformed in Log).
Target Amount	TAR	The target amount in US dollars (Transformed in Log).

Website	WEB	The number of website links.
Social Media Links	SOC	The number of social media links dedicated to the project.
Images	IMG	The number of images (Transformed in Log).
Videos	VID	The number of videos (Transformed in Log).
Platform Age	AGE	The difference in years between the date of the campaign and the year the platform was established.
The Media Richness Simple Index	MRSI	It is a standardized additive measure, calculated as the average of the z-scores for the number of images and videos, providing a composite score where both components contribute equally.
The Media Richness PCA Index	MRPCA	It is derived from a Principal Component Analysis (PCA) of the number of images and videos. The Kaiser-Meyer-Olkin measure of sampling adequacy has an overall value of 0.5*.
The Media Richness Index	MRI	It is the Media Richness Index, constructed using either a PCA or a simple additive method.

Notes: * Although the Kaiser-Meyer-Olkin measure of 0.5 indicates limited sampling adequacy, we constructed the PCA index following theoretical justification and referee recommendation, with parallel analysis using a standardized additive index confirming result robustness. In the regression analysis, the following variables were log-transformed to address skewness: OCP, DUR, MIN, UPD, FAQ, COM, TAR, IMG, and VID. For variables containing zero values (OCP, UPD, FAQ, COM, IMG, VID), the transformation is ln(variable+1). For variables with no zero values (DUR, MIN, TAR), the transformation is ln(variable). OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established.

The selection of variables is consistent with the dominant empirical research on crowdfunding. Project quality signals, such as images and videos, are central to technology projects because uncertainty is higher (Zhang et al., 2021). Engagement variables are necessary to reduce information asymmetry and reinforce trust between creators and backers (Kraus et al., 2016; Xu et al., 2014). External validation through social media and websites strengthens credibility and facilitates verification (Colombo et al., 2015). The target amount and minimum pledge reflect risk and accessibility, which affect the willingness to contribute (Mollick, 2014; Roma et al., 2017). Platform age is included because platform maturity influences the effectiveness of these determinants (Elrashidy et al., 2024; Roma et al., 2021).

5 Methodology

5.1 Model Specifications

The study employs two complementary econometric methodologies to examine the determinants of success in reward-based crowdfunding technology projects. These approaches facilitate the measurement of average effects of various variables, as well as their influence across different levels of performance.

The dependent variable is the logarithm of the OCP, defined as the ratio of the actual amount collected to the predetermined target. This transformation addresses asymmetries and aligns with empirical recommendations in the analysis of digital platforms (Mitra & Gilbert, 2014; Zhang & Chen, 2019). The baseline econometric model (GLS) is specified in Equation 4 as follows:

$$OCP = \alpha + \beta_1 DUR + \beta_2 MIN + \beta_3 UPD + \beta_4 FAQ + \beta_5 COM + \beta_6 TAR + \beta_7 WEB$$
$$+ \beta_8 SOC + \beta_9 IMG + \beta_{10} VID + \beta_{11} \cdot AGE + \varepsilon, \tag{4}$$

where α is the intercept, β_1 through β_{11} are the regression coefficients, and ε is the error term. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established.

We estimated the above model using the outcome of a crowdfunding project as the dependent variable 4 times. The first one is intended to identify the factors that are believed to affect the success of projects independently of any classification (considering all samples), the other 3 times are estimated with the same objective, but we classify the projects into overfunding, successful, and unsuccessful projects. Then we have integrated an additional variable, which is the age of the reward crowdfunding platform, to deepen the relation between the success of the project and the MRI variable.

To empirically test the moderating role of platform age proposed in Hypothesis 9, we introduce an interaction term between the Media Richness Index (MRI) and platform age. Grounded in Signaling Theory (Spence, 1978), this term $(AGE \times MRI)$ examines whether the effectiveness of media-based signals is contingent upon the maturity and competitive density of the platform environment. The augmented models are specified as follows:

$$OCP = \alpha + \beta_1 DUR + \beta_2 MIN + \beta_3 UPD + \beta_4 FAQ + \beta_5 COM + \beta_6 TAR + \beta_7 WEB$$
$$+\beta_8 SOC + \beta_9(AGE \times MRI) + \beta_{10} AGE + \beta_{11} MRSI + \varepsilon, \qquad (5)$$

$$OCP = \alpha + \beta_1 DUR + \beta_2 MIN + \beta_3 UPD + \beta_4 FAQ + \beta_5 COM + \beta_6 TAR + \beta_7 WEB$$
$$+\beta_8 SOC + \beta_9(AGE \times MRI) + \beta_{10} AGE + \beta_{11} MRPCA + \varepsilon, \qquad (6)$$

where the variable $(AGE \times MRI)$ is the interaction term between the media richness index (MRI) and the age of the platform. The MRI is constructed using two alternative methods to ensure robust results. In Specification 5 (Equation 5), we use a simple additive measure (MRSI) for the MRI in its interaction with platform age as shown in Equation 5, while in Specification 6 (Equation 6), we employ a principal component analysis measure (MRPCA) as expressed in Equation 6. In these specifications (Equations 5 and 6), OCP represents the campaign success ratio; DUR denotes the funding period duration in days; MIN is the minimum pledge amount in US dollars set by the creator; UPD, FAQ, and COM capture engagement through the number of updates, frequently asked questions, and comments, respectively; TAR represents the target amount in US dollars; WEB and SOC measure external promotion via the number of website links and social media links associated with the project; IMG and VID reflect media content through the number of images and videos; and AGE indicates platform age.

5.2 Estimation Techniques

Two estimation methods are employed to enhance the robustness of the results, specifically addressing two structural limitations inherent in crowdfunding data. The first limitation pertains to the presence of non-constant variance in the errors. The second limitation relates to the heterogeneity of funding behavior, which varies according to the success level of the projects.

5.2.1 GLS Method

The GLS method addresses the heteroscedasticity issues identified in the preliminary analyses. This approach enhances the efficiency of the coefficient estimates when the variance of the errors is not constant, as supported by the findings of Greene (2012) and Kennedy (2011). GLS is particularly suited for cross-sectional data derived from Kickstarter, where participation levels exhibit considerable variability. Numerous studies, including those conducted by Colombo et al. (2015) and Hörisch (2018), have employed this methodology to examine the¨ determinants of success in analogous contexts.

The GLS method is employed to estimate the parameters of a linear regression model in situations where the error terms exhibit heteroscedasticity or correlation. The general equation of the GLS model is expressed in Equation 7 as follows:

$$Y = X\beta + \varepsilon, \tag{7}$$

where Y represents the vector of observations, X denotes the matrix of explanatory variables, β is the vector of coefficients to be estimated, and ε indicates the vector of errors. In contrast to Ordinary Least Squares (OLS), GLS posits that the variance-covariance matrix of errors, denoted as (Ω), is not necessarily diagonal or constant. The GLS estimator is formulated in Equation 8 as follows:

$$\beta_{GLS} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}Y. \tag{8}$$

This methodology facilitates the generation of efficient estimators even in the presence of heteroscedasticity or autocorrelation. Although the application of GLS remains infrequent in the field of crowdfunding, it is advocated for the analysis of structured or panel data, where correlation among observations or variance heterogeneity may introduce bias into the results (Alshebami, 2022; Laachach et al., 2025).

Preliminary diagnostic analyses were conducted to validate the model's assumptions. This included assessing correlations to detect potential multicollinearity, alongside formal tests for heteroscedasticity (Breusch-Pagan) and autocorrelation (Breusch-Godfrey). Furthermore, time-trend analysis and a Ramsey RESET test were performed to check for model stability and correct functional form. The significant results of the Breusch-Pagan test substantiate the necessity of employing the GLS method.

GLS yields efficient coefficient estimates for the overall sample as well as for the three specified subsamples (overfunding, successful, and unsuccessful) delineated in the data.

5.2.2 Quantile Regression Method

Quantile regression serves as a methodological framework for analyzing the determinants of success across varying levels of campaign performance. This approach elucidates the influence of explanatory variables on success quantiles, rather than relying solely on mean values. It facilitates the exploration of whether specific factors exert a more pronounced effect on high-performing campaigns in comparison to those with moderate performance.

Quantile regression enables the estimation of the effects of explanatory variables on not only the conditional mean of the dependent variable but also on any specified quantile, such as the median or the 90th percentile. The quantile regression equation for quantile τ (where $0 < \tau < 1$) is shown in Equation 9 as follows:

$$Q_y(\tau|X) = X\beta(\tau), \tag{9}$$

where $Q_y(\tau \mid X)$ denotes the conditional τ^{th} quantile of y given X, and $\beta(\tau)$ represents the vector of coefficients associated with this quantile. The estimator is derived by minimizing the weighted sum of the absolute residuals as formalized mathematically in Equation 10 using the check function $\rho_\tau(u)$ defined in Equation 11:

$$\min_{\beta} \sum_{i=1}^{n} \rho_\tau(y_i - X_i\beta), \tag{10}$$

where

$$\rho_\tau(u) = u(\tau - I(u < 0)). \tag{11}$$

In the field of crowdfunding studies, quantile regression has been employed to examine the distribution of overfunding and the number of investors. This analysis demonstrates that specific factors, such as voting rights and share capital, exert a more pronounced influence on the most successful campaigns, particularly at the 75th and 90th percentiles (Das et al., 2019; Martínez-Gómez et al., 2020). This methodological approach provides a more detailed perspective compared to traditional regression techniques, particularly in contexts characterized by skewed distributions or heterogeneous effects.

This methodology is particularly applicable to crowdfunding data, which is often characterized by a highly skewed distribution of success outcomes. The work of Koenker and Hallock (2001) provides a theoretical justification for the application of quantile regression in contexts involving distributions with significant stretch. In the realm of crowdfunding research, scholars such as Lin et al. (2016) and Skirnevskiy et al. (2017) have employed this approach to effectively capture the heterogeneity of results.

Prior to estimation, preliminary analyses, including the variance inflation factor (VIF) tests, a correlation matrix examination, heteroscedasticity tests, and the distribution of the dependent variable to validate the data's suitability for regression analysis.

Following the quantile regression estimation, F-tests of coefficient equality across quantiles were performed to statistically verify the presence of heterogeneous effects.

