Crowdfunding Platform Mechanisms: Mitigating Fraud and Enhancing Campaign Success

Abdussalam Ben Najee

Dissertation submitted to the University of Ottawa

in partial Fulfillment of the requirements for the Degree of Doctorate in Philosophy degree in

Tri-Faculty Graduate Program

Digital Transformation and Innovation

Faculty of Engineering

University of Ottawa

Abstract

The purpose of this thesis is to explore the role of crowdfunding platforms in protecting investors by investigating the platform governance mechanisms (PGMs) they have implemented to determine their effectiveness in increasing campaign success and reducing fraudulent activities. The specific objectives are (i) to know the prevalence of governance mechanisms implemented by crowdfunding platforms, (ii) to evaluate the effectiveness of PGMs in protecting investors against suspended campaigns on crowdfunding platforms, and (iii) to compare the PGMS of different types of crowdfunding platforms to identify any differences and potential best practices. The data collection method consists of two types of platforms: reward-based crowdfunding that covers the years between 2009 and 2023, and equity-based crowdfunding platforms that cover the years between 2018 and 2021, as well as the PGMs applied to both types.

Using a logistic regression model, the general findings suggest that mechanisms such as social media and Google Analytics have mixed effects. Social media positively influences campaign success on equity-based campaigns but negatively affects campaign success on reward-based campaigns. In contrast, google analytics substantially influence reward-based campaigns positively, while having a negative effect on equity-based campaigns. The third-party verification mechanism was ineffective in campaigns to succeed or reduce fraud. In addition, the number of funders and amount pledged can enhance the successful campaigns, while they cannot distinguish between fraudulent and non-fraudulent campaigns. The duration is mixed with longer duration enhancing campaign success and shorter duration reducing fraud for reward campaigns. However, for equity-based campaigns, a shorter duration enhances campaign success. The study contributes valuable research knowledge by showing the role of crowdfunding platforms in protecting investors and increasing campaign success. The results indicate the necessity for further economic research on PGMs to enhance the campaign's success and prevent fraud, as well as highlight other essential topics for future study.

Acknowledgements

All praise is due to Allah, whose blessing makes good deeds possible. I owe my sincere gratitude to Him and His grace, which gave me the energy and patience to complete this study.

I dedicate this thesis to my loving parents, whom I have been prayed for, encouraged, and supported throughout my studies. I am particularly grateful to my wife, who pushed me to pursue this mission, and my children, who supported me throughout this endeavor and were patient when I was busy with this task. I am also grateful to my brothers, sisters, and other members of my family who inspired and supported me during this time.

My gratitude is also extended to the many people who have helped me in my search and steered me along the path, whose support this project would never have been realized and to whom these few words are woefully insufficient to express my total thanks. First of all, among these extraordinary individuals, I would like to extend my most heartfelt gratitude to my thesis supervisors, Prof. Imed Chkir and Prof. Paula Branco, who guided me through this process with consistent encouragement and inspiration. I was fortunate to have had the opportunity to work under their tutelage over the past few years, and I am indebted to them for the various opportunities they provided me to enhance my understanding of scientific research. His availability and generous allocation of time, particularly during the thesis writing, steered my research in the correct direction.

I would also like to express my gratitude towards my thesis committee members, Prof. Daniel Paré and Prof. Wadid Lamine. They provided tremendous guidance for the thesis. Last but not least, I am incredibly grateful to those who helped me and contributed their time, especially Ranjan Goyal and Nader Nasseri, who saved time and effort for the thesis.

Table of Contents

List of Tables

List of Figures

Chapter One: Introduction

1.1 Introduction

Finance and financial institutions are fundamental players in shaping the economy by facilitating the identification of investment opportunities, resource allocation, and supporting innovation through funding (Hervé, 2018). However, the global financial crisis of 2008, and its aftermath fostered a trend of caution in the banking sector, leaving them less willing to lend and increasingly losing ground to trust in traditional banking institutions (Mónika and Madarász, 2014). This situation necessitated alternative sources of external funding to support new projects (Wati and Winarno, 2018), especially for startups, and existing small and medium-sized enterprises (SMEs). The landscape of finance has further evolved with the rise of digital technology and financial innovation, giving rise to an alternative form of financing: crowdfunding. This new approach uses online platforms to connect entrepreneurs' project ideas with crowds of funders willing to invest money (Mónika and Madarász, 2014). As a new and emerging financial mechanism, crowdfunding is revolutionizing the way entrepreneurs bring new products to market. It has also enabled numerous innovative entrepreneurs to access capital, build brand awareness and have a dialogue with a broad range of potential funders, while still developing their products (Stanko et al. 2016)

Crowdfunding has been introduced as a novel and alternative source of funding for various types of ventures. Generally, it is defined as numerous individuals (funders) who give a certain amount of money within a limited timeframe to support projects or ideas by responding to an open call, mainly through peer-to-peer (P2P) technology. Crowdfunding platforms act as a central intermediary between entrepreneurs and funders. In addition to performing traditional communication roles, they act as a service provider. They also regulate contractual relationships between the entrepreneurs and the funders, and provide the capacity to collect payments from funders according to the crowdfunding methods (Lacan and Desmet, 2017). Without the intermediation services provided by these platforms, entrepreneurs and funders would not be able to interact in an efficient way (Belleflamme et al. 2016).

It is not easy to determine when exactly the general idea of crowdfunding began. Instead, there are several examples of it throughout history. For instance, in the eighteenth century, the composers Mozart and Beethoven used a subscription system to fund compositions and concerts (Gedda et al. 2016). More recently, Prosper.com was one of the first crowdfunding platforms, founded in 2006 (Hainz, 2018). Crowdfunding is a diverse and multifaceted funding model that offers different options for raising funds. The four main types of crowdfunding are reward-based, donation-based, loan-based and equity-based crowdfunding. The first two models are characterized by sponsorship and support, whereas the next two models are commercial in nature, with an investment focus (Kuti and Madarász, 2014).

Over time, crowdfunding has grown into a new financing mechanism alongside traditional institutions to fund ventures. According to a report in 2021 by the International Market Analysis Research and Consulting (IMARC) Group, the market value of the crowdfunding industry was at $13.35 bn USD and is expected to reach $25.93 bn USD by 2027, growing at a compound annual growth rate (CAGR) of 11.65% during the 2022-2027 period (O'connor, 2023). As of 2021, there were over 7,000 crowdfunding platforms worldwide, with more than 2,000 in the US alone, according to crowdfunding industry reports (Chang, 2021). Also, North America is identified as the largest regional market for crowdfunding, primarily driven by the increasing number of startups and the need for innovative funding solutions. North America dominated the crowdfunding market, accounting for more than 29.0% share of the global revenue in 2021 and generating $17.2 bn

(Mazur, 2022). With the recent outbreak of COVID-19, the crowdfunding industry, especially donation-based crowdfunding, has experienced considerable growth in supporting and aiding people, communities, and numerous organizations to fight against the pandemic. For instance, in April 2020, Facebook launched "Facebook Fundraiser," a platform where users can donate funds to charity to help others during the pandemic (Wood, 2021). Similarly, on GoFundMe, a crowdfunding platform in the U.S., over 175,000 crowdfunding campaigns were launched for the COVID-19 pandemic-related needs in 2021 (Igra et al. 2021). With the massive growth of crowdfunding in recent years, there are concerns regarding potential risks due to significant information asymmetry, agency theory, and conflict of interest.

Crowdfunding, while offering an alternative funding source, comes with certain risks and concerns. One of these concerns is agency theory, which refers to the potential for a misalignment of incentives between funders and entrepreneurs (Mohammad and Alabdullah, 2016). The concern is the potential for conflicts of interest, particularly in equity-based crowdfunding, where funders become shareholders in the company. This may lead to disputes where the interests of the entrepreneurs and funders are not aligned, resulting in potential disputes and negative outcomes (Ang et al. 2000; Jensen, 1996). These concerns highlight the importance of implementing appropriate regulations and legislations as well as mechanisms to address these conflicts, ensure transparency, information disclosure, and protection for both funders and entrepreneurs. As the crowdfunding industry continues to evolve and grow, it is imperative that these issues are addressed to ensure the sustainability and success of the industry.

Agency problem describes a principle used to explain the relationship between shareholders and their agents (managers), and between majority and minority shareholders. An agency relationship is a contract where one or more parties (the principal(s)) employ another party (the agent) to perform certain services and make decisions on their behalf (Jensen and Meckling, 1976). Given the agency relationship, shareholders believe that the managers may not always act in their best interests, but rather they may aim to maximize their personal benefit (Ang et al. 2000; Denis et al. 1999) which may lead to conflicts of interest between them (Denis et al. 1999). The result of conflicts of interest leads to agency costs, which are represented by the separation of ownership and control (Mohammad and Alabdullah, 2016). Agency costs emerge when the interests of the firm's managers are not aligned with its owners (Ang et al. 2000; Jensen, 1996). In other words, managers may prioritize their own interests over increasing shareholder value, and this is because of poor management oversight by shareholders, which is more likely to happen when incentives for tasks such as oversight are limited among a wide range of shareholders (Marashdeh et al. 2021). Hence, managers can take advantage of these circumstances to put their own interests first.

Crowdfunding is different from traditional funding in various ways, and the main difference is the funders' profile. According to Oberoi et al. (2022), crowdfunding participants might be seen as parties in an agency contract where the funder is the principal and the entrepreneur is the agent. Entrepreneurs seek funding from funders for their start-up projects (Ley and Weaven, 2011; Oberoi et al. 2022) while funders should trust that entrepreneurs have the skills to develop a product that maximizes their benefit (Wessel et al. 2021). Accordingly, a conflict of interest may arise when the goals and incentives of the entrepreneurs do not align with those of the funders. For instance, entrepreneurs may be more focused on getting the project off the ground, while funders may be more focused on maximizing their return on investment (La Porta et al. 2000). Agency problems may arise if the entrepreneurs are not sufficiently motivated to act in the interest of the funders. For instance, funders on crowdfunding platforms may face an agency problem with regard to product quality (Cornelius and Gokpinar, 2020), due to information asymmetry, which lies at the heart of incentive misalignment (Wessel et al. 2021). As a result, funders may rely on professional investors to assess the information presented because of agency issues.

Conflicts of interest also emerge between majority and minority shareholders. Controlling shareholders, known as majority shareholders, own a significant number of voting shares in a firm, giving them the ability to influence or control the company's policy and operations (Marashdeh et al. 2021). Conflicts can occur when the actions or decisions of the majority shareholders are not in the best interest of the minority shareholders. In other words, a conflict can happen when the majority shareholders use their power to make decisions that benefit themselves at the expense of the minority shareholders, such as seeking to increase their own wealth through high dividends, reputation, and personal needs at the expense of the minority shareholders (Hamdani and Yafeh, 2013; Marashdeh et al. 2021). Minority shareholders may also have difficulty gaining access to information about the company's operations or influencing its direction. To mitigate these conflicts, companies may have governance structures in place, such as independent directors and oversight committees, to protect the rights of minority shareholders.

In crowdfunding, traditional funders (accredited) with investment expertise include financial institutions, venture capitalists, and professional investors, while the majority of funders are often unaccredited funders and first-time participants. Unlike traditional funders, unaccredited funders have neither the resources nor the expertise to evaluate investment opportunities for risks and returns, and thus rely on professional investors to make their decisions (Podar et al. 2018; Podar and Arenas, 2015). Accordingly, a conflict of interest may arise if professional investors do not always act in the best interests of unaccredited investors. For instance, professional investors might collude with entrepreneurs in assessing the project to show that the project is convincing, and thus may not reveal complete and accurate information to funders on a timely basis or at all (Chen et al. 2016; Lin, 2017). In such situations, the project may not receive the necessary funding to succeed, as if unaccredited investors become aware of the conflict of interest between professional investors and entrepreneurs, they may be less likely to invest in crowdfunding projects. This could result in a decrease in the number of funders for a particular project, and consequently, a reduction in the amount of funds raised. Additionally, the lack of trust in the crowdfunding platform and the professional investors may also cause potential funders to refrain from participating in future crowdfunding opportunities, leading to a failure in funding the project (Belleflamme et al. 2014).

In the context of the agency problem and conflict of interest, crowdfunding platforms include additional risks that pose significant challenges to all involved parties: entrepreneurs, funders, and the platforms themselves (Podar et al. 2018). According to Hainz (2018) and Zenone and Snyder (2018), crowdfunding campaigns entail various risks. One concern arises when entrepreneurs collude with funders to exchange money for securities in a nefarious enterprise under the facade of a commercial transaction. For instance, fake funders can fund a sham startup owned by a narcotics distributor (Robock, 2014). Funders may also be exposed to the risk of fraud if the entrepreneurs can raise pledged funds, save production costs, and disappear without delivering anything. For instance, in 2015, Jen Hintz, an American entrepreneur, raised $26,000 on the American platform Kickstarter for FibroFibers, an independent yarn dye company. Hintz did not spend the money on her business, but rather used it to fund her move from North Carolina to Massachusetts (Hainz, 2018). Another risky behavior also occurs when crowdfunding accounts are created by criminals or have been taken over by criminals who devised fake schemes to appear legitimate. Given the unique nature of crowdfunding, it is crucial to identify and understand the specific risks that investors face, which can impact the success of campaigns (Podar and Arenas, 2015).

Insufficient regulations and industry guidelines can expose crowdfunding campaigns to elevated risks. According to a study by Ive et al. (2017), the regulations and legislation are more highly restrictive in Germany, Italy and the USA than they are in Finland and the UK. However, even with these regulations, there are still gaps and limitations in terms of ensuring that crowdfunding platforms are following commitments and informing investors about fraud risks (Ivo et al. 2017; Tenca and Franzoni, 2019). Moreover, a significant challenge faced by the crowdfunding industry is the lack of reliable mechanisms for enforcing rules and punishing misconduct (Belavina et al. 2019). Additionally, the weakness of rules and regulations may increase the asymmetries of information, and the lack of transparency between entrepreneurs and potential funders is also a major concern in crowdfunding (Agrawal et al. 2015). Investors in crowdfunding platforms often drive information from the platform on which the project is deployed; thus, information asymmetry occurs when one party possesses incomplete or misleading information. In addition, the information asymmetry problem is more evident when the platforms have a lack of nascent industry expertise and experience. As a result, this can lead to ineffective exchanges and possibly to campaign failure (Courtney et al. 2017; Cumming and Zhang, 2017; Vismara, 2018). The low entry barriers of the reward-based model enable inexperienced individuals to seek funding without proving creditworthiness (Siering et al. 2016). Due to small investment sizes, individual incentives for due diligence are weak (Agrawal et al. 2014; Perez et al. 2020), emphasizing the need for platforms to clearly communicate verification efforts and services to investors for informed funding decisions (Cumming and Zambelli, 2017).

To enhance the credibility and success of crowdfunding campaigns, platforms need robust mechanisms for verifying the identities and reliability of participants. Compliance with the Jumpstart Our Business Startups Act (JOBS Act), which requires platforms to take measures to reduce the risk of fraud, including background checks, is essential (Robock, 2014). To this end, rigorous participant identity verification holds a pivotal role in reducing fraud risks and amplifying crowdfunding campaign success rates (Weir et al. 2002). The evaluation mechanisms, referred to as the Platform Governance Mechanisms (PGMs), can be conducted internally through mechanisms within the platform through background checks or by external third-party service providers. Internal evaluation processes involve comprehensive assessments that may include background checks, financial information checks, website visits, and account monitoring (Cumming et al. 2019; Freedman and Nutting, 2015; Johari et al. 2020). On the other hand, external evaluation processes can be facilitated by third-party service providers and encompass various verification steps, such as the Know Your Customer (KYC) process, background checks, and Customer Due Diligence (CDD) procedures to identify and prevent suspicious activities (Johari et al., 2020), and Anti-Money Laundering (AML) verification steps into the investor's registration procedures before any transactions are permitted (Robock, 2014).

Crowdfunding platforms should be aware of their legal responsibilities and fulfill their role in verifying the identity, assessing the reliability, and predicting the risks associated with entrepreneurs and funders who participate in crowdfunding platforms (Podar et al. 2018). In this study, we focus on identifying the PGMs implemented by the platforms. Specifically, we aim to explore whether these platforms use internal, external, or a combination of both types of PGMs to provide protection and whether the PGMs used are consistent across different platforms or differ depending on the specific context. Furthermore, we aim to evaluate the Effectiveness of

Mechanisms (EOMs) in enhancing campaign success rates. This evaluation entails considering various indicators, such as the number of funders, the amount of money raised, and the duration of campaigns, along with the different types of PGMs applied over time. By analyzing both indicators and mechanisms, the study seeks to gain deeper insight into how PGMs can be effectively employed to protect investors' interests, mitigate fraud risks, and enhance the potential for successful crowdfunding campaigns.

This study makes significant contributions to the field of crowdfunding, particularly in the context of PGMs. The study conducts a systematic and comprehensive classification of internal and external PGMs to determine: 1) the number of platforms that have used these mechanisms; 2) when the mechanisms started to be used; 3) whether platforms have used one or more mechanisms over the years, and 4) the most adopted ones. Identifying the mechanisms that platforms implement should help develop a deeper understanding of the processes platforms use to protect investors and how seriously they take investor protection, as well as the efficiency of applying these mechanisms. This study also provides a practical contribution to platform policy by identifying the PGMs that have the most influence on campaign success and those that reduce fraud. By estimating the relative contribution of each mechanism, the study provides platform managers with an evidence-based foundation to focus on internal policies, improve or eliminate ineffective ones, and strike the ideal balance between enhancing campaign success and reducing fraud.

As such, the second contribution is the development of a dataset containing manually labelled fraud cases, including sub-categories of fraud. This is a significant contribution as it enhances the overall representation of the fraud landscape by providing a more comprehensive and accurate depiction. This approach enhances the accuracy and depth of the analysis, allowing for a better understanding of fraud patterns in crowdfunding. To date, there is no explicit work targeting the PGMs applied for, and their efficacy and thus, this thesis attempts to fill this research gap. With this study, we aim to show whether applying PGMs helps reduce the risks of fraud and thus increase successful campaigns. Therefore, this thesis will identify PGMs that have been applied to different crowdfunding platforms. Likewise, the analysis will verify the EOMs.

This study aligns with the interdisciplinary objective of the Digital Transformation and Innovation (DTI) program adopted by the University of Ottawa. The study connects finance, as a business process, with digital technology, as a modern medium for raising and managing capital funding. The study does not focus on traditional finance; instead, it examines crowdfunding platforms as a digital alternative method of financial management, in which campaigns and interactions between participants are managed through digital platforms. This study reflects the role of technology in shaping financial business, aligning with the academic and practical focus of the DTI program.