The QREG complements the GLS by offering a comprehensive perspective on the effects across varying levels of success. This approach facilitates a deeper understanding of the disparities between unsuccessful and overfunded projects, insights that the mean alone may fail to explain.

6 Results and Discussions

6.1 Descriptive Analyses

Table 2 provides the descriptive analysis of both dependent and independent variables included in our models. Descriptive statistics for all variables are presented in their original units in Table 2.

Table 2. Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
OCP	600	757.788	3903.833	0	53011.27
DUR	600	35.045	11.519	6	60
MIN	600	162.655	805.953	1	9412
UPD	600	10.97	15.026	0	131
FAQ	600	4.265	6.409	0	32
COM	600	144.185	379.174	0	2799
TAR	600	40217.28	110248.8	271	1222700
WEB	600	0.665	0.4731	0	4
SOC	600	0.985	1.1495	0	6
IMG	600	14.741	13.255	0	57
VID	600	2.588	2.8413	0	26
AGE	600	8.606	2.926	1	14

Note: OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established.

For the regression analysis, the continuous variables OCP, DUR, MIN, UPD, FAQ, COM, TAR, IMG, and VID were log-transformed to address skewness. To preserve observations with zero values, the transformation $\ln(\text{variable} + 1)$ was applied for all variables except DUR and MIN, which had no zero values and were transformed as $\ln(\text{variable})$. The mean of OCP as a measure of the outcome of a crowdfunding project is equal to 757.788 percent, indicating that the average campaign success rate of technology projects is very high. This can be explained by, on the one hand, the reputation and renown of the Kickstarter platform, and the specific nature of technology projects, on the other.

The minimum and the maximum number of days to raise funds were 6 and 60, respectively, with the mean value of 35.045 days. The average of MIN as a measure of minimum pledge was equal to 162.655 US dollars, which varies from 1 to 9412 US dollars. The pledge amount varies depending on the reward offered by the campaign's creators. On average, the technology project creators publish approximately 11 updates during their campaign.

Descriptive statistics also show that the number of frequently asked questions provided by the project creators varies from 0 to 32, with an average of 4.265 per project. Furthermore, both the project creator and the potential backers made, on average, 144.185 comments per project. The number of comments on the project campaign page on the Kickstarter website varies from 0 to 2799 comments. The 600 technology projects included in our sample have, on average, 40217.28 US dollars as a target amount to be raised during their campaign. In addition, the number of website links, other than social media networks, provided by the project creator on the Kickstarter platform varies from 0 to 4, whereas the number of social media links, such as Facebook and LinkedIn, is approximately 1 link on average, which varies from 0 to 6 links.

The average of the number of images as well as the average of the number of videos are equal to 14.741 and 2.588, respectively. The last two variables, IMG and VID, vary from 0 to 57 and from 0 to 26, respectively.

Furthermore, the average technology reward campaign launched about 8.6 years after the platform's establishment, indicating the data primarily reflects its mature phase. The platform's age (AGE) at the time of campaigns ranges from 1 to 14 years with a moderate standard deviation of 2.9.

6.2 Test for Multicollinearity

Table 3 presents the Pearson correlation matrix for the independent variables.

Table 3. Multi-collinearity Test

	DUR	MIN	UPD	COM	FAQ	TAR	WEB	SOC	IMG	VID	AGE
DUR	1.0000										
MIN	0.0203	1.0000									
UPD	0.0444	0.0175	1.0000								
COM	0.0353	0.0628	0.3327 ***	1.0000							
FAQ	0.0791*	0.1847 ***	0.4459 ***	0.4843 ***	1.0000						
TAR	0.0544	-0.0156	0.0612	0.2530 ***	0.1297 ***	1.0000					
WEB	-0.0069	0.0275	0.1726 ***	0.0624	0.1312 ***	0.0333	1.0000				
SOC	0.0219	0.0860 **	0.2106 ***	0.1326 ***	0.2774 ***	0.0808 **	0.1814 ***	1.0000			
IMG	0.0025	0.1590 ***	0.3908 ***	0.1544 ***	0.4094 ***	-0.0565	0.1085 **	0.2815 ***	1.0000		
VID	0.0359	0.2388	0.2905	0.0800*	0.3106	-0.0210	0.1036	0.2080	0.4918	1.0000	

		***	***		***		**	***	***		
AGE	0.1022 **	0.1843 ***	-0.0544	-0.0218	0.0826 **	-0.1791 ***	-0.1218 **	0.0050	0.2902 ***	0.2698 ***	1.0000

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established.

All correlation coefficients are below the conventional threshold of 0.8, confirming the absence of multicollinearity (Kennedy, 2011).

The matrix reveals several notable relationships among campaign characteristics. Engagement variables—comments (COM), updates (UPD), and FAQs (FAQ)—demonstrate the strongest interdependencies, with significant positive correlations (ranging from 0.3327 to 0.4843). This suggests that campaigns generating user interaction tend to do so consistently across multiple channels. Media content variables, images (IMG) and videos (VID), exhibit a strong positive association with engagement metrics (COM, UPD, FAQ), indicating that visual content is closely linked to heightened campaign engagement, which encompasses both creator updates and backer commentary. Platform age (AGE) shows a significant positive relationship with media content (IMG:0.2902; VID:0.2698) but a negative association with target amount (TAR: -0.1791), suggesting that older platforms may host campaigns with richer media but more modest funding goals. The minimal pledge amount (MIN) correlates positively with both engagement and media variables, while project duration (DUR) shows mostly weak relationships with other features. Notably, the target amount (TAR) displays limited correlation with most variables except platform age, indicating that funding goals operate somewhat independently of other campaign characteristics. These outcomes preliminarily suggest that campaign features tend to exhibit interconnected engagement strategies and media-rich presentations rather than relying on isolated factors.

6.3 Model Specification and Diagnostic Tests

It is acknowledged that regression outcomes may occasionally exhibit spurious characteristics, even in the presence of stationary variables or when conventional diagnostic tests yield satisfactory results. Recent research demonstrates that spurious relationships can arise in nearly non-stationary series or within regressions that include stationary variables, due to complex dependence structures or latent nonlinearities (Cheng et al., 2021; Wong et al., 2024). These findings highlight the necessity of adopting a multifaceted approach to diagnostic assessment in evaluating model validity. Accordingly, several complementary procedures were implemented to mitigate such risks, addressing heteroscedasticity, distributional assumptions, temporal dependencies, functional form, and stationarity. Together, Tables 4 and 5 summarize the results of these diagnostic tests.

Table 4. Diagnostic Tests

Test Chi2 (1)		Prob > Chi2	Model
Panel A. Heteroscedasticity Tests Breusch-Pagan / Cook-Weisberg	128.53	0.0000	SPEC.1
Breusch-Pagan / Cook-Weisberg	136.27	0.0000	SPEC.5
Breusch-Pagan / Cook-Weisberg	147.07	0.0000	SPEC.6
Panel B. Distribution Tests (SPEC.1) Skewness Test	42.96	0.0000	–

	2.04	0.1536	–
Kurtosis Test			

H0: Constant variance (A) / Normal distribution (B) Variables: Fitted values of OCP

Panel C. Time Trend Diagnostics

Test	Statistic	p-value
Time Trend	F(1, 600) = 0.0000	1.0000
Year Coefficient	-4.66×10^{-10}	1.0000
R-squared	0.0000	-
Panel D. Autocorrelation test (Breusch-Godfrey)	1.26	0.2070
Panel E. Functional Form Test (Ramsey RESET)	F (33,555) = 1.05	0.3440
Panel F. Nonlinearity Test (Hui et al., 2017)		
Test Statistic	0.3535	-
Bootstrap Std. Error	0.3786	-
Z-value	0.9337	-
P-value	-	0.3505
Parameters: m = 1, Ly = 1, e = 1.5, bootstrap replications = 500		

Note: SPEC. refers to Specification. SPEC.1, SPEC.5, and SPEC.6 refer to the baseline specification (Equation 4) and the specifications with interaction terms (Equations 5 and 6) presented in Table 6, respectively. Distribution tests in Panel B are conducted on the baseline specification (SPEC.1). Panel C reports temporal diagnostics: the Time Trend Test regresses SPEC.1 residuals on campaign launch year (null: no time trend). Panel D reports the Breusch-Godfrey test for residual independence (null: no serial correlation). Panel E reports the Ramsey RESET test for functional form misspecification (null: no omitted variables). All p-values below 0.05 indicate rejection of the respective null hypothesis. Panel F presents the Hui et al. (2017) nonlinearity test, which examines the null hypothesis of no residual nonlinearity. The non-significant p-value in Panel F indicates no evidence of nonlinearity, supporting the linear functional form.

Heteroscedasticity occurs when the variance of the error terms is not constant. Consequently, the OLS could not be optimal in the presence of heteroscedasticity because it gives equal weight to all observations, whereas observations with significant variations produce less information than those with larger variations. It could also bias both the confidence intervals as well as the test statistics (Williams, 2020). The Breusch-Pagan / Cook-Weisberg test was used to detect heteroscedasticity. According to the results displayed in Table 4 (Panel A), the chi-square was found to be large with a prob chi (2) = 0.000. Hence, the heteroscedasticity was present in all models, and to deal with it, we used robust standard errors (Williams, 2020).

Furthermore, tests for skewness rejected the null hypotheses of normality (Table 4, Panel B). These findings empirically justify the application of quantile regression, which does not require constant error variance or normal distribution assumptions and is particularly suited for analyzing heterogeneous effects across the conditional distribution of campaign success.

Additionally, temporal concerns are addressed through multiple diagnostics. To directly test for potential time-related biases, baseline model residuals were regressed against campaign launch year, revealing no time trend (Table 4, Panel C). The Ramsey RESET test shows no misspecification (Table 4, Panel E), while the Breusch-Godfrey test indicates no serial correlation (Table 4, Panel D). These results collectively support the appropriateness of the modeling approach. To further validate the functional form of our models, we conducted the nonlinearity test proposed by Hui et al. (2017). This nonparametric test examines whether the residuals from a linear model contain any remaining nonlinear dependence. We applied the test with lead length m = 1, lag length Ly = 1, and threshold e = 1.5, using 500 bootstrap replications to obtain standard errors. Following Tibshirani and Efron (1993), we consider this number of replications sufficient for stable inference.

The test yielded a test statistic of 0.3535 with a bootstrap standard error of 0.3786, corresponding to a p-value of 0.3505 (Table 4, Panel F). This non-significant result indicates no evidence of residual nonlinearity, confirming that the linear functional form specified in our GLS model is appropriate. This finding aligns with our Ramsey RESET test (Table 4, Panel E) and collectively supports the validity of our model specification. To further verify the robustness of our results, we assessed the stationarity properties of all variables. Table 5 displays the unit root test results.

Table 5. Unit root test.

Variable	ADF test		PP test	
	Level	Order of integration	Level	Order of integration
OCP	-7.3801***	I(0)	-19.7540***	I(0)
DUR	-25.3563***	I(0)	-25.3563***	I(0)
MIN	-19.3362***	I(0)	-19.3362***	I(0)
UPD	-11.5630***	I(0)	-20.0484***	I(0)
FAQ	-8.5658***	I(0)	-17.0179***	I(0)
COM	-5.6438***	I(0)	-13.5751***	I(0)
TAR	-5.7153***	I(0)	-18.5417***	I(0)
WEB	-7.5505***	I(0)	-20.2438***	I(0)
SOC	-22.3330***	I(0)	-22.3330***	I(0)
IMG	-7.8217***	I(0)	-18.2226***	I(0)
VID	-7.2529***	I(0)	-22.0167***	I(0)
AGE	-5.8391***	I(0)	-19.8294***	I(0)
MRSI	-5.6054***	I(0)	-18.5961***	I(0)
MRPCA	-6.5954***	I(0)	-19.1058***	I(0)
MRI	-5.9276***	I(0)	-19.5437***	I(0)

Notes: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. ADF refers to the Augmented Dickey Fuller test. PP refers to the Phillips Perron test. I(0) indicates stationarity at level. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established.

Although the dataset comprises pooled cross-sectional observations rather than a pure time series, unit root tests were performed to ascertain the stationarity properties of the variables and to mitigate potential spurious regression concerns (Table 5). In alignment with established practices in empirical research, the Augmented Dickey-Fuller and Phillips-Perron tests were administered to all variables.

The results presented in Table 5 demonstrate that all variables are stationery at level. Consequently, the variables are integrated of order zero, I (0), thereby confirming that the regression estimates are unlikely to be influenced by nonstationary issues.

In summary, several complementary procedures were implemented to mitigate the risk of spurious findings. First, time-trend diagnostics indicate the absence of systematic temporal patterns in the residuals. Second, the Ramsey RESET test and the Hui et al. (2017) nonlinearity test suggest no functional form misspecification or omitted nonlinear structures. Third, heteroscedasticity and autocorrelation are explicitly addressed through robust standard errors. Finally, unit root tests confirm that all variables are stationary. Collectively, these checks diminish the likelihood that the reported relationships are attributable to spurious correlations.

6.4 Results of GLS Regressions

Six regression models were developed using the ratio of the collected amount to the target amount as the dependent variable. The first model utilized the full sample of 600 technology projects, while the second, third, and fourth models were applied to subsamples of overfunded, successfully funded, and unsuccessful projects, respectively. Table 6 summarizes the regression results. The findings, which are interpreted through established theoretical frameworks, both confirm and contradict prior literature.

Table 6. Regression results using OCP as a dependent variable

Variables			Dependent Variable: Campaign Success			
	SPEC.1	SPEC.2	SPEC.3	SPEC.4	SPEC.5	SPEC.6
	AllSample	*Over funding*	*Success ful*	*Unsuccess ful*	*S.Index*	*PCA.Index*
DUR	-0.0200(0.1840)	-0.0440(0.0880)	-0.0220(0.0090)**	-0.0007(0.0010)	0.0007(0.0060)	0.0001(0.0050)
MIN	0.0380(0.0170)**	0.0780(0.0400)*	0.1730(0.0580)***	-0.0090(0.0120)	0.035(0.0160)**	0.0330(0.0160)**
UPD	-0.0050(0.0080)	0.0530(0.0330)	0.0250(0.0060)***	0.0112(0.0040)**	-0.0081(0.0080)	-0.0080(0.0070)
COM	0.0010(0.0001)**	0.0260(0.0140)*	0.0002(0.0001)***	0.0001(0.0005)	0.0003(0.00020)**	0.0003(0.0001)**
FAQ	0.0730(0.0350)**	0.0580(0.0400)	0.2200(0.1290)*	-0.0020(0.0270)	0.0641(0.0320)**	0.0640(0.0310)**
TAR	-0.0650(0.0260)**	-0.0060(0.0080)	-0.1530(0.0400)***	-0.0140(0.0100)	-0.0570(0.0240)**	-0.0520(0.0240)**
WEB	0.0210(0.0100)**	0.0480(0.0230)**	0.7570(0.2380)***	0.1900(0.0390)***	0.0190(0.0090)**	0.0200(0.0090)**
SOC	0.2430(0.1390)*	0.0730(0.0360)**	0.2130(0.1970)	0.0350(0.0200)*	0.2120(0.1240)*	0.2110(0.1230)*
IMG	0.0040(0.0100)	-0.0080(0.0230)	0.2130(0.1250)*	-0.0730(0.0200)***	–	–
VID	0.0280(0.0150)*	0.0730(0.0440)*	0.0450(0.0310)	-0.0180(0.0310)	–	–
AGE	0.0240(0.0150)	0.0400(0.0730)	0.0170(0.0420)	-0.0070(0.0080)	0.0440(0.0210)**	0.0450(0.0210)**
MRSI	–	–	–	–	0.2310(0.1030)**	–
MRPCA	–	–	–	–	–	0.2490(0.1130)**
AGE*MRI	–	–	–	–	0.0460(0.0260)*	0.0530(0.0280)*
Constant	-1.1020(0.6960)	-3.8510(2.9100)	4.1390(0.6690)***	0.5220(0.1430)***	-0.4510(0.4020)	-0.5660(0.4140)
Observations	600	200	200	200	600	600
R-squared	0.1930	0.2300	0.3850	0.2820	0.2070	0.2100

Notes: Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established.

SPEC refers to Specification. Model specifications are defined as follows: SPEC.1 (All Sample), SPEC.2 (Overfunding Subsample), SPEC.3 (Successful Subsample), SPEC.4 (Unsuccessful Subsample), SPEC.5 (Model with Simple Media Richness Index, MRSI), SPEC.6 (Model with PCA-based Media Richness Index, MRPCA). MRSI denotes the simple media richness index; MRPCA denotes the index derived from principal component (PCA) analysis.

Specifically, the campaign duration (DUR) exhibits a complex relationship with crowdfunding success (Table 6). This effect is isolated to the subsample of successful campaigns, indicating that, within the subset of successful campaigns, a longer timeframe is associated with a lower success rate (Hypothesis 1 is accepted). This effect is absent in the overall sample and in overfunding or unsuccessful projects. This

pattern suggests that duration is not a primary determinant of whether a campaign fails or achieves exceptional funding, but rather a differentiating factor among campaigns that have already achieved a baseline of viability. The significant finding in the successful subsample is consistent with several seminal studies in the field (Burtch et al., 2013; Kuppuswamy & Bayus, 2018; Mollick, 2014; Zheng et al., 2014). Theoretically, this can be viewed through signaling theory (Spence, 1978). For projects that ultimately succeed, a prolonged campaign duration may act as a negative signal to potential backers, interpreted as a lack of confidence or poor planning on the part of the project creators (Mollick, 2014). Consequently, to mitigate this signal and maintain backer confidence, project creators are advised to set a strategically reasonable campaign duration.

Furthermore, contrary to initial expectations, the minimal pledge amount demonstrates a positive and significant impact on campaign outcomes. This suggests that a higher minimum contribution threshold does not deter backers but is instead associated with a greater success rate, leading to the rejection of Hypothesis 2. This result is further corroborated in the overfunding and successful project subsamples. This finding stands in contrast to the work of Makarova and Ulitina (2022), a divergence that may be attributed to the specific dynamics of technology-focused projects, where backers might perceive a higher pledge tier as a commitment to a more premium or serious product development effort. This can be linked to perceived value theory (Zeithaml, 1988), where a higher price point can sometimes signal higher quality or exclusivity, thus attracting, rather than discouraging, a specific segment of backers.

As for the frequency of project updates (UPD), the results present a complex picture, showing a positive and significant impact exclusively within the successful and unsuccessful campaign subsamples. This indicates that proactive communication is a critical differentiator for campaigns that reach a definitive outcome. The positive relationship with success is intuitive, as updates build trust and manage expectations. Crucially, the same relationship with failure suggests that creators of struggling projects use frequent updates in a reactive, final attempt to rescue the campaign by addressing concerns and demonstrating continued commitment, even if ultimately unsuccessful. This result supports the acceptance of Hypothesis 3a. The mechanism behind this can be explained by agency theory, which highlights the problem of information asymmetry between principals (backers) and agents (project creators). Regular updates serve as a vital tool to reduce this asymmetry, demonstrating transparency and maintaining engagement throughout the campaign lifecycle (Etter et al., 2013; Kuppuswamy & Bayus, 2018). The finding that even failing projects are characterized by higher update frequency underscores the universal role of communication in managing backer relationships, a practice confirmed as crucial by numerous studies (Antonenko et al., 2014; Dikaputra et al., 2019; Kraus et al., 2016; Mollick, 2014).

The analysis reveals a differential impact of information-based signals, with their effectiveness contingent upon the project's final outcome. The FAQ variable exhibits a significant positive effect in the full sample and the successful subsample (Hypothesis 3b is accepted), but is non-significant for overfunding and unsuccessful campaigns. This can be interpreted through signaling theory in successful projects; a well-developed FAQ section acts as a low-cost, credible signal of creator preparedness and project clarity, reducing information asymmetry for potential backers (Spence, 1978). However, its non-significance in

overfunding projects suggests that these campaigns likely possess other, more powerful signals (e.g., a revolutionary product, a viral marketing campaign) that render FAQs redundant. In unsuccessful projects, FAQs may be insufficient to overcome fundamental flaws in the project's value proposition or execution, explaining their lack of impact.