1.2 The research questions

In the context of crowdfunding platforms, the agency theory is a contract where the funder is the principal, and the entrepreneur is the agent. Agency problems may arise if the entrepreneurs are not sufficiently motivated to act in the interest of the funders. This can be exacerbated by asymmetric information about a campaign, leading to increased opportunities for fraud and ultimately unsuccessful campaigns. This is particularly concerning for unaccredited funders, who constitute the majority of crowdfunding participants and often rely on professional investors to make decisions. A conflict of interest may appear if professional investors do not reveal complete and accurate information to unaccredited funders in a timely manner or at all (Chen et al. 2016; Lin, 2017). Complicating matters, the relatively new and underdeveloped regulatory landscape for crowdfunding platforms often results in insufficient regulations and legislation (Mamonov and

Malaga, 2018; Powers, 2012). One question addressed in this study is the influence of PGMs on campaign success (or funded campaign) and fraud reduction. While there is no direct answer provided, we argue that crowdfunding platforms employ various internal and external mechanisms to ensure the credibility of both entrepreneurs and funders. The thesis seeks to explore the PGMs employed by crowdfunding platforms, emphasizing the significance of understanding PGMs' role in promoting campaign success. The central research question we aim to answer is: "*How effective are the PGMs employed by crowdfunding platforms in enhancing campaign success and reducing fraud?*" Through a set of research sub-questions, we will explore:

1. Does the number of PGMs used by a platform have a significant impact on campaign success?
2. Do certain types of PGMs have a greater impact on campaign success compared to others?
3. Does the number of fraudulent activities have an impact on the number of successful campaigns?
4. Does the number of funders participating in a crowdfunding campaign have an impact on campaign success?
5. Does the amount of money raised through a crowdfunding campaign have an impact on campaign success?
6. Does the duration of a campaign have an impact on campaign success?
7. Do PGMs' effects differ between reward-based and equity-based crowdfunding?

1.3 Significance of the research

Given the research questions previously described the work to be carried out in this thesis has the potential to contribute to:

- The existing literature on crowdfunding platforms provides a framework for future research on the topic of governance mechanisms and crowdfunding risk management;
- Providing a comprehensive overview of the current state of governance mechanisms used in crowdfunding platforms, which can serve as a valuable resource for industry professionals, policymakers, and academics;
- Demonstrating the importance of governance mechanisms in the success of crowdfunding campaigns and the protection of both entrepreneurs and funders;
- Building datasets that include manually labelled suspended campaigns and different sub-categories of fraud cases, which will provide a more comprehensive and accurate representation of the fraud landscape; and
- Providing insights for policymakers and regulators on how to effectively regulate crowdfunding platforms to reduce risks for both platform operators and campaign creators.

1.4 Objectives of the research

The research aims to:

- Know the prevalence of the types of governance mechanisms implemented by crowdfunding platforms;
- Evaluate the effectiveness of PGMs in protecting investors against suspended campaigns on crowdfunding platforms, and identify any areas for improvement;
- Compare the governance mechanisms and investor protection measures of different types of crowdfunding platforms (e.g., rewards-based and equity-based) to identify any differences and potential best practices;
- Analyze the impact of various factors such as the number of funders, the amount pledged and the campaign duration on a crowdfunding platform, in addition to previous fraud cases,

and thus develop guidelines for investors to help them make more informed choices about which platforms to use and which campaigns to support.

1.5 PGMs and Research Hypotheses

PGMs are mechanisms implemented by crowdfunding platforms to collect information that aims to verify user participation and improve service quality in campaigns, thereby enhancing user trust. The present study examines the effects of four mechanisms on the probability of success as well as the risk of fraud of crowdfunding campaigns. These mechanisms are: social media, cookies, Google Analytics, and third-party identity verification.

1.5.1 Social media mechanism

Social media platforms such as Facebook, LinkedIn, and Twitter are widely used internet-based technologies. These platforms serve as interactive social networks that allow users to disseminate information, exchange ideas, share personal narratives, and connect with others who have similar interests (Jiang et al. 2023). These platforms are built around three primary components: content, communities, and Web 2.0 applications, which are interactive web platforms that focus on the user and emphasize collaboration and user-generated content. Together, these features support many ways for users to engage with online material (Makina, 2017).

Social media platforms are freely accessible, allowing anyone to sign up and contribute to online social networks (Jiang et al. 2023; Kaur et al. 2017). They also allow companies to promote their products or services and expand their markets more quickly and at a lower cost compared to traditional marketing methods. Furthermore, social media platforms help build relationships between investors and startups, which can increase trust and engagement (Kaur and Gera, 2017). Social media can be seen as a mechanism that provides both entrepreneurs and investors with nonfinancial and soft information about campaigns, such as their digital behaviour, interaction patterns and social reputation (Ahlers et al. 2015). In other words, social media platforms help reduce information asymmetry through signalling and disclosure, thereby increasing the likelihood of the campaign's success (Liang et al. 2020).

In the crowdfunding environment, platforms help funders and investors connect with entrepreneurs, revealing valuable information on their projects, previous campaigns, and social networks (Courtney et al. 2017; Mollick, 2014). Indeed, crowdfunding platforms may use social media to provide essential information that enables them to verify participant authenticity and account activity (Colombo et al. 2015; Kaur et al. 2017). They also use social media to monitor behavioural, relying on it to detect inconsistencies or suspicious patterns in entrepreneurial behavioural (Cumming et al. 2023; Cumming et al. 2019). In other words, social media serves as a verification mechanism within the campaigns' digital communities and is also considered an informal due diligence mechanism. Ahlers et al, (2015) indicate that social media has been used as an external indicator to prove the credibility of the entrepreneur and the quality of the project.

Our thesis refers to the concept of social media effectiveness, which is the ability of social media to increase the probability of a campaign's success or reduce fraudulent activity. According to Mollick (2014) there is a positive relationship between social networks and the probability of increasing campaign success. Accordingly, we hypothesize that social media positively influences crowdfunding campaigns by increasing their likelihood of success and reducing the risk of fraud.

Hypothesis 1(H1). Social media increases the probability of campaign success and reduces fraudulent activities.

1.5.2 Google Analytics mechanism

Google Analytics is defined as a digital software used to track and report on website users' activity and web pages (Porsche et al. 2022). It is one of the most widely used analytics tools in platform-based digital environments, developed by Google, designed to generate precise, real-time behavioural data (Järvinen et al. 2015). In other words, Google Analytics is a web analytics tool used on digital platforms that converts users' digital interactions into measurable and analyzable metrics, thereby helping platforms understand user behavior and facilitate data-informed decisions (Wedel et al. 2016).

Google Analytics plays a pivotal role as a mechanism to enhance information transparency (Burtch et al. 2014). The mechanism collects users' behavioural data on platforms during browsing, including page visits, time spent on a page, exit rate, and page navigation by monitoring digital interactions and converting them into data (Porsche et al. 2022). It also transforms individual user interactions, such as the number of users and sessions, and bounce rates, converting them into measurable quantitative indicators. Additionally, it facilitates the identification of website traffic sources, including direct traffic, search engines, and third-party platform traffic. The resulting data is used to analyze users' digital behavioural patterns, to understand how users access digital content, and to support data-driven decision-making, helping stakeholders improve content based on precise analytics results (Järvinen et al. 2015).

On crowdfunding platforms, Google Analytics serves as an internal mechanism that helps platforms to track and monitor the performance of campaign participants, as well as analyze their interactions with campaign content (Ahlers et al. 2015). The data collected provides insights into the behavior of indirect participants and their level of interest in the campaign. This is crucial for mitigating information asymmetry between the platform, entrepreneurs, and funders, especially during the initial phases of campaigns (Järvinen and Karjaluoto, 2015; Porsche et al. 2022), and indicates suspicious activity, such as a sudden spike in traffic without an apparent cause for interaction (Porsche et al. 2022).

In our thesis, the effectiveness of Google Analytics is defined as the value of the information that the mechanism provides to the platform, reflecting the correlation between the behavior indicators derived from digital analysis and campaign outcomes. Effectiveness is not interpreted as a direct cause-and-effect relationship between the mechanism and campaign success or fraud reduction; rather, it refers to the extent to which the behavior data it provides is useful for analysis and interpretation, without asserting that it is the direct cause of success or risk reduction (Järvinen and Karjaluoto 2015; Wedel et al. 2016). Consequently, a significant positive correlation is considered evidence of the mechanism's effectiveness, without assuming a normative or causal judgment. Accordingly, we hypothesize that Google Analytics positively influences crowdfunding campaigns by increasing their probability of success and reducing the risk of fraud.

Hypothesis 2 (H2). Google Analytics increases the probability of campaign success and reduces fraudulent activities.

1.5.3 Cookies mechanism

Cookies are technical instruments that allow a website, with proper authorization, to store a small text file, known as a cookie, on a user's device. Accordingly, they enable the website to track user activities, such as logging into an account, and remember user preferences (Barth, 2011). In addition, cookies allow users to be tracked for analytics and targeted advertising (Barth, 2011; Kristol et al. 2000). They can also serve as an indirect method of de-anonymizing users by assigning a unique identifier, without requiring any explicit personal information (Mayer et al. 2012).

Cookies are files used to store the website; this prevents the user from logging in and out while browsing different pages, thus eliminating the need to log in again (Kuneva et al. 2019). They are, in fact, used to identify the user and store their login credentials while visiting from different parts of the site (Mayer et al. 2012). Such files also contain user preferences, such as language, region or customized template settings (Barth, 2011; Solove, 2021). In crowdfunding platforms, cookies are used to track participants who visit campaign pages, the time spent in each campaign, and movement between campaigns. This allows platforms to understand the pattern of interest and withdrawal from campaigns (Wedel and Kannan, 2016). The data provided by cookies is used to evaluate the campaign's performance, analyze participants' behavior, and improve service quality (Porsche et al. 2022; Mayer et al. 2012). Nonetheless, cookies are a complementary mechanism, rather than an independent verification mechanism (De Reuver et al. 2018; Wedel et al. 2016).

According to Fundraise Up Docs (2024), cookies increase the campaign's success indirectly by enhancing participants' experience and enabling targeted marketing. Cookies also provide behavioral information for platforms that can be used to underpin security and integrity mechanisms, such as spam detection or unauthorized access attempts and can assist in the tracking of potentially suspicious behavior (Cumming et al. 2016; De Reuver et al. 2018). Accordingly, we hypothesize that cookies positively influence crowdfunding campaigns by increasing their probability of success and reducing the risk of fraud.

Hypothesis 3 (H3). Cookies increase the probability of campaign success and reduce fraudulent activities.

1.5.4 Third-party identity verification mechanism

Third-party identity verification is defined as a formal due diligence procedure conducted by an independent platform (Cumming et al. 2019; Ahlers et al. 2015), known as a third-party, which aims to verify the accuracy of information or the identities of participants (Cumming et al. 2018). The term "third-party" encompasses external legal or regulatory compliance mechanisms, such as Know Your Customer (KYC), Anti-Money Laundering (AML), and Customer Due Diligence (CDD) procedures, as well as the review of official documents. A third party is considered a strong credibility signal because it is more difficult to forge than informal signals (Aidoo, 2025; Robock, 2014).

The primary purpose of third-party verification is to provide an independent mechanism that validates credibility among participants by verifying individuals' identities and the accuracy of the information provided through an external entity with no direct interest in the user or platform (Spence, 1973; Cumming et al. 2019). Although the third-party mechanisms serve as a reliable tool for verification and reporting that enhances credibility and trust among participants, it also contributes to improving information accuracy, reducing fraud risks, and strengthening corporate integrity (Ahlers et al. 2015; Cumming et al. 2019). However, its effectiveness remains limited and depends on the scope of implementation and the regulatory framework of the platform (Spence, 1973; Ahlers et al. 2015; Cumming et al. 2019).

Platforms such as Kickstarter and Indiegogo share information with third parties to verify users and ensure their credibility. This step aims to mitigate information asymmetry by bridging the gap between entrepreneurs and funders, thereby helping investors make informed decisions (Cumming et al. 2019; Ahlers et al. 2015), ensuring compliance with regulatory requirements through necessary identity verification, financial capacity assessments, and "suspicious entities" screening to guarantee that platforms operate in accordance with legal standards (Aidoo, 2025). However, it should not be considered a guarantee against fraud (Cumming et al. 2019; Cumming et al. 2021).

Our thesis defines the effectiveness of third-party verification as the extent to which this mechanism contributes to campaign success and reduces the risk of fraud, thereby enhancing trust within crowdfunding platforms. The verification mechanism acts as a deterrent, reducing the incentives of opportunistic actors because it is perceived as a formal procedure that reflects the platform's commitment to governance and risk reduction. The literature shows that third-party verification has the potential to be more effective on equity-based platforms, due to their stricter requirements, procedures, and higher verification and disclosure standards compared to reward platforms (Hornuf and Schwienbacher, 2017), where funders do not seek a return on investment, leading to a somewhat softer regulatory regime (Mollick, 2014). Accordingly, we hypothesize that third-party identity verification positively influences crowdfunding campaigns by increasing their probability of success and reducing the risk of fraud.

Hypothesis 4 (H4). Third-party identity verification increases the probability of campaign success and reduces fraudulent activities.

Chapter Two: Literature Review

2.1 Successful crowdfunding campaigns and challenges

In this literature review, we shed light on successful campaigns and fraud risks by examining published studies and research in this field. Our primary focus is on the success of campaigns and the risks that investors face when investing in crowdfunding platforms, with a particular emphasis on the risk of fraud. The review highlights various mechanisms and strategies that researchers have proposed to identify and detect this risk. By considering both of these aspects, the goal is to provide a comprehensive overview to identify the research gap that the study seeks to address.

2.1.1 Risks of fraud

The literature on crowdfunding platforms offers a significant understanding of fraud risks that may arise due to agency costs and conflicts of interest. In equity crowdfunding, agency conflicts primarily revolve around the relationship between entrepreneurs and funders. Chen et al. (2023) focus on the relationship between professional investors' insider ownership and funders' agency concerns in the context of investor-led equity crowdfunding. They examine how the insider ownership of professional investors affects the concerns of other crowd investors. In other words, the study explores how professional investors' influence impacts the decision-making and perceived risks of crowd investors. The finding reveals that higher levels of trust reduce funders' insider ownership concerns, thereby moderating the negative impact on fundraising. The study contributes substantial comprehension of the complexities of crowdfunding, particularly regarding the role of professional investors and their influence on other investors' concerns. Gerber et al. (2013) assert that crowdfunding platforms, acting as intermediaries, do not guarantee a return on funding and actually do not have a resolution center if a conflict emerges. This absence of a centralized dispute resolution mechanism increases the vulnerability of investors to fraudulent activities. Tenca et al. (2019) state that the risk of fraud arises when the platform is not credible enough to guarantee the security of funds donated after the target limit is obtained. The study finds that the risk of fraud emerges when the entrepreneur does not set a specific limit to prevent the unaccredited investors from donating in excess. It also finds that the ease with which funds from illicit activities can be transferred to compliant crowdfunding projects poses a potential risk of money laundering.

Existing literature on crowdfunding examines the risk of fraud in crowdfunding platforms. Kim et al. (2022) indicate the effect of risk disclosure in crowdfunding and find that higher salience for project risks generally leads to lower funding success, particularly for high-risk campaigns. Their results indicate that although transparency matters, explicit risk disclosure can lead to a negative impact on potential backers by adding perceived uncertainty and underscoring the trade-off between information sharing and campaign success. In addition, Huo et al. (2024) demonstrate how the content of risk disclosure influences entrepreneurs' resource acquisition in crowdfunding and observe that the main contents of risk disclosure portend a negative influence on fundraising amount and number of backers in general. The study also suggests that this adverse effect can be alleviated by the structure of rewards because more optional reward levels dilute the negative association between risk topics and crowdfunding performance, and the topic for risk disclosure keeps changing with external circumstances.

A study by Firoozi and Jalilvand (2016) focuses on two significant aspects of crowdfunding: information asymmetry and adverse wealth effects. The paper delves into the implications of information asymmetry, exploring how unequal information distribution can hinder accurate project evaluation and potentially deter potential investors. Additionally, the study examines adverse wealth effects in the crowdfunding realm. The paper provides a significant understanding of the challenges faced by both entrepreneurs and funders in the crowdfunding landscape. It offers essential guidance for further research and understanding in this rapidly evolving field. Cumming and Zambelli (2017) examine the interplay between information systems, agency problems, and fraud within organizations. The study investigates how information systems influence agency relationships and the potential consequences of agency problems leading to fraudulent activities. The paper emphasizes the need for effective governance and control mechanisms to mitigate fraud risks and sheds light on the complexities of information management and its impact on organizational behavior. The findings offer valuable insights for researchers and practitioners seeking to understand the dynamics between information systems, agency theory, and fraud prevention in various organizational contexts. Table 1. Presents the references that were used for each category of fraud risk and campaign success.

Table 1. Studies on fraud risks and crowdfunding campaign success.

Topic	References
Risks of fraud	(Chen et al. 2023); (Cumming et al. 2017); (Firoozi et al. 2016); (Gerber et al. 2013); (Huo et al. 2024) ; (Kim et al. 2022); (Tenca et al. 2019).
Successful campaigns	(Cornelius et al. 2020); (Mamonov et al. 2018); (Parhankangas et al. 2017); (Ullah et al. 2020); (Wehnert et al. 2019); (Yin et al. 2024); (Younkin et al. 2016).

2.1.2 *Successful campaigns*

This literature review explores various aspects of crowdfunding and examines its effectiveness in addressing different challenges. In the context of crowdfunding, successful campaigns can be defined as those that achieve or surpass their funding goals within the designated timeframe, attracting abundant support from funders.

Wehnert et al. (2019) focus on investigating the role of crowdfunding success as a signal for enhancing trust in sustainable product features. The study aims to examine how the success of crowdfunding campaigns can act as a credibility signal for consumers, leading to increased trust in the sustainability attributes of products. The study offers valuable perspectives on how consumers perceive and trust the eco-friendly characteristics of crowdfunded products. The findings shed light on the potential of crowdfunding as a trust-building mechanism for sustainable innovations, offering important implications for researchers and practitioners interested in leveraging crowdfunding platforms to enhance consumer trust and uptake of environmentally friendly products. Parhankangas et al. (2017) examine the relationship between linguistic style and crowdfunding success, specifically among social and commercial entrepreneurs. The study delves into how the language used in crowdfunding campaigns by entrepreneurs can influence the outcomes of their fundraising efforts. The study aims to uncover potential patterns and differences that may impact funders' perceptions and campaign success rates. The results provide a valuable understanding regarding the significance of linguistic strategies in English. In addition, Cornelius et al. (2020) analyze customer involvement in crowdfunding campaigns, highlighting the positive impact of customer feedback, particularly from experienced individuals in other categories, on funding success. Entrepreneurs are encouraged to incorporate customer input, respond to feedback, and make relevant changes to project descriptions to improve their chances of success. This research sheds light on the non-financial effects of customer involvement in crowdfunding.

Ullah et al. (2020) explore the determinants of crowdfunding success on Kickstarter, with a specific emphasis on the role of gender, anonymity, and team characteristics. The research investigates how these factors influence the outcomes of crowdfunding campaigns on the platform. The study provides a significant understanding of the complexities of crowdfunding dynamics and the factors that contribute to project success. The findings shed light on the significance of these factors in shaping backers' perceptions and decisions, offering essential guidance for researchers and practitioners seeking to optimize crowdfunding strategies, promote inclusivity, and understand the nuances of campaign success on Kickstarter. Younkin et al. (2016) analyze the performance of crowdfunding platforms in terms of site numbers, venture capital funding, and total contributions processed, and highlighting variations in crowdfunding success across platforms. The advantages and disadvantages of generalist and specialist crowdfunding sites are also discussed, providing valuable insights into the potential and limitations of crowdfunding. Mamonov et al. (2018) propose a theoretical framework based on angel investor decision-making to understand the role of equity crowdfunding in early-stage venture funding, emphasizing market risk, execution risk, and agency risk. The study suggests that ventures with completed product development and those with significant corporate clients are more likely to secure funding through online crowdfunding, while traditional angel investors should remain the primary focus, with equity crowdfunding as a supplementary funding option. Yin et al. (2024) analyze what drives information disclosure, looking at eight different features from how long the campaign has been running to the length of titles and the emotion conveyed in introductions. The analysis reveals that duration, title length, and length of introductions are critical determinants for success.

2.2 Governance mechanisms

Governance in crowdfunding refers to the set of rules and processes that govern the behavior of both project initiators and capital-givers. It encompasses various mechanisms that ensure coordination and integration of these rules and processes to facilitate a smooth functioning of the crowdfunding system (Blohm et al. 2018). The current literature on crowdfunding explores the contributions of various strategies and mechanisms for crowdfunding campaigns. Some studies have focused on identifying ways to detect fraudulent activities in crowdfunding campaigns that have been conducted on various platforms. Other studies rely on alternative approaches or mechanisms to determine whether implementing these mechanisms will increase the rate of successful campaigns.

2.2.1 Strategies and mechanisms to reduce fraud

The current body of research in the field of crowdfunding has been primarily focused on exploring strategies for reducing and mitigating the risk of fraudulent activities on many crowdfunding platforms. Torabi Aa et al. (2018) introduce the "Fame" reputation mechanism to tackle information asymmetry in crowdfunding. Fame aims to reduce moral hazard and information asymmetry by providing a measurable reputation index for all users involved in the crowdfunding process. Game theory analysis demonstrates that crowdfunding with Fame yields superior outcomes, benefiting both funders and entrepreneurs by improving utility functions and increasing net surplus. Renwick et al. (2017) propose three primary requirements as an AML framework to achieve regulatory compliance while containing costs. First, crowdfunding platforms must implement an effective Customer Identification Program (CIP), which aims to collect and identify information about the investors. Second, crowdfunding platforms must maintain a program to monitor, and report suspected money laundering activities to the Financial Crimes Enforcement Network (FinCEN), which maintains a database for every Suspicious Activity Report (SAR Program). Third, crowdfunding platforms must maintain a system for compliance with requests for information from FinCEN and other law enforcement agencies. It is evident that several types of governance exist and that their success levels differ depending on the scope and nature of the projects undertaken. In addition, Robock (2014) addresses the critical issue of money laundering risks within crowdfunding and offers valuable recommendations for funding platforms to effectively manage these risks. One prominent suggestion is to conduct comprehensive background checks on entrepreneurs, directors, officers, and shareholders to identify any potential negative news or derogatory information. Additionally, the study emphasizes the need to verify the accuracy of identifying information provided by both funders and entrepreneurs. Central to the proposed approach is the implementation of a risk-based strategy which involves the strategic allocation of anti-money laundering (AML) resources. By doing so, crowdfunding platforms can fortify their defenses against money laundering and uphold stringent regulatory compliance standards, contributing to a more secure and trustworthy crowdfunding industry. Baucus and Mitteness (2016) argue that traditional SEC-based safeguards, which involve oversight, due diligence, and licensing, may not be effective in curbing crowdfunding fraud due to limited government resources. Instead, they propose a multi-faceted approach to reduce fraud in equity crowdfunding. First, they suggest certifying crowdfunding platforms as legitimate intermediaries to evaluate projects and ensure investor compliance. Second, entrepreneurs should obtain certification before listing investment opportunities. Third, transparency and honest communication from legitimate entrepreneurs are essential to distinguish them from fraudsters. Fourth, investors are urged to carefully read and understand project guidelines and associated risks. Frequent interaction between entrepreneurs and funders is also highlighted. Finally, Baucus and Mitteness emphasize the importance of reporting suspicious opportunities to the SEC. While these safeguards offer potential solutions, their effectiveness in preventing fraud remains uncertain, and the ease with which investors can bypass these purported protective measures remains largely unexplored. As well, Li (2013) denotes that the existence and continued prevalence of fraud in the funding processes could be due to the relaxation of rules on crowdfunding. The author suggests more disclosures to avoid fraud before it occurs, but he does not propose a solution to compensate funders for losses caused by an entrepreneur's major misrepresentation or omission. To address this gap, the author proposes that the Securities and Exchange Commission (SEC) mandate crowdfunding issuers under the Jumpstart Our Business Startups Act (JOBS) to get a special insurance model against liability. In other words, the SEC should adopt private insurance as a mechanism to protect investors against the cost of disclosure and cover losses for crowdfunding investors. Hence, the private insurance model can help to reduce the impact of crowdfunding fraud and recover investors' losses as well. Yet, the proposed insurance that covers all failed crowdfunding offers could be extremely costly and may not cover all the losses, but only those occurring from a material misrepresentation or omission. Entrepreneurs who are not able to obtain insurance will not be permitted to use crowdfunding. Nonetheless, we believe that reliance on private insurance may lead to poor due diligence from the platform and investors, and thus increase the number of fraud cases.

In the context of mechanisms to reduce fraud, Song et al. (2015) advocate that the detection of fraudulent activities is prudent and crucial as a task. They strongly recommend that entrepreneurs post all the relevant data about a project on the crowdfunding platform, so funders can have reliable data to make informed decisions before supporting a project. Butticè et al. (2018) focus on investigating the impact of information asymmetries on serial crowdfunding and campaign success. The study suggests that online communities can provide a platform for information sharing and knowledge exchange which can help mitigate the effects of information asymmetries. Furthermore, the authors discuss the importance of social capital in crowdfunding campaigns. They argue that social capital, which refers to the resources and relationships that individuals have within a social network, can help reduce information asymmetries. The findings shed light on the importance of transparency and accurate information dissemination in serial crowdfunding ventures, enhancing campaign effectiveness and overall success in the crowdfunding domain. Xie et al. (2025) apply text analytics and deep learning in order to explore how contextual features of risk disclosures drawn from the "Risks & Challenges" section contribute to crowdfunding performance. They discover that two-sided persuasion topics learned from risk/challenge texts are positively correlated with success and that inclusion of these risk narratives in predictive models leads to improved prediction accuracy, indicating personalized risky-topic sense-making might drive the credibility/performance of a campaign. Table 2. Presents the references used for each category of strategies and mechanisms to reduce fraud, as well as mechanisms to increase the annual number of successful campaigns.

Social media, defined as a digital platform enabling content creation, sharing, and user interaction, has gained attention as a potential tool for detecting fraudulent behavior in crowdfunding platforms. Dong et al. (2018) conduct a critical study comparing financial and social media data from both fraudulent and non-fraudulent organizations and find that social media information is crucial in detecting the risk of fraud. This notion is supported by Cumming et al. (2016) who support the latter by claiming that social media serves as a tool for identifying fraud. Usman et al. (2019) investigate the potential roles of media coverage and the entrepreneur's past success in mitigating the problem of information asymmetry in the context of a UK crowdfunding platform. The study explores how media exposure and the track record of entrepreneurs can influence the perception of potential funders and reduce the information gap between entrepreneurs and funders. The findings shed light on the significance of media presence and the entrepreneur's credibility in attracting crowdfunding support, offering important insights for researchers and practitioners seeking to enhance campaign success and investor confidence in the crowdfunding domain. However, it must be noted that expert fraud leaders are not always active on social media (Cumming et al. 2016) funders do not have complete access to such information (Kuti et al. 2017), making social media an unreliable detector of fraud in crowdfunding campaigns.

Table 2. Studies on mechanisms to reduce fraud and increase the annual successful campaigns.

Topic	References
Strategies and mechanisms to reduce fraud.	(Butticè et al. 2018); (Baucus and Mitteness, 2016); (Broere and Christmann, 2024); (Cumming et al. 2016); (Dong et al. 2018); (Kuti et al., 2017); (Kim et al. 2022); (Lee et al. 2022); (Lee et al. 2025); (Li, 2013); (Mamonov et al. 2018); (Perez et al. 2020); (Petrov et al. 2021); (Renwick et al. 2017); (Robock, 2014); (Song et al. 2015); (Shafqat et al. 2019); (Siering et al. 2016); (Torabi et al. 2018); (Usman et al. 2019); (Wang et al. 2019); (Xie et al. 2025); (Xu et al. 2016).
Mechanisms to increase the annual number of successful campaigns.	(Courtney, 2017); (Cumming and Zhang, 2017); (Cumming et al. 2019); (Li and Wang, 2024); (Molik, 2014); (Rossi and Vismara, 2018); (Schulz and Blohm, 2019); (Ye et al. 2024).

To address this, Xu et al. (2016) employ different methods to analyze false loan inquiries in different crowdfunding platforms. The authors' method emphasizes the behavioral traits of business leaders by analyzing their previous performance and social networks to identify fraudulent behaviors. The study concludes that by analysing the behavior of confirmed borrowers, some useful patterns can be captured for fraud detection. Perez et al. (2020) also attempt to reveal the existence of fraud in project campaigns through the analysis of different texts and images. The study aims to develop a system that can differentiate between fraudulent and non-fraudulent activities and finds that fraudulent campaigns can be detected and removed from crowdfunding platforms. The detection of fraud in crowdfunding activities can be achieved through the use of content-based linguistics. Siering et al. (2016) propose the utilization of linguistic and content-based cues to identify fraudulent behavior and suggest that a single structural feature, such as project and user characteristics, could be used for deception detection. Additionally, Shafqat and Byun (2019) analyze comments posted on fraudulent and non-fraudulent campaigns to uncover hidden topics and find that fraudulent campaigns generally receive comments that exhibit negative emotions, anxiety, and frustration, sometimes leading to legal action against the campaign founder. Conversely, non-fraudulent campaigns receive positive feedback that focuses on the product being offered. This highlights the importance of critically analyzing the reactions of other target audiences before making a funding decision (Petrov and Emelyanova, 2021). Wang et al. (2019) also use a machine learning approach to analyze linguistic cues to detect fraud. The study finds that lower linguistic cues linked to fraud are negatively correlated with successful fundraising and that linguistic cues have a significant impact on the success of a campaign. A study by Lee et al. (2022) discusses the rising fraud activities in crowdfunding campaigns, analyzing a sample of one hundred scam campaigns. The analysis develops a scam-detection model using features related to the project, attributes of project entrepreneurs, and content-based indicators like linguistic cues. The findings show that the model's accuracy is 87.3%. A more recent study (Lee et al. 2025), expands the methodology by examining various features derived from campaigns, including entrepreneurs' profiles and behaviors, social traits, and linguistic cues from campaign content, updates, and comments. The results indicate that linguistic traits in the comments, insights, and causal words possess the most features that refer to fraudulent activities. Broere and Christmann (2024) use a game-theoretic model to identify when and why the quality of signalling in crowdfunding fails, resulting in fraud. The model includes two variables and assumptions: one for a high-quality product and another for a low-quality product. The findings indicate that effective signaling is not always achievable because the signals' accuracy can be unreliable, which can ultimately lead to fraud. These studies demonstrate different visualizations and techniques that can be used to identify scam campaigns through comments and linguistics. However, it should be noted that relying solely on linguistic cues may not be sufficient for detecting fraud, as investors may lack knowledge and experience, and may also depend on sophisticated investors for investment decisions (Kuti et al. 2017; Mamonov and Malaga, 2018).

2.2.2 Mechanisms to increase the annual number of successful campaigns

To enhance the annual number of successful crowdfunding campaigns, various mechanisms have been explored. One of the mechanisms for increasing success is to apply due diligence, which aims to evaluate campaigns and ensure their quality. This practice can have a positive impact on the success rate of campaigns and the amount raised. Cumming et al. (2019; 2017), explore the critical role of due diligence in the crowdfunding sector, specifically addressing two pivotal questions: 1) What kind of crowdfunding platforms apply due diligence? and 2) What benefits do platforms receive through due diligence application? The study focuses on factors such as agency costs, information asymmetries, and the relationship between due diligence and platform performance. By analyzing these factors, the study aims to provide insights into the importance and effectiveness of due diligence in the crowdfunding industry. The study's findings indicate that platforms with fewer projects, but more employees, tend to prioritize due diligence procedures. Additionally, platforms engaged in security crowdfunding exhibit a higher propensity for conducting due diligence. Importantly, the application of due diligence is linked to favorable outcomes, including a greater percentage of fully funded projects and increased capital raised through the platform. These findings illuminate the crucial role of due diligence in enhancing crowdfunding platform performance and underscore its potential benefits for project creators and funders alike (Cumming et al. 2017). The challenge is that conducting due diligence is resource-demanding for platforms and cannot be fully overseen by regulators, which implies that there may be challenges in effectively carrying out due diligence activities.

In Courtney's (2017) study on crowdfunding success, the focus is on signals and endorsements within Kickstarter projects. Signals from startups, such as media usage, and endorsements from third parties, like entrepreneurs' crowdfunding experience, are analyzed in a large Kickstarter sample. The study reveals that both signals and endorsements positively impact crowdfunding success, with media usage and entrepreneur success increasing the likelihood of funding goal achievement. Furthermore, it emphasizes the synergy between signals and endorsements, showing that positive funders' sentiment intensifies the positive effects of media and entrepreneurs' success. This research underscores the crucial role of information in crowdfunding, addressing information asymmetry and trust-building for potential funders. Li and Wang, (2024) present a study on the reward-based crowdfunding research by modelling signal interactions, as it goes beyond the individual effects of different signals. The findings suggest that success in crowdfunding depends on the coordination of several, and potentially all possible signals, where such degrees differ according to both the capabilities of fundraisers themselves and the characteristics of projects. Another study by Mollick (2014) suggests that network size is a factor influencing crowdfunding success. On Kickstarter platforms, the more campaigns succeed, the more friends on the Facebook account for entrepreneurs. However, the study also indicates that Facebook friends may not increase substantially as the result of campaigns' success, since entrepreneurs tend to separate the crowdfunding campaigns from their personal pages. The size of social networks is thus valuable in the determination but not always constitutive as a cause and effect for project success.

Rossi and Vismara (2018) also focus on the services provided by the platforms to entrepreneurs and how these services affect the number of successful campaigns that have been completed. They find that a higher number of post-campaign services provided by the platforms leads to an increase in the annual number of successful campaigns. Yet, pre-launch and continuing campaign services do not seem to have a significant effect. According to Schulz and Blohm, (2019), there is a set of governance mechanisms that enable project funders to raise the probability of implementing a successful crowdfunding project. Hence, the authors seek to measure the effectiveness of these governance mechanisms by showing their impact on the funding success of crowdfunding projects. They find that crowdfunding projects that rely on equities and loans may require different sets of governance mechanisms compared to donation projects. According to the study, the governance mechanisms also have an impact on the funding performance of the different crowdfunding projects. Ye et al. (2024) discuss how Artificial Intelligence (AI) can significantly increase the success rates of small business crowdfunding campaigns. The study constructed a machine learning model to predict campaign success based on their text descriptions of these campaigns. The study shows that by targeting certain linguistic variables, even small changes to campaign narratives enabled through an LLM (Large Language Model) system — such as ChatGPT — can improve the likelihood of funding.

After reviewing the existing literature, we have observed that previous research often emphasizes the importance of funders conducting due diligence to prevent fraud and ensure campaign success. However, this approach overlooks the fact that many funders lack the resources, access to comprehensive information, and the means to cover the high costs associated with due diligence. Simultaneously, some studies suggest that funders should rely on external tools, such as social media and content-based linguistic analysis, to inform their investment decisions. However, this approach faces a substantial challenge, as a significant portion of funders rely on more experienced and sophisticated investors for guidance and decision-making. This research gap highlights the need for a nuanced understanding of the crowdfunding platform's role in protecting investors and enhancing the chance of campaign success. Our study aims to assess the ability of the platforms in addressing fraud during the campaign process and increase the chance of campaign success through PGMs. Our approach is to identify the internal and external PGMs that crowdfunding applies and whether these mechanisms are effective in achieving the goal. Table 3 provides an overview of the references addressed in the Governance Mechanisms section. This table comprehensively presents the research questions, samples, and methods, as well as the findings and challenges described in each of the reference papers.

Table 3. Overview of references addressed in governance mechanisms.

Paper	Research question	Samples and Methods	Findings and challenges
(Blohm et al. 2018)	The study seeks to identify combinations of governance mechanisms that contribute to successful funding in crowdfunding projects.	The researchers used Qualitative Comparative Analysis (QCA).108 projects from 18 platforms	Finding that archetypes of governance mechanisms affecting funding success exist, and intends to contribute to the theory explaining the use of governance mechanisms in crowdfunding.
(Baucus and Mitteness, 2016).	How easily can they circumvent the safeguards purported to protect investors?	The study relied on a platform named Ponzi	The study offers six safeguards to help reduce fraud in crowdfunding. Certified crowdfunding portals: Don't settle for less. Certified entrepreneurs: Due diligence that improves survival. Ethical entrepreneurs: Model transparency and trust Investor certification: Educate for affordable losses. Local crowdfunding communities: Truly capitalizing on the power of the crowd.

Paper	Research question	Samples and Methods	Findings and challenges
(Courtney, 2017)	This study investigates the interaction between signalling factors and third-party approvals that may inform the public about the feasibility of a project and thus influence the likelihood of a project obtaining the required crowdfunding capital.	The study based on Kickstarter crowdfunding projects during the period 2009-2015	The study found that multiple signals and third-party endorsements have a significant impact on crowdfunding success. Specifically, the use of media and past success of the founder were found to be positively associated with the likelihood of reaching the funding goal.
(Cumming et al. 2016).	Identifying characteristics can help detect fraudulent campaigns.	All fraud cases from 2010 through 2015	The study indicates that the rate of fraud in the crowdfunding market is still very low, but fraud is not a random phenomenon that can be explained by empirical models. No challenges
(Cumming et al. 2019)	The role of due diligence in crowdfunding	Insurance model against liability	- Protecting investors from the cost of disclosure and covering the losses of crowdfunding investors Entrepreneurs who are not able to obtain insurance will not be permitted to use crowdfunding. The proposed insurance could be extremely costly and may not cover all the losses. Relying on private insurance may lead to poor due diligence on the part of the platform and investors and thus increase the number of fraud cases
(Cumming and Zambelli, 2017).	Due Diligence and investee performance	Applying due diligence is associated with improved investee performance	Having clear agency costs underlying due diligence delegated to external agents.