Conversely, the number of comments is positively and significantly related to success in the full sample, successful, and overfunding subsamples, while being insignificant for unsuccessful campaigns (Hypothesis 3c is accepted). This finding is strongly supported by the literature on community engagement and herding behavior (Antonenko et al., 2014; Kraus et al., 2016; Mollick, 2014; Petitjean, 2018). A high volume of comments in successful and overfunding projects creates a dynamic of observable social proof, where potential backers interpret active discussion as a validation of the project's quality, thereby boosting confidence and encouraging participation. For unsuccessful projects, the insignificant relationship suggests that the comment section may be dominated by critical or skeptical inquiries rather than supportive discourse, failing to generate positive herding.

The goal amount demonstrates a significant negative impact on success in the full sample and, notably, the successful subsample, but is non-significant within the overfunding and unsuccessful subsamples (Hypothesis 4 is accepted). This outcome is explained by signaling theory (Spence, 1978). The negative impact in the full and successful subsamples reflects backers' risk aversion, where a high goal signals a greater risk of failure. For overfunding campaigns, a powerful quality or novelty signal overrides this risk aversion, making the goal amount irrelevant. Conversely, in unsuccessful campaigns, fundamental flaws, not the goal, are the primary cause of failure. Our findings contrast with prior studies (Agrawal et al., 2011; Ahlers et al., 2015; Belleflamme et al., 2014; Burtch et al., 2013; Hobbs et al., 2016; Lagazio & Querci, 2018; Lelo De Larrea et al., 2019), likely due to the distinct nature of technology projects, where backers are highly sensitive to funding thresholds.

According to the results provided in Table 6, the existence of external website links significantly increases the success rate across the full sample and all three subsamples (Hypothesis 5 is accepted). This serves as a powerful signal of legitimacy and external validation (Lagazio & Querci, 2018). By linking to an official project page or collaborators, creators leverage established third-party credibility to reduce perceived risk and assure backers of their seriousness, a strategy that is effective regardless of the campaign's eventual outcome. Moreover, the number of social media links has a positive and significant impact in the full sample, overfunding, and unsuccessful subsamples, but is not significant for successful projects (Hypothesis 6 is accepted). This supports the role of social identity and online communities in building initial awareness and mobilizing support (Alazazi et al., 2020; Belleflamme et al., 2014; Hong et al., 2018; Kraus et al., 2016; Mollick, 2014; Petitjean, 2018). Its effectiveness in overfunding and unsuccessful projects highlights its dual nature. It can be a key driver for viral, breakout successes, but can also attract scrutiny that leads to failure if the project does not meet community expectations. The non-significance in the successful subsample suggests that for many standard successful projects, core product attributes and internal platform dynamics may be more critical than a broad social media presence.

The impact of multimedia elements reveals a differential application of signaling theory (Spence, 1978). The number of images exhibits a significant positive effect on the success rate in the successful subsample (Hypothesis 7 accepted). Furthermore, its significant negative effect in the unsuccessful subsample provides a powerful complementary finding. For campaigns that ultimately fail, a higher number of images is associated with a higher final success rate. In other words, among failed projects, those with more visuals secured a greater degree of funding before their campaign ended. This indicates that images act as a positive signal that mitigates the severity of a campaign's failure by building backer trust and securing more partial funding, even when the project does not reach its full goal. Kraus et al. (2016) and Zhang et al. (2021) support these findings

Conversely, the influence of videos is significant only in the full sample and the overfunding subsample (Hypothesis 8 accepted). This can be explained via signaling theory, where a high-quality video acts as a high-cost, high-involvement signal. This signal is highly effective for capturing broad audience attention (full sample) and is a near requisite for achieving viral, exceptional overfunding. Its insignificance in the successful and unsuccessful subsamples, however, implies that for campaigns which have already passed a basic quality threshold, the presence of a video alone is not a key differentiator; other factors, such as community engagement or product feasibility, become more critical determinants of the final outcome. Butticè et al. (2017), Courtney et al. (2017), Kraus et al. (2016), Mollick (2014), Petitjean (2018), and Wheat et al. (2013) similarly note this pattern in prior research.

Finally, the consistent insignificance of platform age across all models (SPEC.1 - SPEC.4) suggests that the maturity of the Kickstarter platform itself at the time of a campaign's launch does not systematically influence its outcome. This finding indicates that backers of technology projects do not perceive campaigns differently based on whether they launched on a newer or more established version of the platform. Instead, their funding decisions are predominantly based on project-specific signals, including multimedia content, updates, and the funding goal, rather than on the platform's evolving ecosystem or the perceived value of being a first-backer potential. The legitimacy of the platform is a constant background factor, and its specific age at any given point is not a simplified decision rule for backers assessing project quality or risk. Overall, these outcomes comply with previous studies along with several theories.

6.5 GLS Regression Analysis: Platform Age as a Moderator of Media Impact on Campaign Success

This subsection tests the moderating effect of platform age on the relationship between visual signals, measured by a composite media richness index, and campaign success (H9). We focus on media richness as it constitutes a high-cost, strategic signal that is directly controllable by project creators. Furthermore, we theorize that the value of such a clear, information-rich signal becomes increasingly critical as a platform matures and the competitive landscape intensifies, making it a prime candidate for interaction with platform age. To construct this index robustly, we employ two distinct methodologies. The first is a Simple Additive Index (Standardized), which provides a transparent baseline by summing the z-scores of image and video counts with equal weighting, a method widely used for its simplicity and comparability

across different scales (Nardo & Saisana, 2008). The second is PCA, a statistically rigorous data reduction technique that derives objective weights from the data's own covariance structure, thereby maximizing the explained variance and avoiding subjective weighting (Jolliffe, 1986). Using both indices allows us to verify that our results are robust to the choice of construction method.

The interaction term between platform age and the simple media richness index (AGE × MRI[1]) has a positive and significant impact on success (Table 6, SPEC.5), supporting H9. This finding demonstrates that platform age acts as a positive moderator, systematically strengthening the relationship between media richness and campaign success over time. Therefore, indicating that as the platform matured, the effect of visual media on a campaign's success became stronger. This can be explained by an increasingly competitive signaling environment, as more projects launched on the platform over time, backers began to rely more heavily on high-quality visual indicators to efficiently assess project quality, compelling creators to use more images and videos to stand out.

Crucially, the results are robust to the choice of index construction. When the PCA-based media richness index (MRPCA) is used, the interaction effect (AGE × MRI) remains positive and statistically significant (Table 6, SPEC.6). This consistency across methodologies confirms that the finding is not driven by the specific weighting scheme but reflects a true underlying phenomenon.

The results demonstrate the critical importance of model specification. The initial model (SPEC.1, Table 6), which included platform age, images, and videos as separate predictors, found only videos to be a significant positive signal. However, this specification failed to capture the underlying construct of media richness and its evolving role. By employing a composite Media Richness Index (MRI) and testing for its interaction with platform age, a more complex and powerful relationship is revealed. The positive and significant coefficients for the MRI, platform age, and their interaction indicate that the effectiveness of visual signaling is contingent upon the platform's maturity. This aligns with signaling theory in a competitive landscape. Specifically, as the platform aged, a rich media presentation became a progressively more critical factor for cutting through the noise and securing backer trust. The significance of the composite index, where its individual components were not, confirms that MRI is a more robust measure of the visual signaling construct, and the significant interaction term confirms our hypothesis that its value is not static but increases with platform maturity.

These findings offer clear strategic guidance for project creators and platform managers. For creators, the study underscores that a high-quality media portfolio is not merely an optional enhancement but a strategic necessity, especially on mature platforms. Allocating sufficient resources to produce a comprehensive set of images and a professional video is a critical investment that significantly increases the campaign's success by building trust and reducing perceived risk. For platform managers, these results highlight the importance of guiding creators toward best practices. Platforms could develop tools or templates that

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[1] In SPEC.5, we interact platform age with a simple additive measure of media richness (MRSI), while in SPEC.6, we use a principal component analysis measure (MRPCA) for this interaction.

facilitate the creation of rich media content and explicitly advise new projects on the critical role these elements play in a competitive environment.

6.6 Quantile Regression Results

This section presents the results of a quantile regression analysis, a methodology implemented to move beyond the average effects of GLS and uncover how determinants differentially influence projects across the entire conditional distribution of success (Koenker & Hallock, 2001). This approach is empirically motivated and particularly crucial in crowdfunding, where the influence of key determinants likely differs significantly between low-performing and high-performing campaigns (Tseng, 2025). By directly modeling this distributional heterogeneity, quantile regression provides a more complete and detailed understanding of underlying relationships, which is essential for robust theory building and for deriving actionable, context-specific practical implications (Koenker, 2005).

6.6.1 Baseline Quantile Effects: Heterogeneity Across the Success Distribution

As presented in Table 7, the effects of the key determinants are not homogeneous but vary significantly across the conditional distribution of campaign success.

Table 7. Quantile Regression Results Across Success Distribution

Variable	Q05	Q25	Q50	Q75	Q90
DUR	-0.0490 (0.0520)	-0.1690(0.0600)**	-0.2860(0.1130)**	0.0540(0.2060)	-0.3100(0.3990)
MIN	0.0080(0.0080)	0.0390(0.0140)**	0.1090(0.0320)**	0.3560(0.1220)**	0.8740(0.3010)**
UPD	0.0190(0.0030)**	0.0330(0.0040)**	0.0270(0.0080)**	0.0880(0.0420)**	0.1200(0.0930)
COM	0.0002 (0.0000)**	0.0003(0.0010)	0.0050(0.0020)**	0.0110(0.0080)	0.0260(0.0180)
FAQ	0.0040 (0.0030)	0.0170(0.0050)**	0.0090(0.0110)	0.1730(0.1230)	0.2970(0.1130)**
TAR	-0.0150(0.0070)**	-0.0880(0.0130)**	-0.1870(0.0270)**	-0.3260(0.0620)**	-0.4060(0.1990)**
WEB	0.0210(0.0280)	0.1630(0.0430)**	0.1670(0.0810)**	0.1690(0.2710)	0.9940(0.5700)*
SOC	-0.0050(0.0090)	0.0280(0.0200)	0.0380(0.0330)	0.0270(0.1190)	0.0840(0.3790)
IMG	0.0030(0.0020)**	0.0050(0.0030)*	0.0090(0.0060)	0.0110(0.0170)	-0.0220(0.0500)
VID	0.0020 (0.0190)	0.0450(0.0350)	0.0550(0.0230)**	0.2610(0.2200)	0.6470(0.1940)**
AGE	0.0200(0.0350)	0.0300(0.0610)	-0.0540(0.1710)	-0.1490(0.1150)	-0.1640(0.4820)
Constant	0.2690(0.2030)	1.3350(0.2650)**	2.6900(0.3920)**	2.6500(0.9150)**	4.0670(2.6620)
Pseudo R²	0.0360	0.0660	0.1100	0.2160	0.3570
Observations	600	600	600	600	600

Note: This table presents coefficient estimates with robust standard errors in parentheses. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Quantiles of the conditional success distribution: Q05($\tau = 0.05$) = 5th percentile (lowest performers), Q25($\tau = 0.25$) = 25th percentile, Q50 ($\tau = 0.50$) = 50th percentile (median), Q75($\tau = 0.75$) = 75th percentile, Q90($\tau = 0.90$) = 90th percentile (highest performers).

Specifically, most variables are significant at the lower and median quantiles ($\tau = 0.25$ and 0.50, corresponding to Q25 and Q50), while the number of significant determinants in the other quantiles ranges from three ($\tau = 0.75$, labeled Q75) to five ($\tau = 0.90$, labeled Q90). Crucially, the direction and significance of these effects within each quantile demonstrate considerable consistency with the corresponding GLS

full sample and subsample analyses (Table 6). Platform age, for instance, remained insignificant across success distribution.

A comparative analysis between the quantile regression and GLS subsample results reveals heterogeneous effects in how determinants influence projects at different tiers of success. For projects in the lower tail of the success distribution ($\tau = 0.05$ and $\tau = 0.25$, labeled Q05 and Q25), the findings largely align with the GLS model for unsuccessful campaigns, with a notable exception being the weak positive effect of images (IMG) at the 5th quantile, which contrasted with its negative association in the subsample analysis. The 25th quantile further uncovered additional significant determinants, namely DUR, MIN, FAQs, and TAR, that were not fully revealed by the unsuccessful subsample. At the median ($\tau = 0.50$, Q50), the significant variables were nearly identical to those in the successful project subsample, with the key distinctions being the significance of videos (VID), consistent with the full sample GLS model (SPEC.1, Table 6), and the insignificance of images (IMG). For the highest performing projects ($\tau = 0.75$ and $\tau = 0.90$, corresponding to Q75 and Q90), MIN, WEB, and VID emerged as common determinants with the overfunding subsample, while quantile regression identified UPD as an additional driver at the 75th quantile and FAQ and TAR at the 90th quantile.

Overall, the comparison reveals that while GLS and quantile regression often identify the same key drivers, the latter provides a more detailed, success-contingent view that GLS subsamples could not fully uncover. For instance, GLS found the FAQ significant only in the full and successful subsamples, but quantile regression shows its effect is concentrated in the top success level ($\tau = 0.90$), explaining why its impact was obscured in the broader successful subsample. Similarly, VID was significant in the GLS overfunding subsample, a finding quantile regression refines by showing its strong, uniform impact from the median ($\tau = 0.50$) upwards (Table 7). Crucially, quantile regression identified that UPD is a significant positive driver for the upper-mid performers ($\tau = 0.75$), a detail missed by the GLS subsamples, which only found it significant for successful and unsuccessful campaigns. This demonstrates that quantile regression uncovers the specific success tiers at which determinants become active, moving beyond the oversimplified view of success, failure, and overfunding provided by GLS subsamples.

Theoretically, these findings reveal a hierarchy of signals that backers prioritize at different success levels. The growing importance of MIN and VID for top-tier projects aligns with Spence's (1978) signaling theory, as these costly elements serve as credible quality assurances in a context of high information asymmetry (Akerlof, 1978). Similarly, the critical role of FAQ at the 90th percentile ($\tau = 0.90$) and UPD for the 75th percentile ($\tau = 0.75$) can be interpreted through the Levels of Processing Theory (Craik & Lockhart, 1972). These inputs provide the substantive information that builds the deep trust necessary for success, with FAQ becoming a decisive differentiator only where backers conduct the most rigorous evaluation. This dynamic is amplified by social proof (Cialdini et al., 1999) where the compelling herding effect of COM and WEB at the highest levels creates a social proof effect that drives overfunding (Antonenko et al., 2014; Petitjean, 2018). Conversely, the persistent insignificance of platform age confirms that backers rely on these project-specific signals, not static contextual factors, in their decision-making.

Furthermore, the increasing pseudo-R-squared values across the success distribution indicate that the model possesses greater explanatory power for highly successful projects than for their less successful counterparts. While the Ramsey RESET test confirms our baseline linear model is correctly specified (Table 4), quantile slope equality tests reveal significant heterogeneity across the success distribution for key determinants such as comments and target amount (Table 12). This heterogeneity, absent for variables like platform age, consistent with their GLS insignificance (Table 6), justifies our use of quantile regression to uncover differential effects that average models obscure. This demonstrates that while certain factors exert differential effects contingent on a project's success level, others operate uniformly across the distribution, consistent with the GLS results. This provides strong empirical justification for the use of quantile regression.

6.6.2 Quantile Regression Results: The Interaction of Media and Platform Age

Table 8 summarizes the quantile regression results for key quantiles ($\tau = 0.05, 0.25, 0.50, 0.75, 0.90$), which include interaction terms but exclude IMG and VID as they are constituent components of the Media Richness index.

Table 8. Quantile Regression Results with Interaction

Quantile Regression Results when using the standardized index					
Variable	**Q05**	**Q25**	**Q50**	**Q75**	**Q90**
DUR	-0.0040 (0.0020)*	-0.0050 (0.0090)	-0.0070(0.0140)	-0.2410(1.9350)	-0.5730(3.4210)
MIN	0.0220 (0.0150)	0.0310(0.0570)	0.1080(0.0910)	0.1680(0.3830)	0.5220(0.6770)
UPD	0.0180 (0.0020)**	0.0300(0.0070)**	0.0290(0.0120)**	0.1080(0.0490)**	0.1220(0.0870)
COM	0.0002 (0.0000)***	0.0001 (0.0001)***	0.0050(0.0001)***	0.0110(0.0005)***	0.0270(0.0008)***
FAQ	0.0070 (0.0040)*	0.0180(0.0150)	0.0140(0.0240)	0.0590(0.1020)	0.1260(0.1810)
TAR	-0.0230 (0.0100)**	-0.0880(0.0390)**	-0.1710(0.0620)**	-0.1940(0.2590)	-0.1360(0.4580)
WEB	0.0390 (0.0420)	0.1910(0.1630)	0.2290(0.2600)	0.4720(1.0760)	0.1360(0.1900)
SOC	-0.0080 (0.0190)	-0.0001 (0.0700)	0.0220(0.1200)	0.0590(0.5020)	-0.0230(0.8870)
AGE	0.0740(0.0780)	0.3650(0.3010)	0.9590(0.4810)**	0.4930(0.2670)*	0.1190(0.4720)**
MRSI	0.0070(0.0110)	0.0470(0.0420)	0.1380(0.0680)**	0.4860(0.3150)	0.1080(0.0557)
AGE*MRSI	0.0160(0.0110)	0.0640(0.0420)	0.1780(0.0681)**	0.1604(0.0603)**	0.1500(0.0530)**
Constant	0.1470(0.2150)	0.3010(0.8290)	0.0570(1.3260)	-0.1270(0.7390)	-0.0541 (0.1300)
Pseudo R²	0.0360	0.0660	0.1160	0.2390	0.3770
Observations	600	600	600	600	600

Quantile Regression Results when using PCA index					
Variable	**Q05**	**Q25**	**Q50**	**Q75**	**Q90**
DUR	-0.0660(0.0600)	-0.2060(0.2230)	-0.2620(0.4790)	0.0630(1.8660)	-0.7200(3.4130)
MIN	0.0080(0.0110)	0.0370(0.0420)	0.0740(0.0940)	0.2280(0.3660)	0.7540(0.6700)
UPD	0.0180(0.0020)***	0.0320(0.0060)***	0.0320(0.0120)***	0.1050(0.0480)**	0.1240(0.0870)
COM	0.0002(0.0000)***	0.00040(0.0001)***	0.0050(0.0001)***	0.0110(0.0004)***	0.0250(0.0008)***
FAQ	0.0050(0.0030)	0.0180(0.0120)	0.0110(0.0250)	0.0740(0.0990)	0.1600(0.1800)
TAR	-0.0160(0.0080)*	-0.0890(0.0300)**	-0.1480(0.0640)*	-0.2560(0.2500)	-0.2960(0.4570)

WEB	0.0420(0.0340)	0.1680(0.1240)	0.3040(0.2670)	0.3200(1.0390)	0.1190(0.1900)
SOC	-0.0040(0.0160)	0.0160(0.0580)	-0.0090(0.1240)	0.0440(0.4840)	-0.0320(0.8860)
AGE	0.0270(0.0570)	0.0970(0.2100)	0.9580(0.4930)*	0.3240(0.1920)*	0.7080(0.3510)**
MRPCA	-0.0060(0.0050)	-0.0060(0.0180)	0.1210(0.0580)**	0.3530(0.2250)	0.7100(0.4110)*
AGE*MRPCA	0.0190 (0.0390)	-0.0350(0.1440)	0.1520(0.0550)**	0.4460(0.2130)**	0.9320(0.3900)**
Constant	0.2990(0.2440)	1.3970(0.9040)	0.5040(2.0160)	-4.2810(7.8560)	-8.4940(14.3690)
Pseudo R²	0.0360	0.0670	0.1210	0.2360	0.3690
Observations	600	600	600	600	600

Note: This table presents coefficient estimates with robust standard errors in parentheses. Significance levels are indicated as follows: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. MRPCA is the Media Richness Principal Component Analysis (PCA) Index. Quantiles of the conditional success distribution: Q05($\tau = 0.05$) = 5th percentile (lowest performers), Q25($\tau = 0.25$) = 25th percentile, Q50($\tau = 0.50$) = 50th percentile (median), Q75($\tau = 0.75$) = 75th percentile, Q90($\tau = 0.90$) = 90th percentile (highest performers). MRSI denotes the simple media richness index; MRPCA denotes the PCA-based media richness index.