Paper	Research question	Samples and Methods	Findings and challenges
(Cumming and Zhang, 2017)	What role platforms should play in the governance of crowdfunding marketplaces?	Crowdfunding platform due diligence comprises background checks, site visits, credit checks, cross-checks, account monitoring, and third-party proof on funding projects	Due diligence improves platforms performance and rejects lower-quality projects. If the extent of the due diligence application is exaggerated, the impact of applying true due diligence on the platform's performance will be underestimated. Platforms with fewer employees, fewer affluent platform resources and more projects listed are less likely to conduct due diligence
(Dong et al. 2018)	The study seeks to examine how to extract useful features from UGC on social media platforms and develop a text analytics framework to automatically detect corporate fraud	Assemble a unique data set including 64 fraudulent firms and a matched sample of 64 nonfraudulent firms	The study extracts signals such as sentiment features, emotion features, lexical features, topic features, and social network features, which are then fed into machine learning classifiers for fraud detection. The sample size is small since financial social media platforms are relatively new. Fraudulent firms prior to the establishment of these platforms, were not used in our study
(Kuti et al. 2017)	The study aims to investigate the perceptions, motivations, and risks of users in equity-based crowdfunding with financial returns.	ASSOB, the Australian platform. The sample consists of 104 campaigns.	We find that intellectual capital (as measured by patents) and social capital had little or no significant impact on funding success.
(Lee et al. 2022)	Backers Beware: Characteristics and Detection of Fraudulent Crowdfunding Campaigns	A hundred fraudulent campaigns on crowdfunding projects	The findings identify 17 key features for fraud detection. However, a limitation of the study is that the fraud cases used for the analysis do not constitute legal proof of a scam.
(Lee et al. 2025)	Fraud Detection on Crowdfunding Platforms Using Multiple Feature Selection Methods	A hundred fraudulent campaigns on crowdfunding projects	The findings identify 10 key features for fraud detection. However, a limitation of the study is that the fraud cases used for the analysis do not constitute legal proof of a scam.

Paper	Research question	Samples and Methods	Findings and challenges
(Li, 2013)	The SEC adopts a private insurance model to reduce the impact of fraud in crowdfunding.	Insurance model against liability	- Protecting investors from the cost of disclosure and covering the losses of crowdfunding investors. - Entrepreneurs who are not able to obtain insurance will not be permitted to use crowdfunding.
(Li and Wang, 2024)	How do signals configurationally affect the funding performance of crowdfunding projects?	The data collected from Kickstarter and Indiegogo includes 64 projects. Using Qualitative Comparative Analysis	Signals in crowdfunding, such as project preparedness, engagement and third-party endorsements, operate interactively in a complex manner.
(Mollick, 2014)	The study examines a few issues of importance in understanding the rapid rise of crowdfunding and presents preliminary analyses of some of the underlying dynamics of the phenomenon.	The data collected includes 48,500 projects with combined funding over $237 M.	The study finds that the vast majority of entrepreneurs seem to fulfill their obligations to funders, but that over 75% deliver products later than expected, with the degree of delay expected depending on the level and amount of funding a project receives. The study only addresses reward-based and patron-based crowdfunding, instead of equity or other forms of investment model crowdfunding. Scholars have also argued that the motivations of funders acting as patrons and customers are similar to those of investors, but there are likely to be differences in how these crowdfunding markets operate.
(Perez et al. 2020)	What characteristics can expose such behavior and allow its automatic detection and blocking?	Data collected from different crowdfunding platforms and annotate 700 campaigns as fraud or not.	The results show that it is possible to detect fraudulent campaigns with a high degree of certainty and allow crowdfunding platforms to remove them semi-automatically. There is a limitation, which is the bias that the commenters may have introduced.

Paper	Research question	Samples and Methods	Findings and challenges
(Petrov and Emelyanova, 2021)	The article analyzes the financial flows of crowdfunding implemented in various types of crowdfunding platforms.	The study proposed machine learning algorithms into clusters based on a key characteristic, a naive Bayesian classifier, and other predictive models for predicting project success.	The study proposes using machine learning as a tool to improve the quality of risk-based preventive supervision of crowdfunding and accelerate the development of crowdfunding platforms. This would increase the transparency and efficiency of markets and increase the financial stability of the state. No challenges
(Renwick and Mossialos, 2017)	The research objectives: determine how crowdfunding is applied in the health sector and assess the important economic benefits and risks of crowdfunding in the health market.	The research methodology was a rapid evidence review of peer-reviewed and non-peer-reviewed literature. The search was restricted to papers published between January 1, 2006, and May 10, 2017, in English, and either journal articles, comments, editorials, or reviews.	Crowdfunding can economically benefit the health sector by expanding market participation, attracting funds and awareness to neglected health issues, improving access to funding, and enhancing project accountability and social participation. However, the economic risks of health-related crowdfunding include inefficient priority setting, inconsistent regulatory policies, intellectual property rights concerns, and fraud. A valuable first step would be a comprehensive mapping and quantification of health-related crowdfunding campaigns to identify measures to mitigate the economic risks identified in this review.
(Rossi and Vismara, 2018)	The study is to investigate the factors influencing the number of successful campaigns in investment-based crowdfunding	The sample for this study consists of 127 projects, each of which represents an investment-based platform.	The finding is that a higher number of post-campaign services offered by crowdfunding platforms is associated with a higher number of annual successful campaigns.
(Shafqat and Byun, 2019)	What role can the comments of backers play in understanding the creator's attitude towards the campaign?	Data collected from comments of 200 projects in total, i.e. 100 projects of each category for both scam and non-scam projects.	The results show that comments of non-scam campaigns, to our expectations, reflected that funders are discussing the product itself, e.g., if they liked it or not, etc., confirming that they have received the product.

Paper	Research question	Samples and Methods	Findings and challenges
(Siering et al. 2016)	What is the role of linguistic and content-based cues in deception detection on crowdfunding platforms?	A sample of fraudulent and non-fraudulent projects published on Kickstarter.	The results should be helpful to the stakeholders of crowdfunding platforms and fraud detection researchers.
(Song et al. 2015)	How should new ventures balance innovation and risk when developing a new product?	A database with 127 consumer electronics, namely 3D printers and smart watches, is collected from Kickstarter and Indiegogo.	The findings propose an initial framework of innovation and risk balance for crowdfunding NPD success. A statistical model is developed to correlate the amount of crowdfunding raised with predictability. The adapted Real-Win-Worth metric might require further refinement before becoming applicable to a wider selection of products and crowdfunding platforms.
(Rossi and Vismara, 2018)	What platforms do for proponents as a determinant of platform success?	Data covers France, Italy, Germany, and the UK, and it uses a sample of 127 platforms in these countries. Services provided to entrepreneurs, which are pre-launch, ongoing, and post-campaign services	- A higher number of post-campaign services provided by the platforms leads to an increase in the annual number of successful campaigns, but the number of pre-launch and continuing campaign services has little effect. The authors did not refer to the disadvantages regarding the safeguards
(Torabi Aa et al. 2018)	The authors aim to address the problem of trust and asymmetric information in crowdfunding by introducing a reputation mechanism called "Fame".	The mechanism employed in this paper is aVickrey–Clarke–Groves mechanism (VCG)	The main finding of the research is that the reputation mechanism Fame can help reduce information asymmetry and improve the outcomes for both funders and entrepreneurs. The reputation mechanism also increases the self-worth of funders and the net profit for entrepreneurs.

Paper	Research question	Samples and Methods	Findings and challenges
(Wang et al. 2019)	The study examines the impact of fraudulent texts on crowdfunding financing has both theoretical and practical merit.	A total of 136,309 raw projects were collected from Kickstarter.	The results show that, in general, the lower linguistic advantage related to fraud attracts investors to contribute more funds. However, some fraud indicators have no significant negative effects on funding or even show positive effects. No challenges
(Xie et al. 2025)	The study aims to examine how the contextual characteristics of risk disclosure affect crowdfunding performance	The data included 21,287 projects on Kickstarter from 2009 to March 2022.	This result indicates that providing two-sided persuasion content in the R&C section can increase the credibility of crowdfunding project narratives and thus the crowdfunding performance. This paper is limited to the English language.
(Xu et al. 2016)	The study addresses the problem of fraudulent loan requests on peer-to-peer (P2P) platforms.	The study suggests a set of features that capture the behavioral characteristics (e.g., learning, past performance, social networking, and herding manipulation)	They find that using the widely adopted classification methods such as Random Forest and SVM, the proposed feature set outperforms the baseline features in detecting fraud.

Paper	Research question	Samples and Methods	Findings and challenges
(Ye et al. 2024)	How do GPT-augmented and GPT-extended campaign introductions influence donors' likelihood to provide financial support in crowdfunding campaigns?	The data was collected from GoFundMe. A total of 11,274 fundraising campaigns. Also using GPT to generate campaign descriptions.	The GPT plays a significant role in improving the effectiveness of campaign descriptions. GPT- augmented descriptions are preferred by 83% of participants. GPT-augmented increases the chance of funding.

The table provides a concise overview of various research papers, encompassing their paper titles, research questions, sample populations, research methodologies, as well as their findings and challenges. These studies aim to explore diverse strategies to enhance the likelihood of campaign success while mitigating fraud risks.

Chapter Three: Methodology

3.1 The research design and methodology

This section outlines the research design and methodology of the dissertation. To achieve its research objectives, two distinct approaches will be employed. Firstly, the descriptive method will be used to examine theories and concepts related to success, fraud and PGMs. The purpose of employing this method is to provide a comprehensive overview of the current state of knowledge on factors of success and PGMs. This will include exploring various theoretical frameworks and mechanisms that have been developed. The use of the descriptive method will allow for a systematic examination of the literature, enabling the researcher to identify gaps and inconsistencies in current knowledge. Through this approach, the dissertation aims to establish a solid theoretical foundation for the subsequent empirical investigation.

The second approach is the analytical method, which involves analyzing quantitative and qualitative data. The research design and methodology of the study will involve analyzing quantitative data from various sources, including www.KingCrowd.com, which represents thirty-two equity-based crowdfunding platforms, and https://webrobots.io, a web-scraping service that represents two reward-based crowdfunding platforms. The quantitative data has already been collected and analyzed, which provides valuable information, and it will be presented in the dataset analysis section. Additionally, the qualitative research method involves collecting information from two different sources. Primarily, the data collected thus far encompasses information obtained from all the platforms specified within the "Privacy Policy" page. Also, a questionnaire will be conducted with representatives from the same crowdfunding platforms that were analyzed quantitatively (see Appendix A). The questionnaire should provide details that are not available on platforms related to the PGMs used by crowdfunding platforms. The questionnaire will allow for open-ended questions to gather more detailed insights into the PGMs and provide information that quantitative data alone cannot provide. The study uses Python for that, and it will be aimed at drawing conclusions and insights into the effectiveness of PGMs in enhancing campaign success and preventing fraudulent behavior in crowdfunding campaigns. The qualitative data have not been collected yet.

The study will involve measuring variables, including a dependent variable, which will be different based on the data, and an independent variable, which pertains to PGMs. The study will also incorporate several control variables, such as the number of funders, the amount of money raised, campaign duration… etc. Lastly, the discussion section will focus on highlighting the potential correlation between applying PGMs, increasing success, and reducing fraud in campaigns.

3.2 Model development

In our case, we will use the Logit/Probit regression models, which are used to estimate the probability of an event occurring. Given the nature of our dependent variables and our aim to estimate probabilities of both success and fraud, it is more appropriate to use two separate models for each.

The first model:

$$\text{Sucess}_{i\,k\,t} = \beta_0 + \beta_1\,[\text{PGMs}_{\text{Background check}\ k\,(t-1)}] + \beta_2\,[\text{PGMs}_{\text{Financial information}\ k\,(t-1)}] + \beta_3\,[\text{PGMs}_{\text{Social media}\ k\,(t-1)}] + \beta_4\,[\text{PGMs}_{\text{Cookies}\ k\,(t-1)}] + \beta_5\,[\text{PGMs}_{\text{Google Analytics}\ k\,(t-1)}] + \beta_6\,[\text{PGMs}_{\text{Third-party verification}\ k\,(t-1)}] + \beta_7\,[\text{Number funders}_{i\,t}] + \beta_8\,[\text{Amount pledged}_{i\,t}] + \beta_9\,[\text{Duration}_{i\,t}]$$

Where "Success" is the dummy variable indicating whether a crowdfunding campaign is successful (1) or not (0), using a set of independent variables. These independent variables include "PGMs" representing various mechanisms implemented by the platform, such as social media, Google Analytics and third-party verification, as detailed in Table 6. As well, control variables like the number of funders, the amount pledged, and the campaign duration are detailed in Table 4. The coefficients ($\beta0$ to $\beta9$) represent the effect of each variable on the likelihood of a campaign's success. A positive coefficient suggests an increase in the variable is associated with a higher probability of success, while a negative coefficient suggests the opposite.

Here, (i) represents the campaign on the platform, (k) represents the platform implementing the PGMs, and (t) denotes the year range between 2011 and 2022.

The second model:

$$\text{Fraud}_{\text{i k t}} = \beta_0 + \beta_1 [\text{PGMs}_{\text{Background check k (t-1)}}] + \beta_2 [\text{PGMs}_{\text{Financial information k (t-1)}}] + \beta_3 [\text{PGMs}_{\text{Social media k (t-1)}}] + \beta_4 [\text{PGMs}_{\text{Cookies k (t-1)}}] + \beta_5 [\text{PGMs}_{\text{Google Analytics k (t-1)}}] + \beta_6 [\text{PGMs}_{\text{Third-party verification k (t-1)}}] + \beta_7 [\text{PGMs}_{\text{Previous fraud cases k (t-1)}}] + \beta_8 [\text{Number of funders}_{\text{i t}}] + \beta_9 [\text{Amount pledged}_{\text{i t}}] + \beta_{10} [\text{Duration}_{\text{i t}}]$$

The purpose of this model is to explore the factors influencing the success of crowdfunding campaigns, with a specific focus on predicting the probability of fraud, where "Fraud" is the binary variable (1 for fraud, 0 for no fraud), using a set of independent variables. These independent variables include "PGMs," which represent various mechanisms implemented by the platform, such as social media, Google Analytics and third-party verification.' Additionally, control variables like the amount pledged, the campaign duration, and 'Previous fraud cases' are included. In this instance, the inclusion of previous fraud cases as a variable is intended to enhance the model's predictive capacity for fraud. The coefficients ($\beta0$ to $\beta10$) represent the effect of each variable on the likelihood of a campaign's success. A positive coefficient suggests an increase in the variable is associated with a higher probability of fraud, while a negative coefficient suggests the opposite.

Here, (i) represents the campaign on the platform, (k) represents the platform implementing the PGMs or having previous fraud cases, and (t) denotes the year range between 2009 and 2023.

Table 4. Definition of control variables used.

Control Variables	Definition	Expected signs
Number of funders	Number of Investors who invested in the raise	More is better
Pledged amount	Maximum raise target amount	Higher is better
Campaign duration	The time from the beginning of campaigns to their end.	Less is better
Fraud cases	Refer to the number of fraud cases that the platform has suspended.	Less is better

This table presents different types of control variables that will be used in the analysis, along with their definitions.

3.3 Data collection

The empirical analysis consists of two main categories: quantitative and qualitative data. To obtain the quantitative data, we utilize numerous crowdfunding platforms operating in the USA. The dataset comprises thirty-four crowdfunding platforms, including thirty-two platforms that use equity-based crowdfunding and two that use reward-based crowdfunding. For equity-based crowdfunding platforms, the dataset covers the period from January 2018 to June 2021, which is the only available data, and it consists of 3,171 campaigns. Each campaign has 153 features of information, providing complete details such as the name of the campaign, the number of funders, the amount pledged, and the start and end of each campaign (duration). The data is obtained from www.KingCrowd.com. For reward-based crowdfunding, we used data from Kickstarter and Indiegogo platforms, and the database covers the period from January 2009 to December 2023.

The Kickstarter database consists of 258,555 campaigns, and each campaign has 35 features of information, providing details such as the name of the campaign, the number of funders, the amount pledged, and the start and end of each campaign (duration). The Indiegogo database consists of 75,048 campaigns, and each campaign has 21 features, providing details such as the name of the campaign, the number of funders, the amount pledged, and the start and end dates of the campaign (duration). The dataset for reward-based crowdfunding is obtained from https://webrobots.io. The full set of features provided in the original dataset for all platforms is listed in Appendix C.

The research incorporates qualitative data that encompasses details regarding the types and number of PGMs employed by crowdfunding platforms. To obtain this data, we used two methods. The first step was to send a questionnaire to the target platforms in order to collect data on the types of PGMs they have employed over the years (see Appendix A). However, we received no responses from the platforms we contacted, despite sending multiple emails. The second method was meticulously collected by examining these platforms using archival tools like the Wayback Machine and Time Travel, focusing on equity and reward-based crowdfunding platforms. The initial PGMs applied included "Personal Information," which encompasses details such as names, dates of birth, mailing addresses, email addresses, and phone numbers. Secondly, the "Financial Information" is the second mechanism, covering bank account details, payment card information, and income verification. The "Cookies" mechanism involved tracking user interactions with the Kickstarter site, providing insights into user visits and interactions. Additionally, used a mechanism like "Google Analytics" to gather specific information when visitors access the site. Personal data was also collected from "Social media," including profile names, pictures, and posted content. Lastly, platforms rely on "Third-Party" services to verify investors' identities comprehensively and detect fraudulent activities. The platforms from which we were able to collect PGMs are Kickstarter and Indiegogo, as well as six equity platforms, including Wefunder, StartEngine, Mainvest, SeedInvest and TruCrowd.

3.4 Data analysis

The analysis is divided into two parts. The first part, which involved descriptive and exploratory analysis, was carried out to understand the characteristics of the dataset and the distribution of PGMs and control variables. Summary tables and graphics or charts were used to illustrate: (i) platform governance mechanisms (PGMs) that were implemented in different years, for reward-based and equity-based crowdfunding, (ii) distributions, patterns and trends of campaigns in the number of funders, pledge amount and duration time of the campaigns; and (iii) the distributions of fraudulent campaigns in comparison to cancelled and non-fraudulent campaigns. This phase aims to provide an initial overview of the impact of implementing these mechanisms, both positive and negative, and their effect on fraudulent campaigns.

The second part is to examine the hypothesis of the study using Python. A logistic regression model was employed to test the relationship between PGMs and campaign outcomes. The assessment considers the influence of PGMs on campaign success and the reduction of fraud related to reward and equity-based crowdfunding. It also tests whether the influence of PGM on campaigns varies according to the platform implemented. Further, the analysis compares the different PGMs applied to identify the mechanisms that were most affected in the campaigns. The final part of the analysis considers how the COVID-19 pandemic affected campaigns conducted both before and during the pandemic period.