Across both the standardized and PCA-based models, the UPD and COM are consistently positive and statistically significant across nearly all quantiles. This underscores their fundamental role in driving campaign success, irrespective of a project's eventual performance level. Conversely, the TAR exhibits a significant negative relationship across the lower to median quantiles, indicating that more ambitious monetary goals are associated with lower success rates for low to median successful campaigns. Both COM and TAR align in significance and direction with the prior GLS regression results (Table 6, SPEC.5 and SPEC.6). Furthermore, AGE emerges as a positive and significant factor at the median and upper quantiles, a finding consistent with the GLS model results, underscoring the broad advantage of launching on a mature platform (Table 8).

The analysis reveals a detailed, conditional relationship between media richness and campaign success, which can be interpreted through the integrated perspectives of signaling theory, social exchange, and social capital. The positive and significant interaction effect between platform age and media richness, initially identified in the GLS model (Table 6, SPEC.5 and SPEC.6), is concentrated almost exclusively among median ($\tau = 0.50$, labeled Q50) and upper-quartile ($\tau = 0.75$, labeled Q75) campaigns in both indices (Table 8). This indicates that for projects already positioned for moderate to high success, the competitive advantage of a rich media presentation intensifies as the platform matures. In an aging platform context, information asymmetry is exacerbated by market saturation and a more selective backer community, making credible signals, as outlined by signaling theory (Spence, 1978), increasingly critical. For these viable campaigns, high media richness acts as a powerful signal of quality, attracting backer attention through deeper cognitive processing (Craik & Lockhart, 1972) and fulfilling social exchange expectations (Blau, 1964) by effectively communicating reward value. Moreover, in a mature platform environment where social networks and trust are paramount (Putnam, 1995), a polished media presentation helps a project stand out, fostering the social capital necessary for knowledge sharing and building upon the positive social proof generated by early support (Cialdini et al., 1999).

Conversely, the insignificant interaction effect for the least successful campaigns (Table 8) suggests they cannot take advantage of this moderating benefit. Their challenges likely arise from more fundamental deficiencies, such as a compromised product concept or an inability to establish initial trust, that cannot be overcome by sophisticated signaling alone. In such cases, the project may be perceived as a lemon (Akerlof, 1978), where even substantial information provision fails to mitigate the underlying risk. The robustness of this finding across both media richness indices confirms it is not a measurement consequence but a stable reflection of a market where the efficacy of visual signaling is conditional upon a campaign's inherent potential. Thus, while these results provide a detailed, quantile-level analysis of the interaction effect, they also corroborate the GLS findings on the significant moderating role of platform age (Table 6, SPEC.5 and SPEC.6).

Regarding explanatory power, the Pseudo $R^{\dagger}$ values demonstrate a clear and consistent outcome across both indices, increasing substantially from the lowest to the highest quantiles. This indicates that the explanatory variables are far more effective at accounting for variation among the top 10 percent of successful campaigns than among the least successful ones. Consequently, the models possess stronger predictive capability for highly successful campaigns, suggesting that the factors influencing campaign failure are more complex. This finding holds true for both indices, confirming the robustness of this finding across different measurement approaches.

6.7 Robustness Check

To assess the sensitivity of our results to the campaign success proxy, we employed the number of backers as an alternative dependent variable, maintaining the full set of independent variables from the baseline model (Column 1, Table 6). The initial specification (SPEC.1, Table 9) regressed BACKERS on eleven independent variables.

Table 9. Robustness checks using BACKERS as a dependent variable

Variables	SPEC.1	SPEC.2 S.Index	SPEC.3 PCA.Index
DUR	-0.0030(0.0050)	-0.0210(0.1680)	0.0010 (0.1680)
MIN	-0.0070 (0.0090)	-0.0290 (0.0310)	-0.0410 (0.0310)
UPD	0.0400 (0.0060)***	0.0410 (0.0070)***	0.0400 (0.0070)***
COM	0.0300(0.0050)***	0.0310 (0.0050)***	0.0310 (0.0050)***
FAQ	0.0090 (0.0920)	0.0400(0.0930)	0.0340 (0.0930)
TAR	0.0830 (0.0230)***	0.0800 (0.0240)***	0.0930 (0.0240)***
WEB	0.4980 (0.1190)***	0.5190 (0.1300)***	0.4440(0.1340)***
SOC	0.0540(0.0460)	0.0690(0.0450)	0.0530(0.0450)
IMG	0.6030 (0.0730)***	—	—
VID	0.0390(0.0200)*	—	—
AGE	0.4280(0.2620)	0.4920 (0.2670)*	0.5470(0.2690)**
MRSI	—	0.8190 (0.0960)***	—
MRPCA	—	—	0.6740(0.0780)***
AGE*MRSI	—	0.2530 (0.1030)**	—
AGE*MRPCA	—	—	0.5040 (0.1250)***

Constant	1.7500(0.4860)***	3.7530 (0.7430)***	4.1080 (0.7360)***
Observations	588	588	588
R-squared	0.5220	0.5000	0.5030

Note: Significance levels are indicated as follows: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. Robust standard errors are reported in parentheses. Model specifications (SPEC) are defined as follows: SPEC.1 (Baseline model with individual media variables), SPEC.2 S.Index (Model with Simple Media Richness Index, MRSI), SPEC.3 PCA.Index (Model with PCA-based Media Richness Index, MRPCA). MRSI denotes the simple additive media richness index; MRPCA denotes the index derived from principal component analysis.

Results reveal that six, UPD, COM, TAR, WEB, IMG, and VID, displayed positive and statistically significant coefficients. To further examine these relationships, we introduced interaction terms, specifically AGE × MRI, measured via a simple composite index (SPEC.2$_{\text{S.Index}}$) and a PCA-constructed index (SPEC.3$_{\text{PCA.Index}}$), in specifications 2 and 3, respectively, while omitting the individual IMG and VID variables. The results demonstrated remarkable consistency. Specifically, the main variables retained their signs and significance, and the interaction term AGE × MRI itself exhibited a positive and statistically significant relationship with the number of backers. This pattern confirms that the findings are robust and not sensitive to model specification. Interpreting these results through established theoretical frameworks provides theoretically rich insights. The significant coefficients for UPD, COM, IMG, VID, and WEB align with Signaling Theory (Spence, 1978; SPEC.1, Table 9), positing that these elements act as credible signals of project quality and creator commitment, thereby reducing information asymmetry. Furthermore, the positive effect of community engagement (COM and UPD) in all 3 specifications is explained by Social Proof (Cialdini et al., 1999), where visible activity signals legitimacy and encourages broader participation. Again, the TAR is found to have a positive and statistically significant effect on the number of backers. This apparent contradiction, as compared to the baseline model (SPEC.1, Table 6), aligns with Signaling Theory and the nature of different success metrics. A higher funding target signals greater project ambition and quality, attracting more backers, but simultaneously creates a higher threshold that reduces the likelihood of achieving full funding.

The positive and significant interaction term, AGE × MRI (SPEC.2 and SPEC.3, Table 9), suggests a complex dynamic related to the platform's maturity. As the Kickstarter platform itself has aged and evolved, the user base has become more sophisticated. In this mature platform environment, technology campaigns require a richer set of communication media (higher MRI) to effectively stand out and capture attention. As backers are exposed to a greater volume of campaigns over time, they become more selective, favoring more professional campaigns. A high media richness campaign thus acts as a critical signaling mechanism (Spence, 1978) in a crowded and competitive marketplace, demonstrating a creator's professionalism and commitment, which in turn attracts a broader base of backers.

The stability of the baseline model's coefficients, even after substituting individual media variables with the composite interaction term, underscores the robustness of these underlying theoretical mechanisms. Therefore, fostering a large backer community is driven by a project's ability to effectively signal quality,

demonstrate social validation, and strategically employ rich media, especially as it matures, providing a comprehensive understanding of crowdfunding success.

6.8 Robustness Check: Heterogeneity Across the Backer Distribution

We conducted a further robustness check by re-estimating our models using the quantile regression method with the number of backers as an alternative success metric, while maintaining the full suite of independent variables from the baseline specifications. These results are reported in Tables 10 and 11.

Table 10. Quantile Regression Results Across Backer Distribution

Variable	Q05	Q25	Q50	Q75	Q90
DUR	-0.0050 (0.0140)	-0.0140 (0.0070)	-0.0240 (0.0090)**	0.0060(0.0060)	-0.0090(0.0080)
MIN	0.0001 (0.0003)	0.0001 (0.0002)	-0.000 (0.0002)	-0.0001 (0.0001)	-0.0002 (0.0002)
UPD	0.0310 (0.0120)***	0.0400(0.0060)***	0.0380 (0.0080)***	0.0350(0.0050)***	0.0510 (0.0070)***
COM	0.0002 (0.0001)	0.0002 (0.0001)***	0.0005 (0.0002)***	0.0004 (0.0005)***	0.0003 (0.0006)***
FAQ	0.0080(0.0250)	0.0450(0.0130)***	0.0510(0.0190)**	0.0200(0.0110)	0.0210(0.0140)
TAR	-0.0430(0.0630)	0.0650(0.0340)	-0.0260(0.0430)	0.1030(0.0270)**	0.1010(0.0360)**
WEB	0.2460(0.2650)	0.6320(0.1420)***	0.8200(0.1650)***	0.4230(0.1140)***	0.3680(0.1530)**
SOC	0.1220(0.1230)	0.0890(0.0660)	-0.1580(0.0840)	-0.0450(0.0520)	-0.0370 (0.0700)
IMG	0.0310 (0.0130)**	0.0290 (0.0070)***	0.0400 (0.0080)***	0.4190(0.0750)***	0.4950 (0.1010)***
VID	0.0720(0.0560)	0.0180(0.0300)	0.0350(0.0360)	0.0570(0.0230)**	0.0530(0.0320)
AGE	0.1750(0.2070)	0.0960(0.1110)	-0.1670(0.1320)	0.1010 (0.0890)	0.1070 (0.1200)
Constant	0.8170(0.8120)	1.5430(0.4350)***	3.1320(0.5570)***	2.1590 (0.3680)***	3.0780 (0.4950)***
Pseudo R^2	0.2690	0.2910	0.3410	0.3450	0.3770
Observations	588	588	588	588	588

Note: This table presents coefficient estimates with robust standard errors in parentheses. Significance levels are indicated as follows: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. MRPCA is the Media Richness Principal Component Analysis (PCA) Index.
Column headers denote quantiles of the conditional backer distribution: Q05(τ = 0.05) (5th percentile, campaigns with the fewest backers), Q25(τ = 0.25) (25th percentile), Q50(τ = 0.50) (50th percentile, median), Q75(τ = 0.75) (75th percentile), and Q90(τ = 0.90) (90th percentile, campaigns with the most backers).