Chapter Four: Descriptive Analysis and Graphical Representation of Campaign Data

4.1 Reward-based crowdfunding

4.1.1. Kickstarter Platform

Kickstarter, founded in 2009, is a crowdfunding platform that has revolutionized the way creative projects are funded. Through this platform, entrepreneurs can raise funds for a wide range of projects, including films, games, and technology, from a community of funders. Kickstarter operates an all-or-nothing funding model, which ensures that projects must reach their funding goal in order to receive any money. If a project fails to meet its funding goal, no money is collected from funders. According to Kickstarter's official website, as of March 2023, the platform has helped fund over 198,000 projects, with over 22 million backers pledging over $6 billion dollars in total (Kickstarter, 2023). These statistics are a testament to the platform's immense popularity and effectiveness in raising funds for creative projects. The analysis relies on two different steps to show the results: (i) Data Collection and Pre-processing; and (ii) Explanatory Data Analysis (EDA).

Data Collection and Pre-processing

The dataset was created by aggregating and preprocessing data and then combining it into a single file, providing details about campaigns on the Kickstarter platform. For preprocessing the dataset, the first step was to remove duplicate entries based on the crawled date. The second step involved dropping thirty-one columns that either contained redundant or unwanted data due to irrelevance to the analysis, such as id, location, profile, slug, burls, source, staff-pick, used_type, fx_rate, goal, disable communication, current_currency, main_category, and country. Two columns are retained for the analysis: "the number of funders" and "pledged amount". We also removed several campaigns with very large pledge amounts; for example, one campaign exceeded $400 million, resulting in 258,399 campaigns. Further, the columns containing timestamps, such as the launched date and the deadline date, were converted into date format (YYYY-MM-DD), and the original columns were dropped. A new column, "duration" was introduced, calculated as the number of days between the campaign's launch date and deadline date. Additionally, several PGMs were added to the dataset that include "background checks," "financial information," "social media," "Cookies," "Google Analytics," and "third-party identity verification". Lastly, columns representing "fraud cases," "success," "COVID-19," and "Kickstarter" were added to the dataset. The final dataset contains thirteen features, which are outlined in Appendix D.

According to Kickstarter (2023), campaigns shown as suspended have been associated with cases of fraud. This was due to violations, including misleading content (support misrepresentations), fake prototypes, presenting others' work as one's own, failure to disclose relevant project information, and account issues (spam, fraud). When a campaign is suspended, all funds are revoked, and a refund is issued. Cancelled campaigns are considered potentially fraudulent; this term refers to campaigns that entrepreneurs choose to end before the deadline, often because of unforeseen issues, low interest, or realizing the project is not viable, or suspension by the platform due to rule violations.

The dataset was labelled to identify fraudulent campaigns using the following columns: "is_fraud" and "fraud_subcategory." The "is_fraud" column indicates whether a campaign is fraudulent, with labels such as "Yes," "No," or "MAYBE." The "fraud_subcategory" column further specifies the type of fraud involved. Successful or failed campaigns were labelled as "NO" for "is_fraud" and "Not Fraud" for the "fraud_subcategory." Cancelled campaigns were labelled as "MAYBE" for "is_fraud" and "Potential Fraud" for the "fraud_subcategory." As for suspended campaigns, they were labelled as "Yes" in the "is_fraud" column.

To determine whether a given campaign was misleading, we observed if it lacks a clear concept or includes hidden information and false promises. For example, “Apocalypse Now”, was a canceled campaign that was considered misleading due to not being presented comprehensively and having unclear details. Fake products, whether there are no actual product details, or whether the campaign was feasible (i.e., how it would be built). Regarding copy product, it refers to a product that exists on the market, such as a campaign that claims to create a 3D printer—something currently on the market—would be marked as a copied product. By doing this, we classified all types of fraud. Table 5. describes how the subcategory is decided.

Table 5. Fraud subcategory description.

Subcategory Name	The question that decides the subcategory
Misleading	Does the campaign not make any sense?
Fake Product	Does the campaign promote a non-existent or counterfeit product?
Copy Product	Does the campaign promote an existing product?

The table outlines the definition of the fraud subcategory. The "Subcategory Name" column lists fraud types, while the other column provides their respective definitions and explanations.

Table 5 provides a method for determining subcategories related to fraud in crowdfunding. The "Subcategory name" helps identify the specific type of fraud, while the "Question that decides the subcategory" serves as a clear definition for each type of fraud. This approach enables us to effectively and accurately classify different fraudulent crowdfunding campaigns based on their characteristics.

Platforms' governance mechanisms (PGMs)

The research data was obtained from the Wayback Machine and Time Travel, shedding light on the mechanisms employed by Kickstarter for user information collection. In the beginning, Kickstarter relied on background checks, financial information, cookies and Google Analytics to collect information about users. The platform also shares users' information with third-party identity verification and payment providers such as Stripe, a financial services company. The information collected by Kickstarter includes personal details such as name, date of birth, email address, and gender. Additionally, they gather financial information like credit card and bank account information. It is essential to emphasize that Kickstarter's use of collected information aims to protect investors and provide better services. In contrast, Kickstarter explicitly states that it does not provide any warranties, including implied warranties related to customary business practices, merchantability, and non-infringement. Further, the platform clarifies that no advice or information obtained from Kickstarter, whether oral or written, shall establish any warranty (Kickstarter, 2023).

Table 6 highlights the specific types of PGMs that the Kickstarter platform applied. These mechanisms, initiated in 2012 with two primary components, background checks and financial information, followed in later years by social media, cookies, third-party identity verification, and Google Analytics.

Exploratory Data Analysis (EDA)

EDA involves examining and visualizing data to gain insights and identify patterns, relationships, and potential anomalies. As part of the EDA analysis, two tables present summary statistics for different variables, including mean, standard deviation, minimum value, 25%, 50% (median), 75%, maximum, unique, top value, and frequency.

Table 6. Detailed information about PGMs for the Kickstarter platform.

PGMs Applied	Platform name							
	Kickstarter							
	2012	2014	2015	2016	2017	2018	2020	2022
Background check	✓	✓	✓	✓	✓	✓	✓	✓
Financial information	✓	✓	✓	✓	✓	✓	✓	✓
Social media	✓	✓	✓	✓	✓	✓	✓	✓
Cookies	✓	✓	✓	✓	✓	✓	✓	✓
Google analytics	-	-	-	-	-	✓	✓	✓
Third-party verification	-	✓	✓	✓	✓	✓	✓	✓

The table consists of two columns: the first column contains the names of the mechanisms used, and the second column consists of the years. Thus, it is easy to determine the year in which the mechanism was implemented.

Table 7. Descriptive statistics of numerical features on the Kickstarter platform.

Statistic	Mean	Std	Min	25%	50% (median)	75%	Max	Count
The number of funders	175.215	909.40	0.0	4.0	31.0	104.0	73,206	258399
Pledged amount	22,687.47	149,705.7	0.0	150.0	1,834	8,041	4,968,148	258399
Duration	31.90	12.74	0.0	29.0	30.0	34	120	258399

The table presents numerical features for three variables: 'the number of funders,' 'the amount of money raised,' and 'duration time.' The table includes the mean, standard deviation, minimum, %25, median (%50), %75, maximum, and count for whole variables, offering a holistic view of campaign performance.

Table 7 presents descriptive statistics for various variables for the Kickstarter platform. A significant disparity exists in the number of funders; campaigns ranged from having no participants to those that attracted up to 73,206 funders per campaign. Pledge amounts also vary considerably, ranging from unfunded campaigns to campaigns under $5 million. Campaign duration data reveal that the average duration is almost 32 days, with a range of 0 to 120 days, indicating that some campaigns lasted for long periods.

Table 8. Descriptive statistics of non-numerical features on the Kickstarter platform.

Statistic	Freq	Top	Unique	Count
Campaigns status	153301	Successful	4	258399
Is fraud	246975	No	3	258399
Fraud subcategory	246975	Nor fraud	7	258399

The table presents non-numerical features for three variables: 'is_fraud' determines if a campaign is fraudulent, with options of yes, maybe, or no. The 'fraud_subcategory' variable describes the specific type of fraud, such as misleading information, fake products, or copied products. The table includes unique, top value and frequency and count for whole variables.

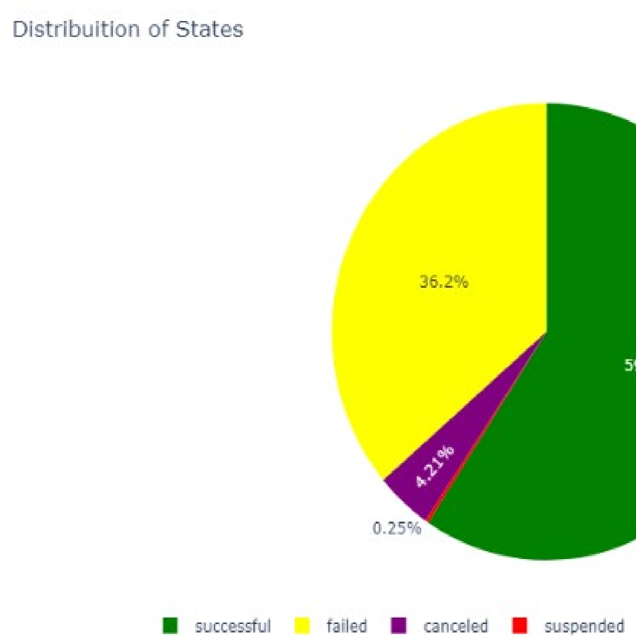
Table 8 provides a summary of statistics or categories within a dataset, along with corresponding frequency counts, most common values (top), unique value counts, and the overall dataset count. It encompasses three main statistics: "Campaigns status," which appears 153,301 times with "Successful" being the top value and having four unique values; "Is fraud," occurring 246,975 times with "No" as the top value and three unique values; and "Fraud subcategory," also occurring 246,975 times with "Nor fraud" as the top value and featuring seven unique values. The table's total count is 258,399, shedding light on the distribution and characteristics of the data across these statistical categories.

Exploratory analysis of control variables indicators

A. Number of fraudulent activities (Num Frd)

Figure 1 presents a pie chart depicting the distribution of campaign statuses on the Kickstarter platform. Notably, the chart reveals that suspended campaigns, which are associated with fraudulent activities, make up a very small percentage, specifically 0.25% of the total campaigns. On the other hand, cancellations account for nearly 5% of the campaigns. These findings indicate that instances of fraud in crowdfunding campaigns are relatively infrequent compared to the overall number of campaigns.

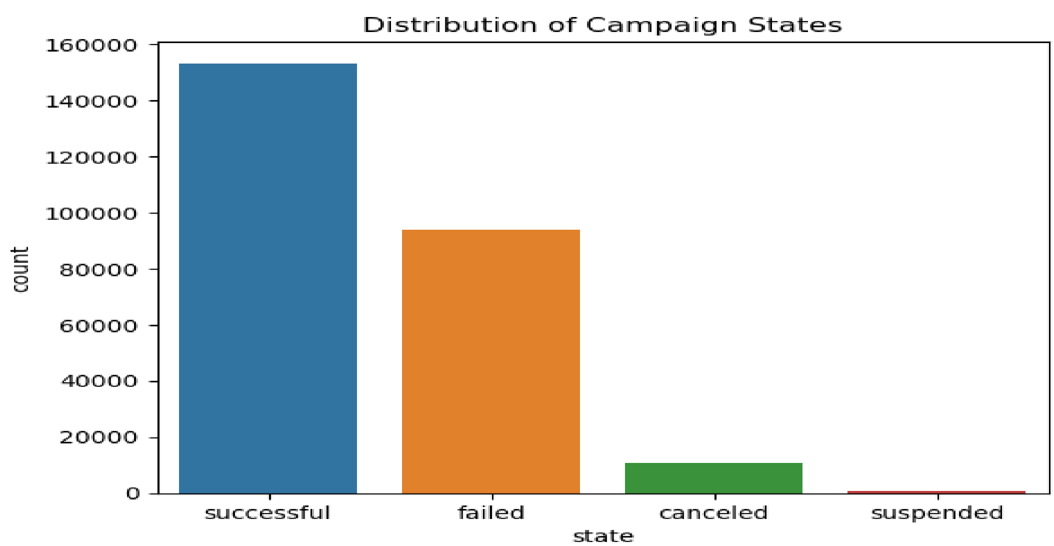
Figure 1. Distribution of campaign status.



The graph represents four campaigns' status: successful, failed, canceled, and suspended campaigns. Additionally, there are numerical values indicating the size of each campaign category.

Figure 2 presents a bar plot that serves as additional evidence to support the earlier conclusions by visually presenting the frequency of suspended campaigns in relation to successful and failed campaigns. This plot provides further confirmation of the rarity of suspended campaigns when compared to the other campaign states, effectively emphasizing the scarcity of fraudulent activities occurring within the Kickstarter platform.

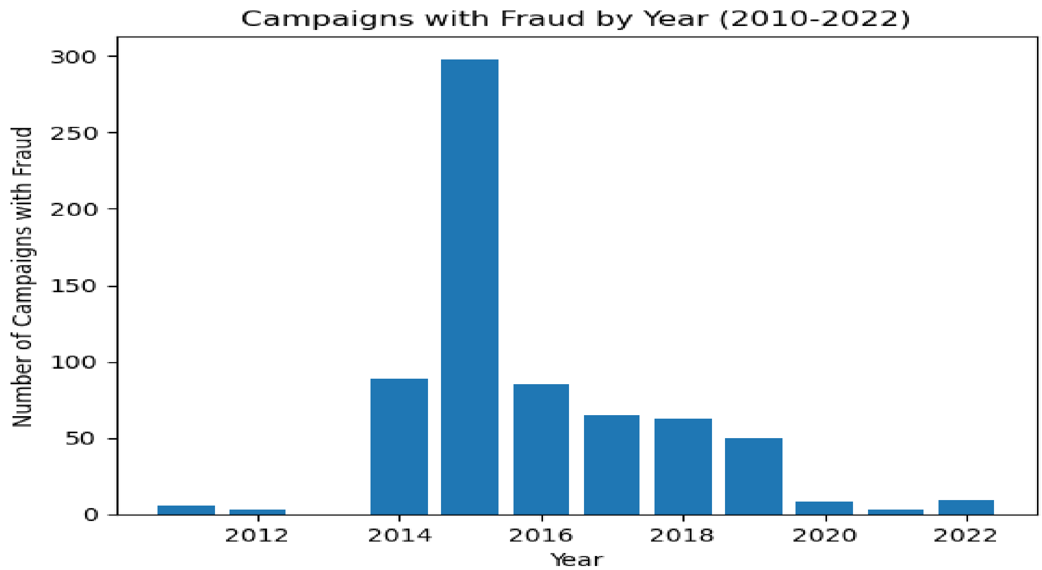
Figure 2. The number of campaign status.



The figure plots represent different campaign statuses: successful campaigns, failed campaigns, canceled campaigns, and suspended campaigns, including a count that represents each status.

For a deeper understanding, the bar plot in Figure 3 provides valuable insights into the trend of suspended crowdfunding campaigns from 2010 to 2022. An analysis of the plot reveals a significant peak in suspensions occurring in 2015, with an alarming count of nearly 300 reported cases. However, subsequent years saw a noteworthy decline in suspensions, bringing the numbers back to a level comparable to 2014, with less than 100 cases reported. This downward trend continued over the following years, ultimately reaching its lowest point in 2021.

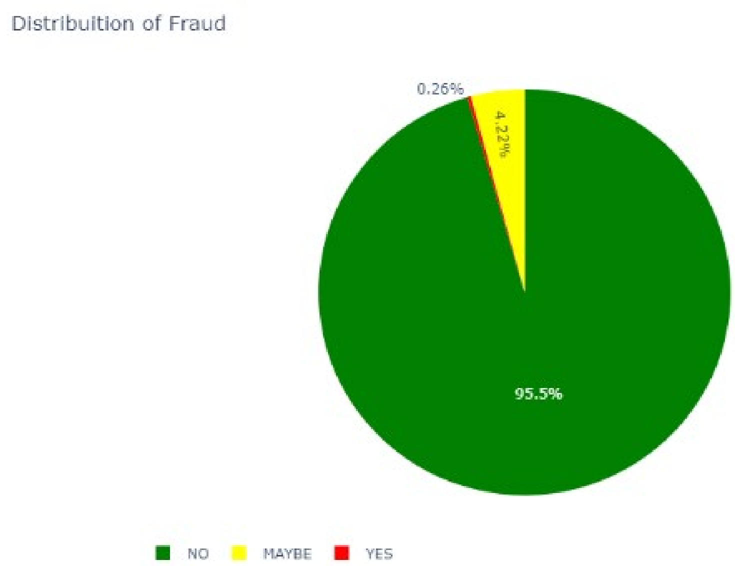
Figure 3. The number of suspended campaigns by year.



The bar plot represents the number of suspended campaigns between 2010 and 2022. Each year represents the count of suspended campaigns on the Kickstarter platform.

Figures 4 and 5 exhibit the instances of cancelled and suspended campaigns, which are categorized as either fraud or potentially fraudulent cases. The pie chart presented below shows the distribution of fraud cases and potential fraud cases in relation to the larger pool of non-fraudulent cases. It emphasizes the relatively small representation of fraudulent incidents and potential fraud cases compared to the vast majority of non-fraudulent cases, which account for less than 1% of the total, as depicted in Figure 4.

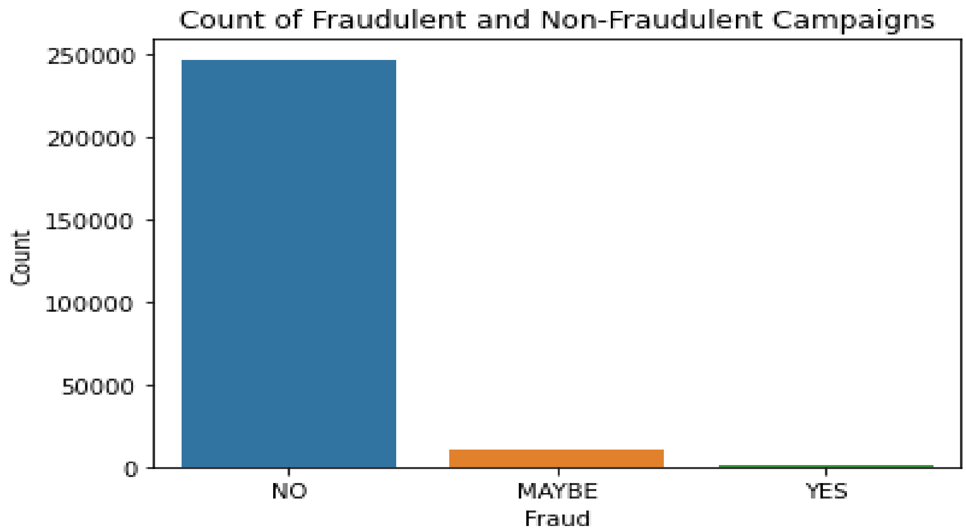
Figure 4. Distribution of suspended campaigns.



The graph represents suspended campaigns: one for 'No,' meaning no fraud cases; 'Maybe,' indicating a chance of fraud; while 'Yes' confirms fraud. The figure also includes numerical values that indicate the quantity of each category.

This trend is further supported by the bar plot depicted in Figure 5, which clearly indicates that the number of suspended campaigns categorized as fraud or potential fraud is extremely reduced in comparison to the non-fraudulent cases. However, the fraud cases that have been confirmed were categories based on the projects supported, as in Figures 6 and 7, which show fraudulent and non-fraudulent campaigns by main categories.

Figure 5. The number of fraudulent and non-fraudulent campaigns.



The bar plot represents fraudulent and non-fraudulent cases categorized as No, Maybe and Yes. Each category is represented by the number of cases.

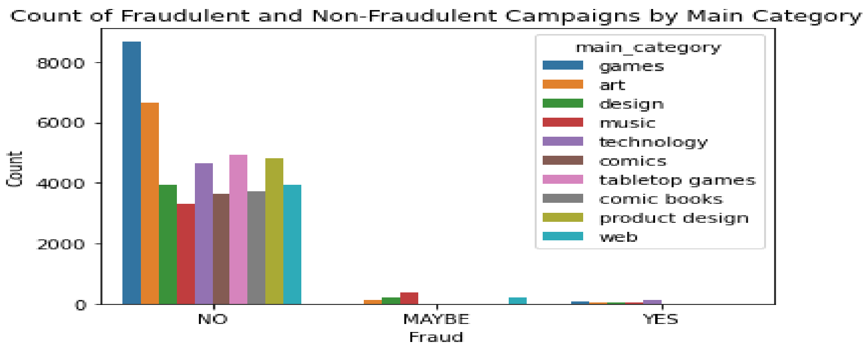
Figure 6 presents a bar plot displaying the distribution of fraud across the top 20 categories in crowdfunding campaigns. The bar plot categorizes fraud status into confirmed fraud, not fraud, and maybe fraud, providing valuable insights into the prevalence of fraudulent activities in different campaign categories. By examining the bar plot, it can be observed that the Technology and Games categories have the highest incidence of fraud, indicating that campaigns in these categories are more likely to be fraudulent than others. Additionally, the Music and Design categories, followed by Web, exhibit the highest incidence of potentially fraudulent campaigns, highlighting the need for greater scrutiny when evaluating campaigns in these categories.

Figure 6. Distribution of fraudulent and non-fraudulent campaigns by categories.

A bar chart shows the spread of fraud among the top 20 categories in crowdfunding campaigns. The chart divides fraud into three categories: confirmed fraud, not fraud, and maybe fraud. This shows which campaign categories have more or less fraudulent activity.

Figure 7 reinforces these findings, showing similar results. All campaign categories with 'Yes' for fraud have very low numbers across the categories. However, 'Maybe' fraud appears to be higher in the music category compared to the other categories. On the other hand, 'No' fraud has significantly higher numbers in the games and art categories compared to the rest.

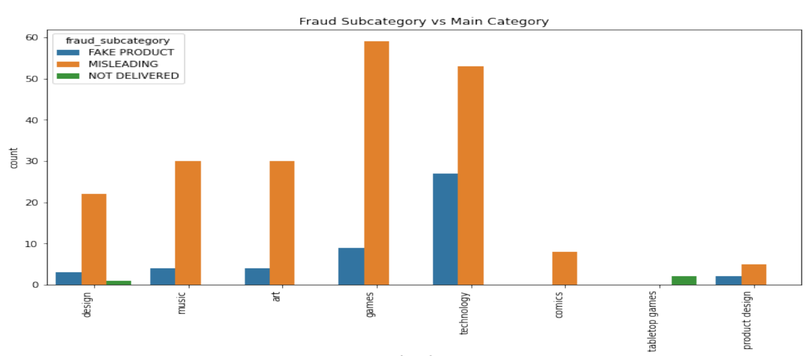
Figure 7. The number of fraudulent and non-fraudulent campaigns by main category.



The legend on the right side of the graph indicates the distinct colors used to represent each category, while on the left side, you can see the count or number of fraud cases for each main category.

Figure 8 displays a bar plot of the different fraud categories that were labeled for suspended crowdfunding campaigns, including misleading, fake product, a copy product and not delivered. The highest percentage of fraud cases across all project types was classified as misleading, followed by fake products, which were particularly prevalent in technology and games. On the other hand, the percentage of cases involving undelivered products was relatively small compared to the other types of fraud.

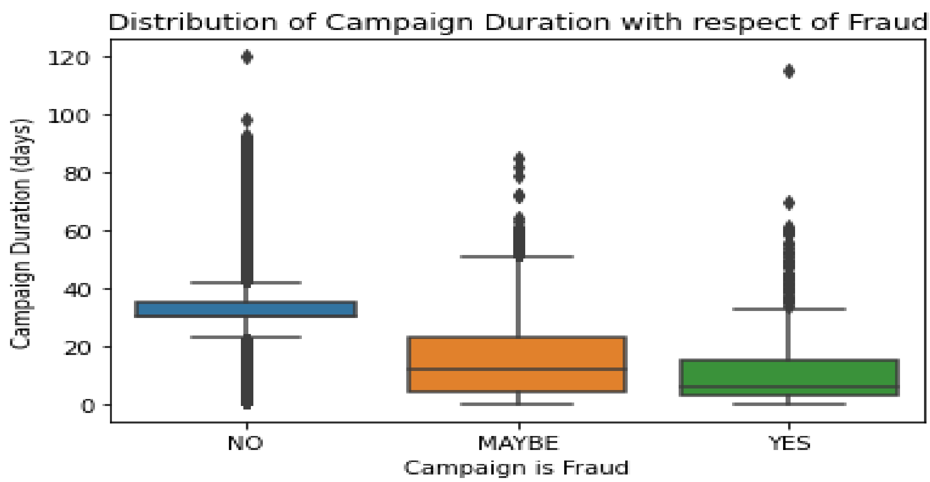
Figure 8. The number of fraudulent campaigns by subcategory.



A bar chart representing various types of fraud associated with suspended crowdfunding campaigns. These categories include misleading information, counterfeit products, copied products, and failure to deliver.

Figure 9 displays a box plot that depicts the duration of crowdfunding campaigns categorized by their fraudulent status. The results indicate that campaigns confirmed to be fraudulent tend to have shorter durations, typically less than 20 days. On the other hand, campaigns that maybe have fraud cases tend to have durations of less than 30 days. Meanwhile, campaigns that are not confirmed to have any fraudulent activity appear to have longer durations, usually less than 40 days.

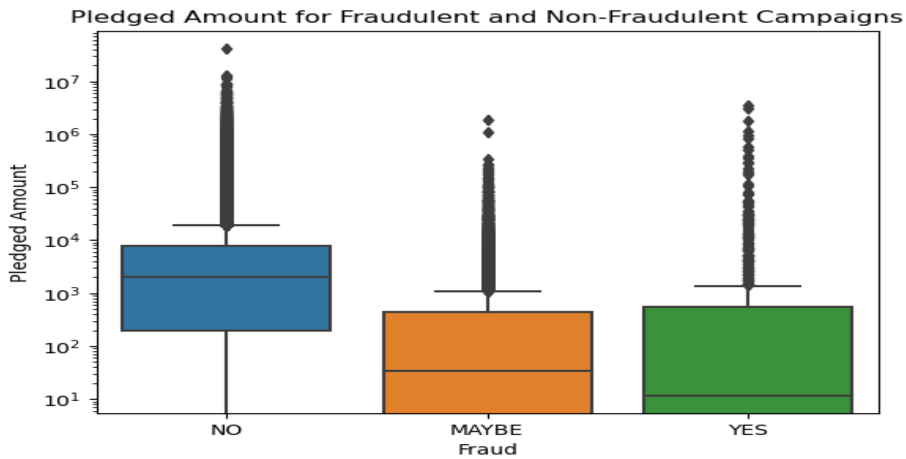
Figure 9. Campaign duration of fraudulent and non-fraudulent campaigns.



The figure shows fraud cases, maybe fraud cases, and non-fraud cases, along with the duration it takes for each category to get funded.

Figure 10 offers valuable insights into the correlation between fraud categories and campaign performance. The figure clearly explains that campaigns categorized as "yes" or "maybe" fraud tended to receive lower pledge amounts in comparison to campaigns labeled as "not fraud." These findings suggest that fraud categories can have a relatively lower impact on the pledged amounts in crowdfunding campaigns.

Figure 10. The amount of funds raised for fraudulent and non-fraudulent campaigns.

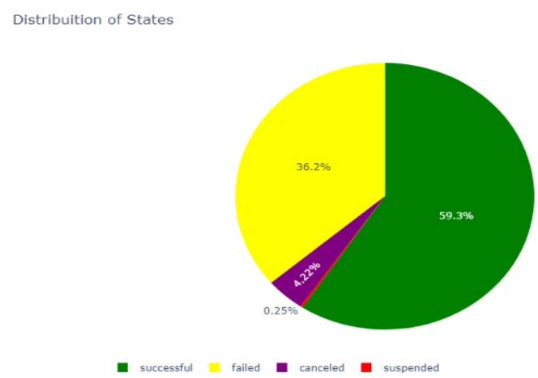


The figure shows the amount of money raised for fraudulent and non-fraudulent campaigns as No, Maybe and Yes. Each category is represented by the amount of money collected.

B. Number of funded campaigns (Num Cam)

Figure 11 presents a pie chart illustrating the distribution of campaign states. The chart reveals that the largest portion, accounting for approximately 60%, is occupied by funded campaigns, "successful campaigns". Failed campaigns make up over 36% of the total, indicating a considerable proportion of campaigns that did not reach their goals. Notably, a relatively small percentage of campaigns, around 5%, were either cancelled or suspended.

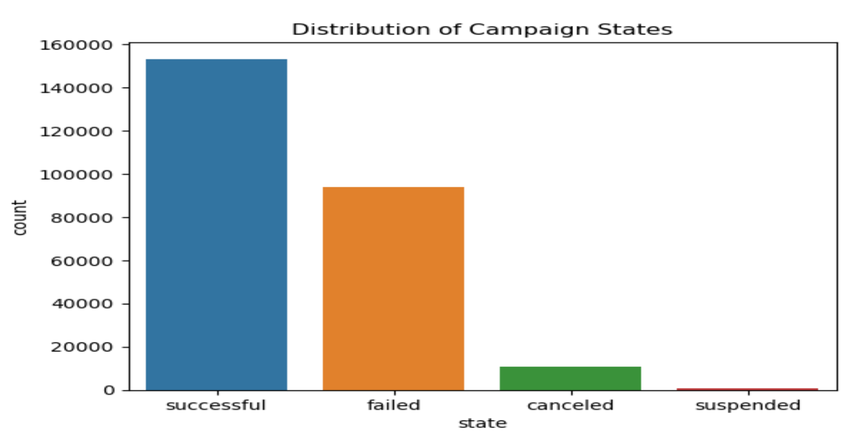
Figure 11. Distribution of funded campaigns.



The graph represents campaign status using four distinct colours: successful, failed, canceled, and suspended campaigns. It also includes numerical values indicating the size of each campaign category.

In Figure 12, a bar plot further demonstrates that the number of successful campaigns is higher compared to those that have been failed, cancelled, or suspended, reinforcing the trends observed in Figure 11. Overall, the data implies that a majority of crowdfunding campaigns tend to achieve success, but it is worth noting that a significant number still fall short of their intended objectives.

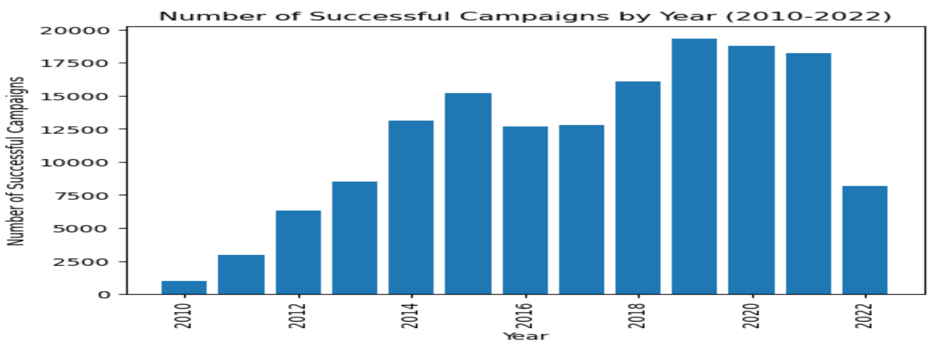
Figure 12. The number of funded campaigns by status.



A bar plot displays campaign statuses for successful, failed, canceled, and suspended campaigns. It also includes numerical values indicating the size of each campaign category.

Figure 13 the number of successful campaigns exhibited a gradual increase from 2010 to 2015, but experienced a plateau in growth during the years 2016 and 2017. However, from 2018 to 2021, there was a notable resurgence in successful campaigns, surpassing the previous year's figures.

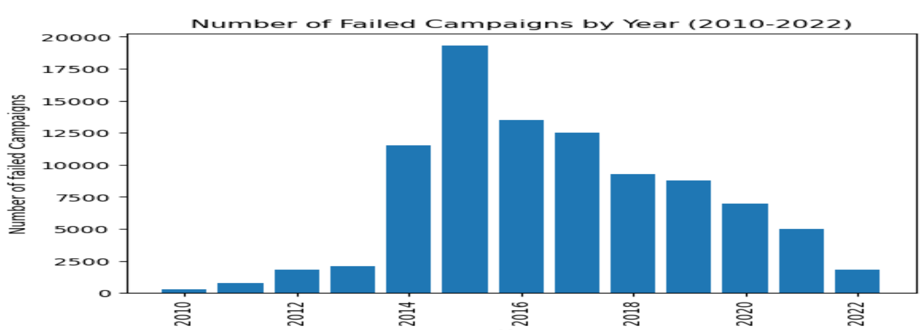
Figure 13. The number of successful campaigns.



The figure shows the years of successful campaigns between 2010 and 2022, along with the number that represents each year for a successful campaign.

Figure 14 displays a bar plot indicating a rise in failed campaigns between 2010 and 2015, with a sharp increase observed specifically in 2014 and 2015. However, since 2016, the number of failed campaigns steadily declined, reaching levels similar to those seen in 2012.

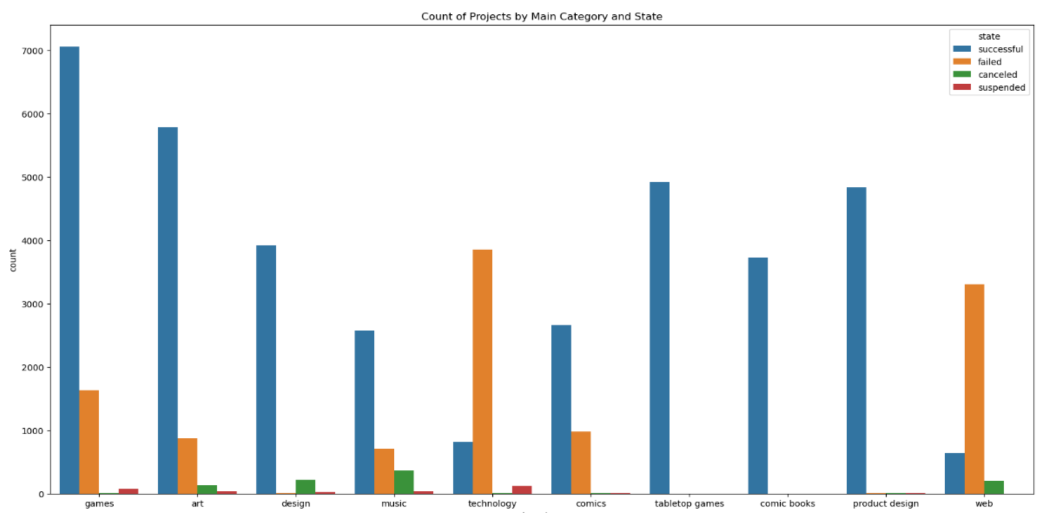
Figure 14. The number of failed campaigns.



The figure shows the years of failed campaigns between 2010 and 2022, along with the number that represents each failed campaign for each year.

To gain a deeper understanding of the relationship between campaign categories and their success or failure by displaying bar plots for each campaign state (successful, failed, canceled, and suspended). We focused on the top 10 categories in terms of the total number of projects, as illustrated in Figure 15. Interestingly, we found that the "Games" category was the most popular overall, also showing the highest number of successful campaigns. However, the "Technology" category had the highest number of failed and suspended campaigns. Meanwhile, the 'Music and Design' categories recorded the highest number of cancellations.

Figure 15. Campaign status and project count.



The figure shows different campaign statuses: successful, failed, canceled, and suspended campaigns, and project categories: games, art, design, music, technology, comics, and web for each status, along with a count number for each campaign.

Taking into account the variation in the category axis across different campaign states, we conducted a more detailed analysis by generating a bar plot focused on the top 20 categories distribution of successful, failed, canceled and suspended campaigns. This supplementary examination provided further support for the patterns observed in Figure 16. The findings indicated that the "games" category tended to have a greater number of successful campaigns, while the "technology" category faced a higher likelihood of failure or suspension. These insights hold significance for both project entrepreneurs and funders, as they shed light on the potential risks and rewards associated with various campaign categories. By understanding these dynamics, stakeholders can make more informed decisions and better navigate the crowdfunding landscape.

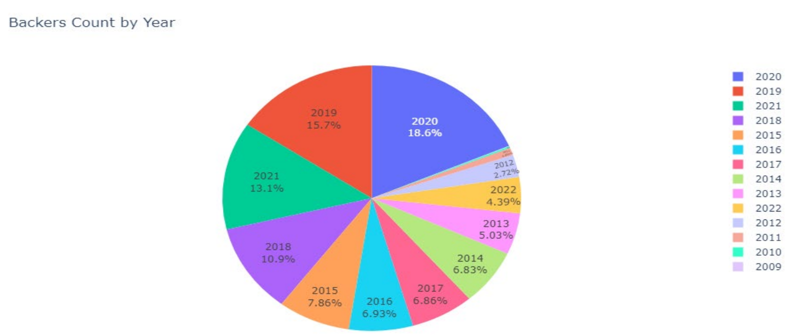
Figure 16. The top 20 main categories of project campaigns.

The graph displays the status of all campaigns, including successful, failed, suspended, and canceled campaigns, along with the top 20 main categories of projects and the respective number of each project.