The outcomes from Tables 10 and 11 largely confirm the robustness of our findings while revealing detailed, conditional effects that align with our theoretical framework. For instance, the positive impact of FAQs (Table 10) specifically at the 25 and 50 quantiles (τ = 0.25 and 0.50) can be interpreted through the perspectives of signaling theory (Spence, 1978) and level of processing theory (Craik & Lockhart, 1972).

As reported in Table 10, for campaigns with low and median numbers of backers, which inherently face greater scrutiny due to perceived risk, providing comprehensive FAQs serves as a credible signal of creator preparedness and actively engages potential backers by reducing information asymmetry (Akerlof, 1978; Table 10) and facilitating deeper cognitive processing of the project's value. Similarly, the finding that a longer duration is detrimental specifically to median campaigns resonates with social proof theory

(Cialdini et al., 1999), as an extended campaign period without rapid early backing may fail to generate the necessary signal of quality (Table 10), thus appearing less attractive to the crowd (Kuppuswamy & Bayus, 2018). Furthermore, the consistent significance of social variables like updates and comments across most quantiles (Table 10) strongly underscores the foundational role of social capital theory (Putnam, 1995) and the principles of social exchange (Blau, 1964), where ongoing communication builds the trust and community engagement essential for converting backer interest into support (Mollick, 2014; Xu et al., 2014).

Having established the baseline quantile effects across the backer distribution, we now turn to Table 11, which examines how the media richness interaction with platform age operates across these same quantiles.

Table 11. Quantile Regression Results Across Backer Distribution with Interaction

Quantile Regression Results when using the PCA index					
Variables	Q05	Q25	Q50	Q75	Q90
DUR	0.0030(0.0150)	-0.0110(0.0080)	0.0370(0.2390)	0.3040(0.1870)	0.4540(0.2910)
MIN	-0.0540(0.0930)	-0.0050(0.0490)	0.0003(0.0460)	0.0190(0.0360)	-0.0490(0.0560)
UPD	0.0390(0.0120)**	0.0480(0.0060)***	0.0290(0.0060)***	0.0430(0.0050)***	0.0360(0.0070)***
COM	-0.0001 (0.0001)	0.0002 (0.0001)**	0.0003(0.0001)***	0.0004 (0.0001)***	0.0005 (0.0001)***
FAQ	0.0760 (0.0260)**	0.0590(0.0140)***	0.0340(0.0130)**	0.0260(0.0100)**	0.0240(0.0150)
TAR	-0.1060 (0.0670)	0.0230(0.0350)	0.0500(0.0320)	0.0680(0.0250)**	0.0840(0.0390)*
WEB	0.2290(0.2840)	0.5610(0.1480)***	0.2260(0.1340)	0.3470(0.1050)***	0.3380(0.1640)*
SOC	0.2190(0.1300)	0.1380(0.0680)*	0.0200(0.0620)	-0.0780(0.0480)	-0.1080(0.0750)
AGE	-0.1010(0.2250)	0.1420(0.1180)	0.9250(0.2260)***	0.7990(0.1760)***	0.5600(0.2750)*
MRPCA	-0.2560(0.1960)	0.0120(0.1020)	0.8360(0.0950)***	0.7430(0.0740)***	0.8090(0.1160)***
AGE*MRI	-0.1310(0.2140)	-0.0600(0.1120)	0.5400(0.0910)***	0.4850(0.0710)***	0.4270(0.1110)***
Constant	1.1780(0.8650)	2.2040(0.4520)***	5.6730(0.9700)***	4.8210(0.7570)***	4.5220(1.1810)***
Pseudo R^2	0.2190	0.2660	0.3330	0.3640	0.3910
Observations	588	588	588	588	588
Quantile Regression Results when using the standardized index					
Variables	Q05	Q25	Q50	Q75	Q90
DUR	-0.0760(0.4550)	-0.0380(0.3040)	0.1520(0.2460)	0.0060(0.0050)	0.2920(0.3280)
MIN	-0.1140(0.0820)	-0.0050(0.0540)	-0.0030(0.0450)	0.0580(0.0360)	0.0050(0.0620)
UPD	0.0290(0.0110)**	0.0380(0.0070)***	0.0260(0.0060)***	0.0350(0.0040)***	0.0410(0.0080)***
COM	-0.0001 (0.0001)	0.0002 (0.0001)**	0.0003 (0.0001)***	0.0004 (0.0000)***	0.0005 (0.0001)***
FAQ	0.0460(0.0230)*	0.0480 (0.0150)**	0.0420(0.0120)**	0.0270(0.0090)**	0.0170(0.0170)
TAR	-0.0080(0.0580)	0.0760(0.0370)*	0.0880(0.0320)**	0.0580(0.0240)*	0.0780(0.0430)
WEB	0.4230 (0.2460)	0.3160(0.1630)	0.2340(0.1340)	0.3340(0.1020)**	0.2350(0.1790)
SOC	-0.0080(0.1140)	0.0340(0.0730)	-0.0130(0.0610)	-0.0890(0.0470)	-0.0420(0.0820)
AGE	0.4160(0.4370)	0.1140(0.1280)	0.1210(0.0230)***	0.1040(0.0180)***	0.8480(0.2990)**
MRSI	0.9650 (0.5970)	-0.4270 (0.5980)	0.8570(0.1140)***	0.1350(0.0190)***	-0.4320 (0.1540)**
AGE*MRI	-0.0030 (0.0610)	0.3540 (0.2800)	0.2750(0.1390)*	0.1650(0.0860)	0.1000(0.0170)***
Constant	2.1590 (1.6890)	2.0220(1.1070)	5.0800(0.9900)***	5.8630(0.4940)***	5.5240(1.3000)***
Pseudo R†	0.2920	0.2570	0.3180	0.3630	0.3920
Observations	588	588	588	588	588

Note: This table presents coefficient estimates with robust standard errors in parentheses. Significance levels are indicated as follows: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign

creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. MRPCA is the Media Richness Principal Component Analysis (PCA) Index. Column headers denote quantiles of the conditional backer distribution: $Q05(\tau = 0.05)$ (5th percentile, campaigns with the fewest backers), $Q25(\tau = 0.25)$ (25th percentile), $Q50(\tau = 0.50)$ (50th percentile, median), $Q75(\tau = 0.75)$ (75th percentile), and $Q90(\tau = 0.90)$ (90th percentile, campaigns with the most backers). MRSI: simple media richness index. MRPCA: PCA-based media richness index. AGE*MRI and AGE*MRPCA are interaction terms between platform age and the respective media index.

The confirmed interaction effect, where platform age moderates the media richness index for median to high-performing campaigns (Table 11, $\tau = 0.50\text{-}0.90$, labeled Q50-Q90) reinforces the argument that in a mature and competitive platform environment, sophisticated visual signals become increasingly critical for cutting through the noise and credibly conveying a project's quality to a more selective backer community. Collectively, these results demonstrate that our key findings are robust to the method of estimation, the construction of the media indices, and the chosen success metric, while the quantile regression provides a more detailed understanding of how these theoretical mechanisms manifest differently across the entire range of success.

The Pseudo R^2 values across all three model specifications (Table 10, 11) demonstrate a consistent and pronounced outcome, increasing substantially from the lowest to the highest quantiles of the success distribution. This robust trend indicates that the explanatory power of the variables is strongest for the most successful campaigns, confirming what is found in other quantile regression equations. Table 12 presents the quantile slope equality tests for the OCP-dependent variable models.

Table 12. Quantile Slope Equality Tests using OCP as a dependent variable

Variable	F-statistic	P-value
COM	10.33	0.0000
TAR	11.59	0.0000
WEB	2.64	0.0328
VID	2.65	0.0326
DUR	2.05	0.0853
MIN	1.79	0.1285
UPD	1.12	0.3471
FAQ	0.91	0.4570
IMG	0.75	0.5608
AGE	0.53	0.7108
SOC	0.28	0.8899

Note: This table presents results from quantile slope equality (QSE) tests. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. For each variable, the test evaluates the null hypothesis H_0: The coefficient (marginal effect) is statistically identical across five quantiles of campaign success (0.05, 0.25, 0.50, 0.75, and 0.90) of the Outcome of Crowdfunding Projects (OCP) variable. A significant p-value ($p < 0.05$) leads to the rejection of H_0, indicating that the variable's effect on OCP varies significantly depending on a campaign's conditional level of success.

The results reveal that COM, TAR, WEB, VID, and DUR exhibit significant heterogeneity across the success distribution, indicating that their effects vary depending on a campaign's conditional performance level. In contrast, variables such as MIN, UPD, FAQ, IMG, AGE, and SOC demonstrate stable effects across quantiles. To assess whether similar patterns hold when using an alternative success metric, we

conducted the same tests using the number of backers as the dependent variable. These results are reported in Table 13.

Table 13. Quantile Slope Equality Tests using Backers as a dependent variable

Variable	F-statistic	P-value
MIN	6.20	0.0001
UPD	0.93	0.4437
COM	0.64	0.6350
FAQ	3.53	0.0073
TAR	1.72	0.1436
WEB	0.42	0.7972
SOC	1.02	0.3979
IMG	4.28	0.0020
VID	0.63	0.6389
AGE	1.31	0.2647
DUR	2.63	0.0338

Note: This table presents results from quantile slope equality (QSE) tests. OCP, DUR, MIN, UPD, FAQ, COM, TAR, WEB, SOC, IMG, VID, and AGE denote, respectively, the ratio of the collected amount to the target amount; the number of days in the funding period; the minimum pledge (in US dollars) set by the campaign creator; the number of updates; the number of frequently asked questions; the number of comments; the target amount; the number of website links; the number of social media links associated with the project; the number of images; the number of videos; and the difference in years between the campaign date and the year in which the platform was established. For each variable, the test evaluates the null hypothesis H_0: The coefficient (marginal effect) is statistically identical across five quantiles of backer support (0.05, 0.25, 0.50, 0.75, and 0.90) of the number of Backers variable. A significant p-value ($p <$ 0.05) leads to the rejection of H_0, indicating that the variable's effect on the number of backers varies significantly depending on a campaign's conditional level of supporter engagement.