C. Number of Funders (Num Fun)

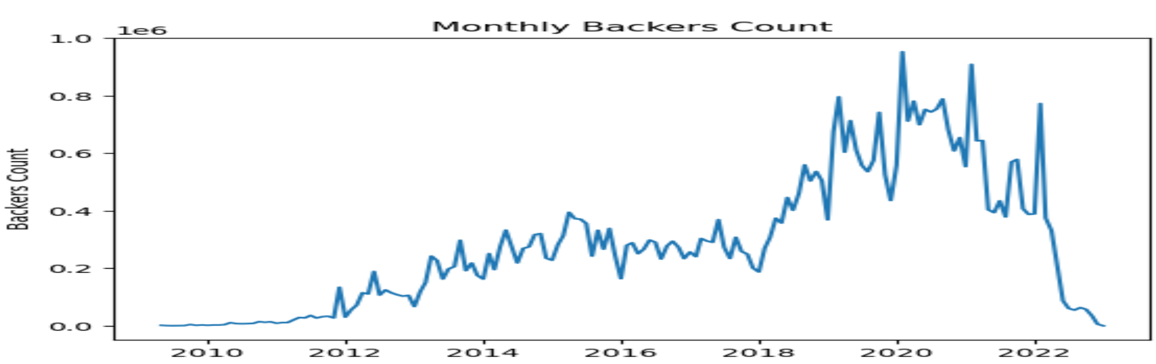
Figures 17 and 18 demonstrate a consistent and notable growth in the num fun engaging in crowdfunding campaigns over the years. The data reveals a steady upward trajectory, with the peak occurring in 2020. From 2010 to 2017, the rise in participation was relatively modest, remaining below 2%. However, it gained momentum in 2018, surpassing 3%, and further accelerated to 10.9% in 2019 and 18.6% in 2020. Nevertheless, there was a decline of nearly 5% in 2021, bringing the participation rate down to 13.1%.

Figure 17. Distribution of participating funders.



The figure represents the number of funders engaging in crowdfunding campaigns from 2009 to 2020. Each year is represented by a distinct color, and numerical annotations indicate the annual increase of funders.

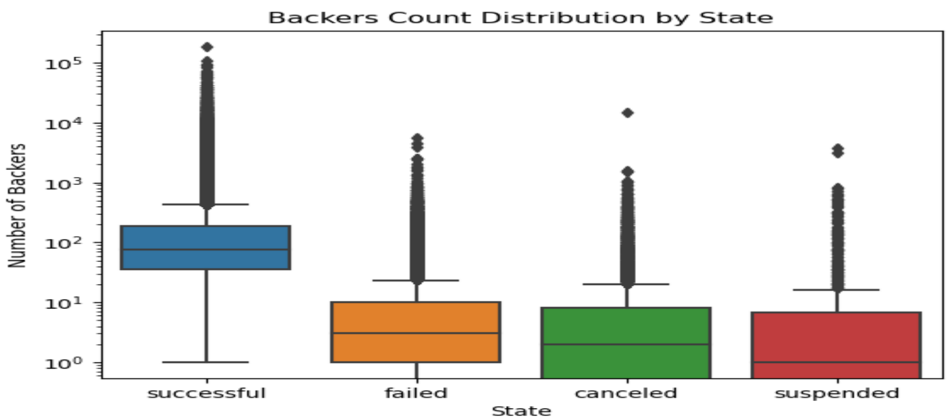
Figure 18. The number of funders participated.



The graph shows the number of funders engaging in crowdfunding campaigns from 2009 to 2020.

The analysis of the box plot displayed in Figure 19 reveals a noteworthy trend: successful campaigns exhibit notably higher values for the variable num fun when compared to failed, canceled, and suspended campaigns, which, in contrast, demonstrate considerably lower numbers of num fun.

Figure 19: Campaign status and participating funders.

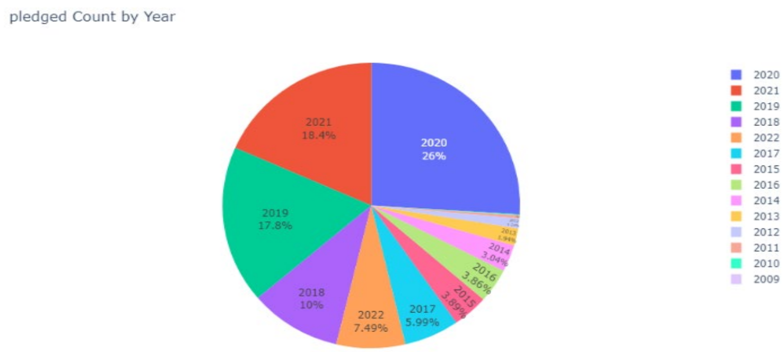


The figure shows the campaign status for successful, failed, canceled, and suspended campaigns, along with the number of funders who participated for each status.

D. Amount of money raised (amnt mon)

The pie chart depicted in Figure 20 demonstrates a consistent growth in the funds raised through Kickstarter over the years, with the most significant increase occurring in 2020 at 26%. Between 2009 and 2016, the growth in funds raised remained below 2%. However, this trend shifted in 2017, with the rate of increase in funds collected accelerating. In 2018, the share of funds allocated to projects climbed to 10%, with the upward trend continuing in 2019 at an increase of 17.8%. The peak growth in funds raised took place in 2020, which can be ascribed to the rising popularity and trust in Kickstarter as a crowdfunding platform, as well as the implementation of PGMs.

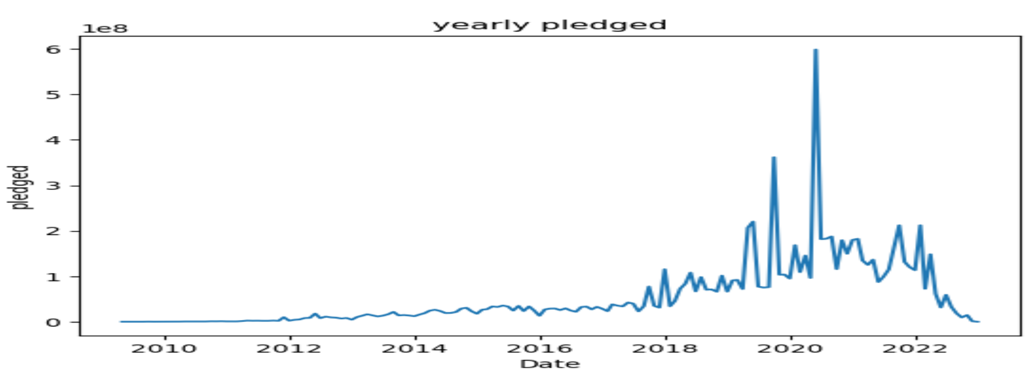
Figure 20. Distribution of funds raised.



The figure represents the amount of money raised in crowdfunding campaigns from 2009 to 2020. Each year is represented by a distinct color, and numerical annotations indicate the annual increase in funding.

However, it is important to note that the growth rate in funds collected has slowed down in 2021 and 2022, with an increase of 18.4% and 7.5%, respectively. Nonetheless, the overall trend of increasing funds collected over the years supports the notion that Kickstarter has become a trusted platform for crowdfunding. The line graph is presented in Figure 21 supports this theory by illustrating how the increase in funds collected has been steadily rising over the years.

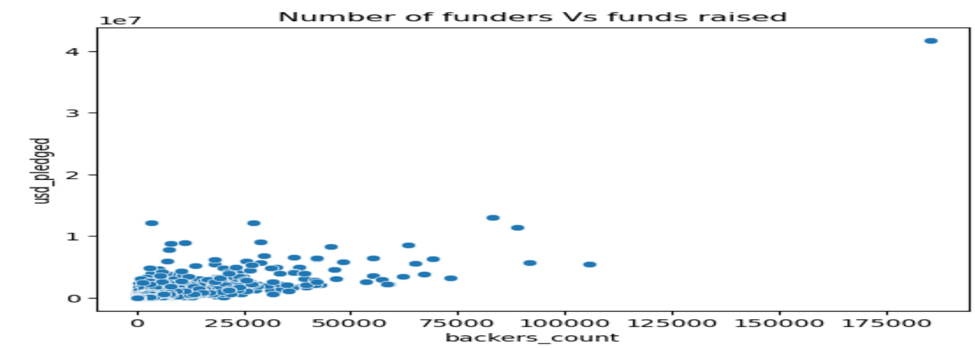
Figure 21. The amount pledged raised.



The graph shows the amount pledged, as well as the amount of money raised annually between 2010 and 2022.

As shown by the scatter plot in Figure 22, a robust correlation can be observed between the increasing num fun and the financial contributions made to support projects. The data indicates that Kickstarter has successfully attracted a larger pool of investors, leading to a subsequent rise in funds gathered.

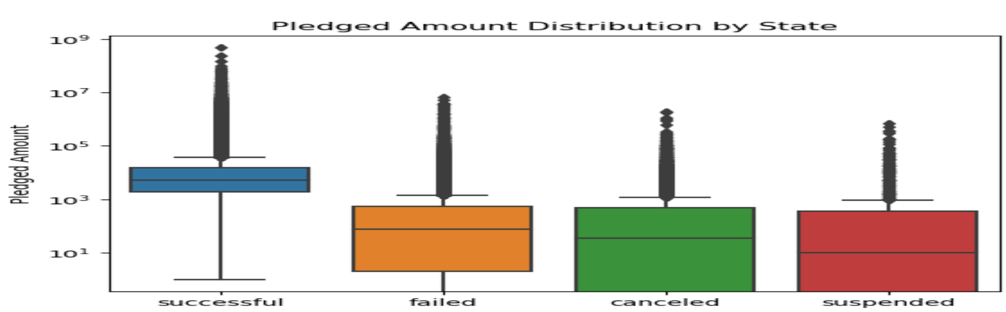
Figure 22. The number of funders who participated and the funds raised.



The graph shows a correlation between the number of funders who participated in crowdfunding campaigns, along with the amount of money collected from those funders.

Figure 23, a noticeable trend can be observed regarding the pledged amount in relation to the state of the campaign. It is evident that failed or cancelled campaigns generally raised a relatively small amount compared to successful campaigns. In other words, successful campaigns are more effective in generating greater financial support from funders.

Figure 23. Campaign status and funding raised.

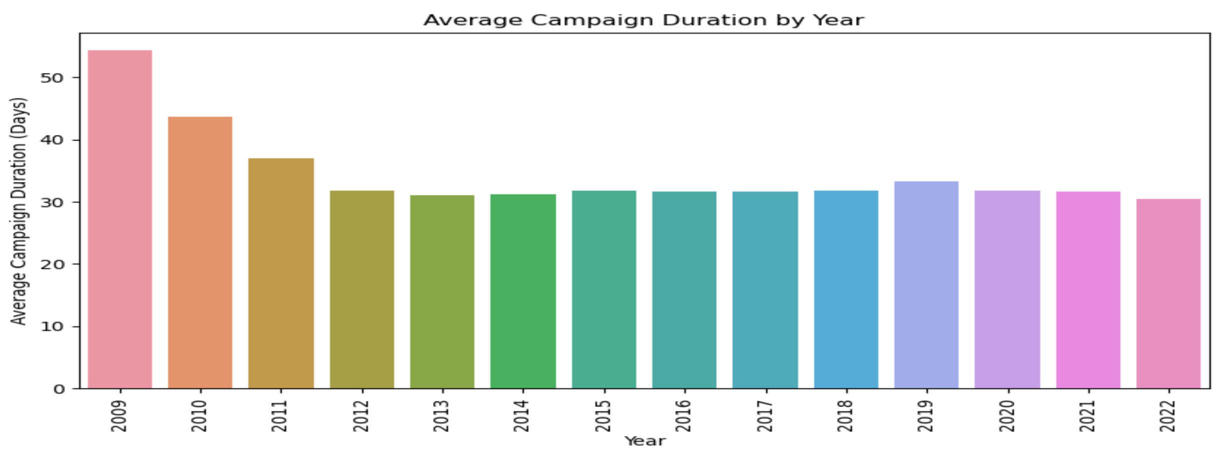


The figure shows the campaign status for successful, failed, canceled, and suspended campaigns, along with the amount of money raised for each status.

E. Campaigns duration (Cam dur)

Figure 24 provides insights into the average duration of crowdfunding campaigns over the years. The data reveals a notable trend: between 2009 and 2012, the cam dur consistently decreased, going from over 50 days to approximately 31 days. However, from 2013 onwards, it has been relatively stable throughout the period until 2022, with an average of 31 days. These findings suggest that there was a significant reduction in the length of crowdfunding campaigns since the earlier years, followed by a period of relative stability in cam dur.

Figure 24. Average campaign duration by year.

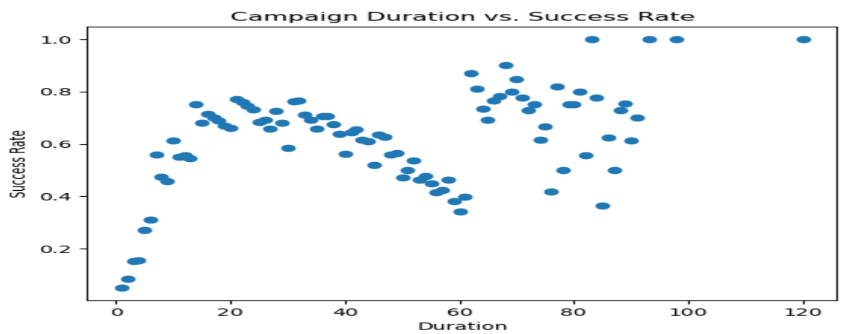


The chart illustrates the mean duration of campaigns spanning from 2009 to 2022, as well as the annual averages for campaign durations.

The previous results suggest that the duration of crowdfunding campaigns has generally remained stable over the years, with a few exceptions where significant increases or decreases were observed. It is worth noting that campaigns with longer durations may have a better chance of success, as they allow more time for the campaign to gain traction and attract more funders. However, longer durations may also result in reduced urgency for potential funders, leading to a lower level of engagement with the campaign.

Observing Figure 25, we notice a significant correlation between the length of a campaign and its success rate. Generally, shorter cam dur are correlated with a greater number of successes; however, there are cases where extending the duration is necessary to achieve a desirable success rate.

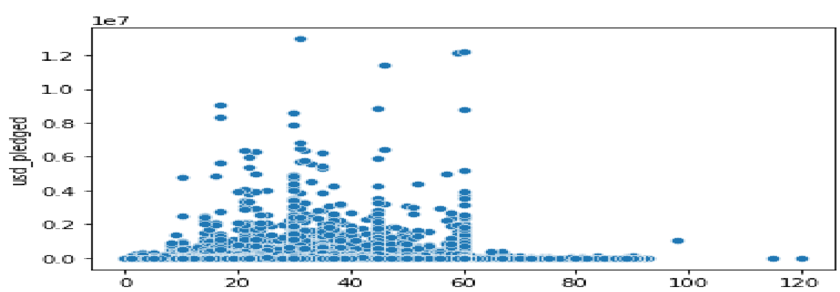
Figure 25. Duration for successful campaigns.



The scatter plot illustrates a relationship between campaign duration and success rate. It shows the duration starting from zero days to 120 days, while the success rate starts from 0.2% to 1%.

The data analysis further indicates a clear relationship between the duration of a campaign and the total amount of funds raised. This can be observed in Figure 26, where it is shown that the greater the amount of money raised, the contribution within a timeframe of 20 to 60 days. Beyond the 60-day mark, there is a significant decline in the amount of money raised.

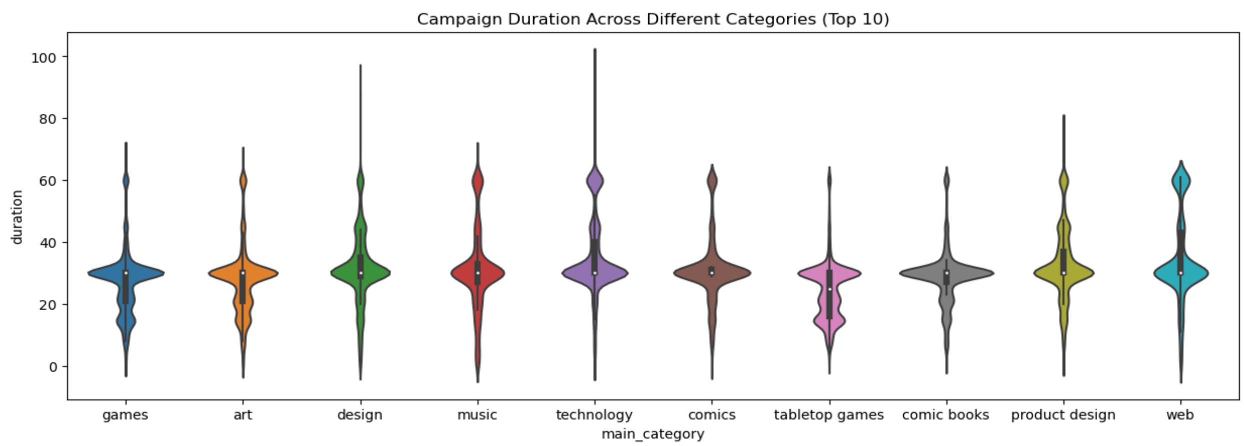
Figure 26. The amount of funds raised and the duration.



The scatter plot displays the relationship between campaign duration times and the amount of money collected during those periods.

Upon examining Figure 27, it reveals that the majority of crowdfunding campaigns across all categories have a duration range of 20-40 days. However, campaigns related to games, art, and tabletop games tend to have a duration range of 10-30 days, while campaigns in the technology, design, product design and web categories tend to have a duration of over 30 days. These results show that some campaigns may require a longer duration to attract funders and reach their funding goals, while other campaigns may require a shorter time frame to reach their funding goals.

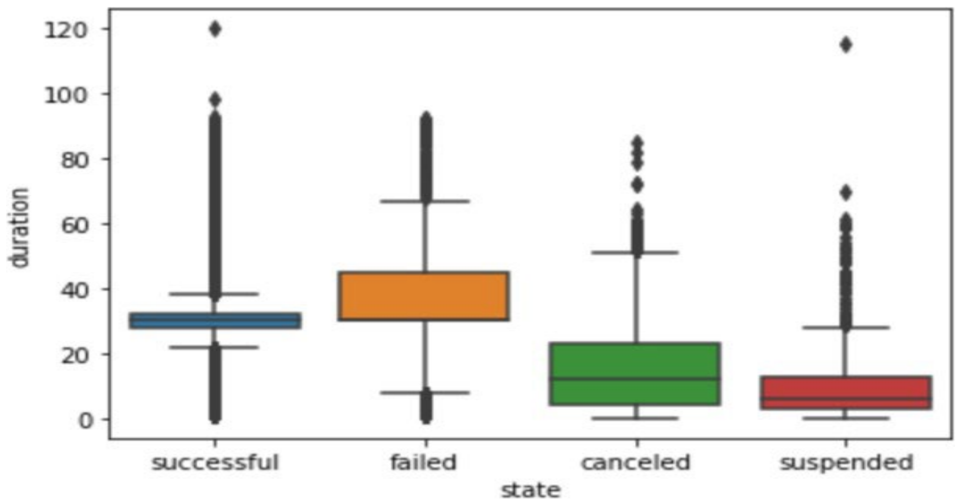
Figure 27. Campaign durations across the top 10 categories.