The quantile slope equality tests using backers as the dependent variable (Table 13) reveal that MIN, FAQ, IMG, and DUR exhibit statistically significant heterogeneity across the backer distribution. This indicates that their influence is contingent on a campaign's level of supporter engagement. In contrast, variables such as UPD, COM, and TAR demonstrate stable effects, as their coefficients are not significantly different across quantiles.

Comparing Tables 12 and 13 reveals an interesting pattern. More specifically, different sets of variables exhibit heterogeneity depending on whether success is measured by funding ratio (OCP) or backer count. This suggests that the determinants of attracting a large audience (backers) may differ from those driving high funding multiples. Collectively, these test results confirm significant coefficient heterogeneity across both success metrics, providing strong empirical support for our use of quantile regression throughout this study.

7 Discussions

This study reveals that technology crowdfunding success is not determined by a static formula but by a dynamic alignment between creator communication and backer assessment, a process shaped by platform maturity and contingent on a campaign's performance level. The initial model (SPEC.1, Table 6), which treated platform age and media elements as independent factors, provided a valid but incomplete picture. The subsequent models (SPEC.5 and SPEC.6) reveal a more complex, moderated relationship. Specifically, the positive interaction between platform age and the Media Richness Index (MRI) demonstrates that the platform's maturity amplifies the value of a rich media presentation. This indicates

an evolution in the competitive environment, where a sophisticated media strategy becomes a critical imperative for differentiating a campaign on a mature platform.

The application of quantile regression further enriches this finding by moving beyond average effects and revealing a precise hierarchy of determinants across the success distribution (Table 7). Crucially, the positive interaction between platform age and media richness, identified by GLS, is driven almost exclusively by campaigns at the median and upper quartiles ($\tau = 0.50$ and 0.75, corresponding to Q50 and Q75). This demonstrates that the competitive pressure to employ rich media in a mature environment applies specifically to projects that have already achieved a baseline of viability.

These findings reveal a dynamic model of backer decision-making, one that evolves with a project's perceived success. For campaigns in the lower tail of the distribution, backers appear to be making a baseline assessment of viability, where fundamental signals like a minimum funding goal and project duration are critical. As we move to the median, backers shift their evaluation towards a project's quality and credibility, engaging in deeper cognitive processing where video evidence and updates become significant. Finally, for the most successful campaigns, backer behavior is characterized by a search for exceptional differentiation and risk mitigation. Specifically, comprehensive FAQs and ambitious goals become decisive, not just by providing information, but by signaling a level of creator preparedness and commitment that justifies a larger financial pledge. This progression, from assessing feasibility to evaluating quality to seeking excellence, provides a detailed theoretical model that moves beyond a simple view of technology campaign success. It implies that creators must not only send signals but must strategically sequence them, adjusting their communication to the specific tier of success they are targeting, as the crowd's criteria for support fundamentally shift at different levels of campaign performance.

This heterogeneity is explained by integrating multiple theoretical viewpoints. The concentration of certain signals at the top reflects their role in building the social capital necessary for network-driven growth (Putnam, 1995). The importance of community engagement through comments (COM) and updates aligns with Social Exchange Theory, where backers expect interactive communication for their support (Blau, 1964). Finally, the evolving informational demands align with the Levels of Processing Theory. Backers engage in shallow processing for median campaigns but require the deep processing that detailed FAQs enable for top-tier projects (Craik & Lockhart, 1972).

The collective findings yield three primary inferences. Theoretically, while signaling theory provides a foundation, our results demand a multi-theoretical explanation grounded in conditionality. The efficacy of any signal is not absolute but is dependent upon a project's position in the success distribution and the platform's maturity.

Methodologically, this research underscores the critical limitation of average effect models. Quantile regression was necessary for uncovering the success-contingent heterogeneity that other methods veil. For instance, it precisely located the influence of the platform age-media richness interaction to the middle of the success distribution and revealed that videos (VID) drive success from the median upwards, while FAQs (FAQ) are decisive only for high performers ($\tau = 0.90$, labeled Q90).

Practically, and with direct relevance to Decision Sciences, these insights form a stratified strategic roadmap for decision-making under uncertainty. The core contribution to applied decision-making is the move beyond a one-size-fits-all model to a contingent framework. By mapping determinants to specific performance quantiles, this study provides a diagnostic toolkit for resource allocation and evaluation. For creators, this means strategies must be targeted. More specifically, those aiming for median success should prioritize mitigating negative signals (like long duration) and invest in media richness, while those seeking overfunding must shift focus to providing deep validation through comprehensive FAQs and credible, ambitious goals. For backers, the findings offer refined evaluation rules for assessment that change with a campaign's performance level. For platform administrators, this research underscores the potential of developing decision-support tools that offer diagnostics and quantile-specific guidance to enhance ecosystem outcomes.

Collectively, success in technology reward crowdfunding relies on understanding that communication is an ongoing process of strategic alignment. This study demonstrates how empirical analytics from Decision Sciences can structure such complex informational environments. Creators must not only send signals but must strategically sequence and emphasize them, dynamically adjusting their campaign to the specific tier of success they are targeting, as the crowd's criteria for support fundamentally shifts at different levels of performance.

8 Conclusion and Policy Implications

The emergence of crowdfunding as a significant financial innovation in the wake of the global financial crisis highlighted a critical need for alternatives to traditional funding mechanisms. This study focuses on reward-based crowdfunding, a model of particular importance for technology projects, which are key drivers of economic growth yet often face funding gaps. Identifying the determinants of success in this domain is paramount for project creators seeking capital, backers seeking to mitigate risk, and platform administrators aiming to foster a dynamic ecosystem. Our research addresses this need by conducting a multi-method empirical analysis of technology projects on Kickstarter, moving beyond average effects to provide a sophisticated, context-dependent understanding of success drivers. The importance of this study lies in its tripartite value. Specifically, for academics, it advances theoretical understanding by testing and refining signaling theory, while also integrating other key frameworks like social proof and information asymmetry, to explain the dynamics of crowdfunding success in a competitive environment. The field of Decision Sciences demonstrates how analytical techniques (e.g., quantile regression) can uncover heterogeneous effects that are critical for building contingent decision rules in complex, data-rich environments. For practitioners, it offers actionable, evidence-based strategies for campaign design and evaluation.

Our findings yield several key conclusions. First, we establish that the determinants of success are not consistent but are profoundly contingent on a project's final outcome. For instance, campaign duration is a detrimental indicator only among successful projects, while the frequency of updates is a critical differentiator for both successful and unsuccessful campaigns, underscoring the universal role of

communication. Second, we reveal that the competitive signaling environment evolves with platform maturity. Our baseline GLS models showed that individual multimedia elements had specific, subsample-dependent effects. However, by introducing a composite Media Richness Index and testing its interaction with platform age, we uncovered a more profound insight. As the platform matures, a rich media presentation transitions from a beneficial enhancement to a critical necessity for achieving competitive distinction. This moderating role of platform age was robustly confirmed in both our GLS and quantile regression analyses, with the latter highlighting that this interactive effect is concentrated among campaigns already positioned for median to high success. Third, our quantile regression results provide a specific map of success, demonstrating a hierarchy of indicators. While factors like social media links and comments drive success across the distribution, others, like a comprehensive FAQ section, become decisive differentiators only at the very highest levels of success, and the positive effect of a higher minimum pledge strengthens for top-performing projects.

The inferences from these findings are threefold. Theoretically, they validate and refine the application of signaling theory, demonstrating that signal efficacy is not static but is conditioned by both a project's inherent viability and the platform's competitive landscape. Methodologically, and for Decision Sciences specifically, our study demonstrates that conventional average effect models can be misleading in heterogeneous populations. The application of quantile regression is not only a statistical choice but a decision-analytic necessity, as it precisely locates where and for whom specific factors become critical. This allows for the development of stratified decision rules and tools, moving from one-size-fits-all advice to conditional, evidence-based strategies. Practically, this research offers a clear strategic roadmap. For project creators, it emphasizes that success requires a sophisticated campaign design. More particularly, allocating resources for a high number of images and a professional video is a strategic investment whose value appreciates on a mature platform, while proactive, transparent communication (through updates and FAQs) is essential for building the deep trust necessary for success. For backers, the research reveals the important value of various project elements, demonstrating that a rich media presentation combined with active community engagement (comments) serves as a robust indicator of creator commitment and project quality, thereby reducing information asymmetry. For platform administrators, the results underscore the importance of actively guiding creators toward these evidence-based best practices, perhaps by developing tools that facilitate the creation of rich media content, to enhance the overall quality and success rate of the ecosystem.

This study contributes to the literature in several original ways. First, it provides a focused analysis on technology projects within reward crowdfunding, a subset with distinct dynamics that often contrast with findings from general crowdfunding studies. Second, it is the first, to our knowledge, to explicitly model and demonstrate the moderating effect of platform age on the relationship between media richness and success, uncovering the evolving nature of competition on crowdfunding platforms. Third, it employs a robust multi-method approach, combining GLS regressions with subsample analysis and quantile regression, to move beyond average effects and offer a more complete, distributional understanding of what drives success at different performance levels.

Despite its contributions, this study is not without limitations. Our sample, while substantial, is confined to a single platform (Kickstarter) and a specific category (technology), which may limit the generalizability of our findings to other platforms or project types. Furthermore, while we control for a wide array of project characteristics, there may be unobserved factors, such as the quality of the entrepreneurial team or the role of external marketing efforts, that were beyond the scope of this study.

These limitations naturally suggest fruitful directions for future research. Subsequent studies could expand the scope to include other crowdfunding models (e.g., equity-based) and diverse project categories to test the boundary conditions of our findings. Researchers could also undertake qualitative work or use advanced natural language processing techniques to analyze the semantic content of updates and comments, moving beyond frequency to understand how the quality of communication influences success. Finally, exploring the interplay between crowdfunding campaigns and subsequent traditional funding rounds could provide valuable insights into the long-term impact of a successful crowdfunding campaign. By building upon this work and overcoming its limitations, future research can continue to illuminate the complex and dynamic mechanisms that underpin success in the digital funding landscape.

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