The Violin plot illustrates the average campaign durations for the top 10 project categories, including games, art, design, music, comics, product, and web campaigns.

Furthermore, Figure 28 confirms the previous observation, showing that successful campaigns tend to have a duration predominantly in the range of 20-40 days, while failed campaigns tend to have a higher range of 30-50 days. It is notable that suspended and cancelled campaigns tend to have a shorter duration of less than 20 days, indicating that the platforms stopped these campaigns a few days after they started.

Figure 28. Campaign status and average duration.



The figure shows the campaign status for successful, failed, canceled, and suspended campaigns, along with the average duration for each status.

4.1.2 Indiegogo Platform

Indiegogo, founded in 2008, is another popular reward-based crowdfunding platform that has played a significant role in transforming the way creative projects are financed. Similar to Kickstarter, Indiegogo provides a platform for entrepreneurs to raise funds for a diverse range of projects, including films, games, technology, and more. Unlike Kickstarter, Indiegogo offers two funding models: fixed funding and flexible funding. Fixed funding is similar to Kickstarter's all-or-nothing model, where a project must reach its funding goal in order to receive any money. On the other hand, flexible funding allows entrepreneurs to keep the funds they raise, regardless of whether they reach their funding goal or not. Indiegogo has helped fund over 900,000 projects in over 200 countries, with over $6 billion pledged by more than 26 million funders (Indiegogo, 2023). Indiegogo has proven to be an effective tool for creative entrepreneurs. The analysis relies on two different steps to show the results: (i) Data Collection and Pre-processing; and (ii) Explanatory Data Analysis (EDA).

Data Collection and Pre-processing

The dataset for Indiegogo campaigns was created by aggregating and preprocessing data from monthly datasets that were obtained. The dataset went through preprocessing to drop duplicate entries according to the crawled date, resulting in a consolidated dataset. Firstly, we removed nineteen columns, such as category, category_url, clickthrough_url, currency, funds_raised_percent, image_url, is_pre_launch, product_stage, project_id, project_type, source_url, tagline, tags, and title, due to redundancy and data unwanted because of their insignificance to the analysis, which are. Subsequently, data regarding campaigns with high pledge values were removed, resulting in 74,413 campaigns. A new column, called "duration," was introduced, which is calculated as the number of days between the open_date and close_date of the campaign, and the original columns were dropped. Two columns are retained for the analysis: "pledged amount" and "duration". Furthermore, several PGMs were added to the dataset that include "background checks," "financial information," "social media," "cookies," "Google Analytics," and "third-party verification". Lastly, columns representing "success," "COVID-19," and "Kickstarter" were added to the dataset. The objective was to ensure that the resulting dataset was dependable, relevant, and devoid of any errors or inconsistencies. The final dataset has eleven features, as described in Appendix D.

Platforms' governance mechanisms PGMs

The research study also extracts insights from data retrieved via the Wayback Machine and Time Travel, shedding light on the mechanisms adopted by Indiegogo for collecting user information. Indiegogo uses different mechanisms like background checks, financial information, cookies, social media and the Google Analytics tool without providing a name. The platform shares user data with third-party identity verification and payment processors. The collected information includes personal details such as name, date of birth, email address, gender, and financial information like credit card and bank account details. Indiegogo's primary focus in using this information is to protect investors from fraud and improve service quality. However, Indiegogo explicitly states that it does not provide any warranties, including implied warranties related to business practices, merchantability, and non-infringement. The platform emphasizes that no advice or information obtained from their platform establishes any warranty (Indiegogo, 2023). Table 9 displays specific information about the PGMs that have been applied over the years.

Table 9. Detailed information on PGMs for the Indiegogo platform.

PGMs Applied	Platform name						
	Indiegogo						
	2011	2014	2015	2016	2017	2018	2023
Background check	✓	✓	✓	✓	✓	✓	✓
Financial information	✓	✓	✓	✓	✓	✓	✓
Social media	-	✓	✓	✓	✓	✓	✓
Cookies	-	✓	✓	✓	✓	✓	✓
Google analytics	-	✓	✓	✓	✓	✓	✓
Third-party verification	-	✓	✓	✓	✓	✓	✓

The table consists of two columns: the first column contains the names of the mechanisms used, and the second column consists of the years. Hence, it is easy to determine the year in which the mechanism began to be implemented.

Table 9 presents various PGMs used on the Indiegogo platform. While certain mechanisms, such as Background checks and financial information, were consistently applied from 2011 to 2022, making them untestable for evaluating their efficacy. However, we will analyze the impact of mechanisms like social media, cookies, Google Analytics, and third-party services before and after 2014 on campaign performance. This analysis will assess the influence of Social media, Cookies, and Google Analytics on campaign outcomes across both platforms.

Exploratory Data Analysis

EDA for Indiegogo involves examining and visualizing data to gain insights and identify patterns, relationships, and potential anomalies. As part of the analysis, two tables present statistics for each feature, including the mean, standard deviation, minimum, 25%, 50% (median), 75%, maximum, unique values, top value, and frequency.

Table 10 presents descriptive statistics for the amount pledged and the campaigns' duration on the Indiegogo platform. These statistics offer a comprehensive overview of the data's central tendencies, variability, and range across the variables. The average pledged is $35,650.2. It varies considerably, ranging from unfunded campaigns to campaigns under $5 million. For the campaign duration, data show an average duration of almost 41 days, with a range of 0 to 1165 days, indicating that some campaigns lasted for long periods.

Table 10. Descriptive statistics of numerical features for Indiegogo platforms.

Statistic	Mean	Std	Min	25%	50% (median)	75%	Max	Count
Pledged amount	35,650.2	213,411.2	0.0	220.0	1,109.0	5,109.0	4,979,652	74,413
Duration	41.41	20.51	0.0	30.0	43.0	60.0	1165	74,413

The table presents numerical features for two variables: the amount of money raised and the duration. The table includes the mean, standard deviation, minimum, %25, median (%50), %75, maximum, and count for the whole variables, offering a holistic view of campaign performance.

Table 11 summarizes statistics for categories within a dataset, including frequency counts, top values, unique value counts, and the overall dataset count. It covers three main statistics: 'Successful campaign,' which occurs 74,413 times with 'Successful' as the top value and one unique value; 'Category,' which appears 12,965 times with 'Film' as the top value and featuring 30 unique values.

Table 11. Descriptive statistics of non-numerical features.

Statistic	**Freq**	**Top**	**Unique**	**Count**
Category	12965	30	Film	74413

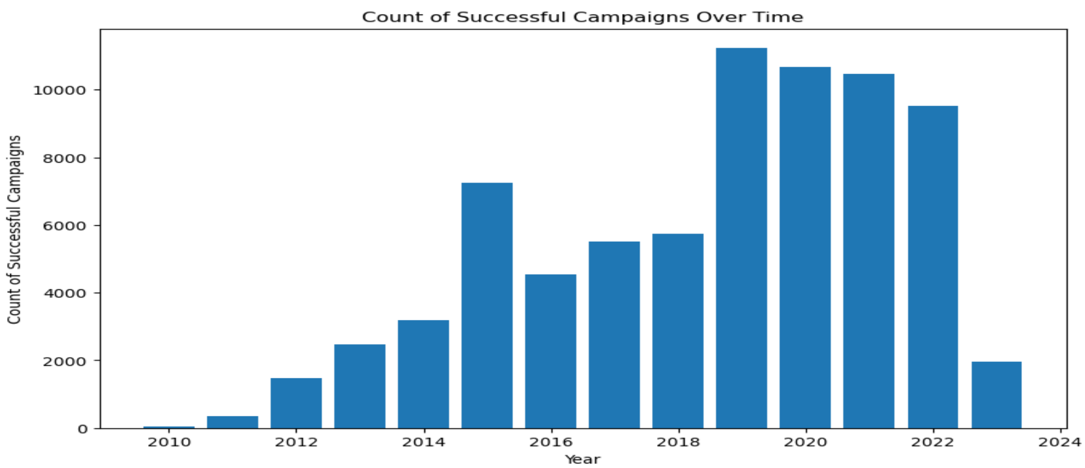
The table presents non-numerical features for two variables: the first is 'category,' indicating campaign types such as games, art, and film. The second variable is 'successful campaign,' which specifically focuses on the campaign's success status. The table provides information on unique values, top values, frequencies, and overall counts for these variables.

It is important to note that the EDA focuses on three indicators that are only available on the site, and they are expected to provide insights into the impact of PGMs on the success of crowdfunding campaigns. These indicators include the successful campaigns, the amount of money raised, and the duration of the campaigns.

A. Number of funded campaigns (Successful campaigns only)

Figure 29 shows the progression of successful crowdfunding campaigns from 2010 to 2022. The data reveals a remarkable upward trend, with the number of successful campaigns consistently increasing over the years. In 2010, the count stood at a few hundred, but by 2019, it had surged to over 10,000 campaigns. However, starting from 2020, there has been a slight decline in the number of successful campaigns, which continued through 2022. The figures dipped below the 10,000 campaigns, indicating a comparatively lower number of successful campaigns during this period.

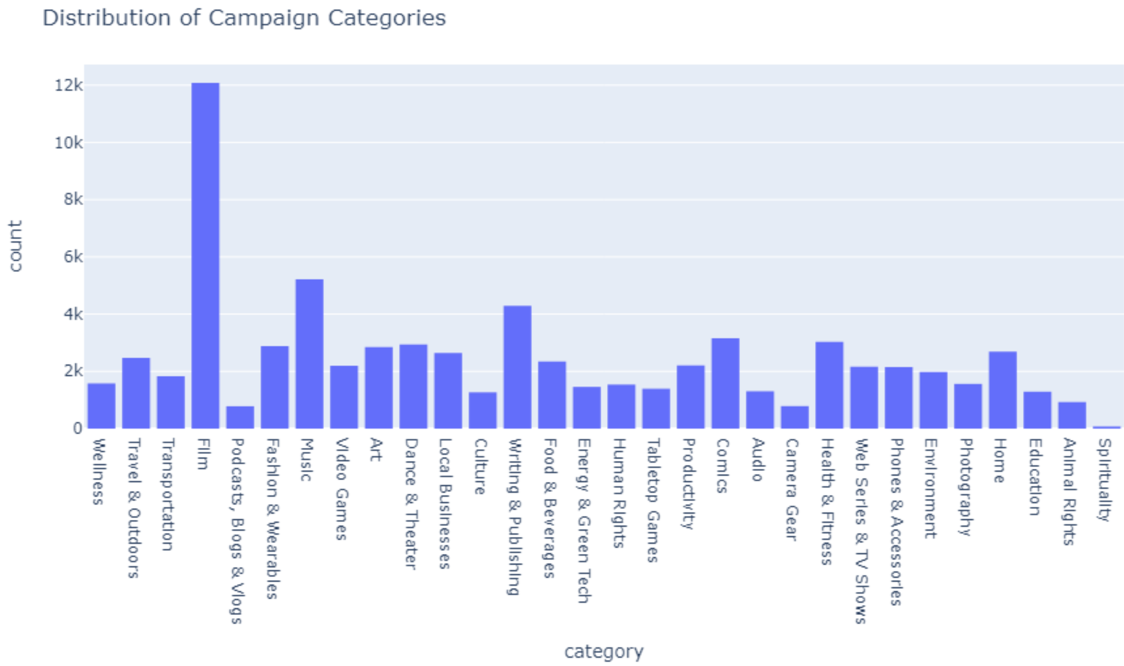
Figure 29. The number of successful campaigns.



The bar plot shows the years of successful campaigns from 2010 to 2022, along with the number of successful campaigns for each year.

Figure 30 displays the distribution of campaigns across different categories from 2010 to 2022. Notably, the film category emerged as the most popular choice, recording the highest number of campaigns during this period. Following closely behind are the music and writing & publishing categories, although they exhibited a relatively smaller number of campaigns compared to the film category. On the other hand, categories such as spirituality, camera gear, and podcasts, blogs & vlogs displayed the lowest number of campaigns. These findings highlight the varying levels of interest and engagement among crowdfunding campaigns across different categories, with film garnering the most attention and support.

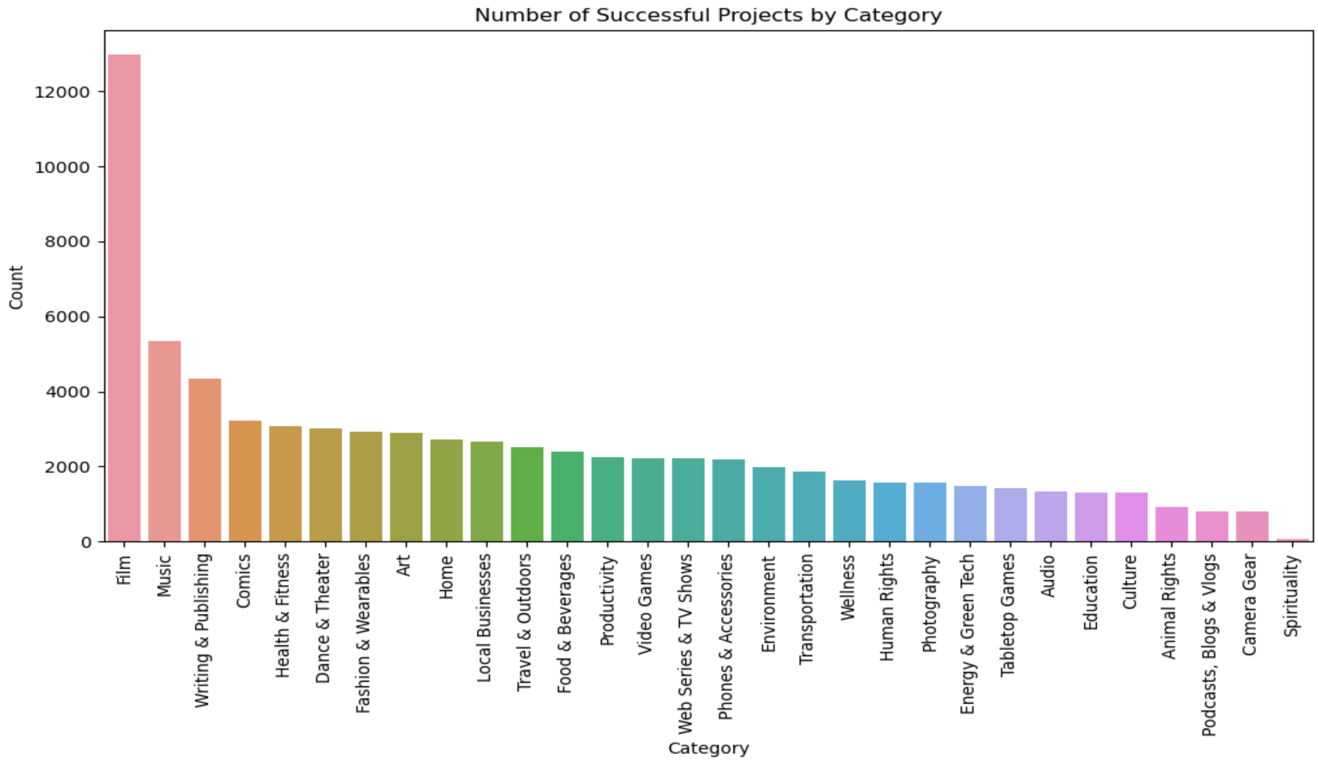
Figure 30. Distribution of campaign categories.



The figure displays different campaign categories: games, music, film, writing and publishing, spirituality, camera gear, podcasts, and blogs and vlogs, along with the number of campaigns for these categories.

On the other side, Figure 31 presents a bar plot depicting the distribution of successful campaigns across various categories. The analysis reveals that the Film category exhibits the highest number of successful campaigns, surpassing all other categories with a count exceeding 12,000. Following Film, the categories of Music and (Writing & Publishing) demonstrate significant success, each recording over 5,000 and 4,000 successful campaigns, respectively. In contrast, the remaining categories display a narrower range of success, with Comics trailing behind with less than 4,000 successful campaigns. This bar gradually decreases until reaching Spirituality, which exhibits the lowest number of successful campaigns among all categories, approximately around 100. These findings offer valuable insights into the distribution of successful campaigns, highlighting the dominance of Film and the varying degrees of success within different campaign categories.

Figure 31. The number of successful campaigns by category.

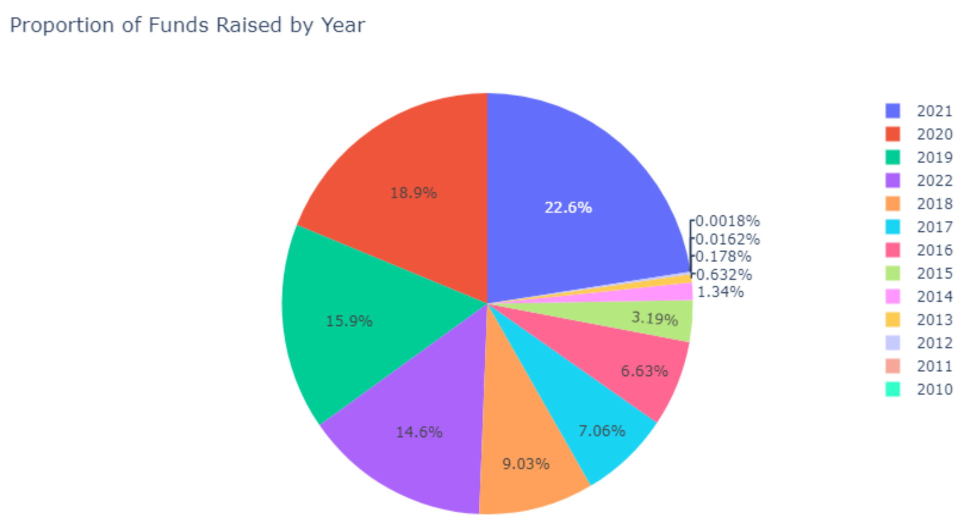


The bar plot presents the distribution of successful campaigns between 2010 and 2022 in various categories, including film, music, writing and publishing, comics, art, culture, and spirituality, along with the number of campaigns for each category.

B. Amount of money raised.

The pie chart presented in Figure 32 points up the distribution of funding raised through Indiegogo between 2010 and 2022. The analysis of the data reveals a consistent growth pattern in funds raised over the years, with a notable surge observed in 2021, accounting for 22.6% of the total funds raised. From 2009 to 2015, the growth in funds collected remained relatively modest, staying below 2%. However, a significant shift in this trend occurred in 2017, marked by an accelerated rate of increase in funding for projects. By 2019, the share of funds allocated to campaigns had reached 9%, indicating a substantial upward trajectory. This upward trend continued into 2020, ultimately culminating in the peak growth observed in funds raised in 2021, accounting for 22.6% of the total.

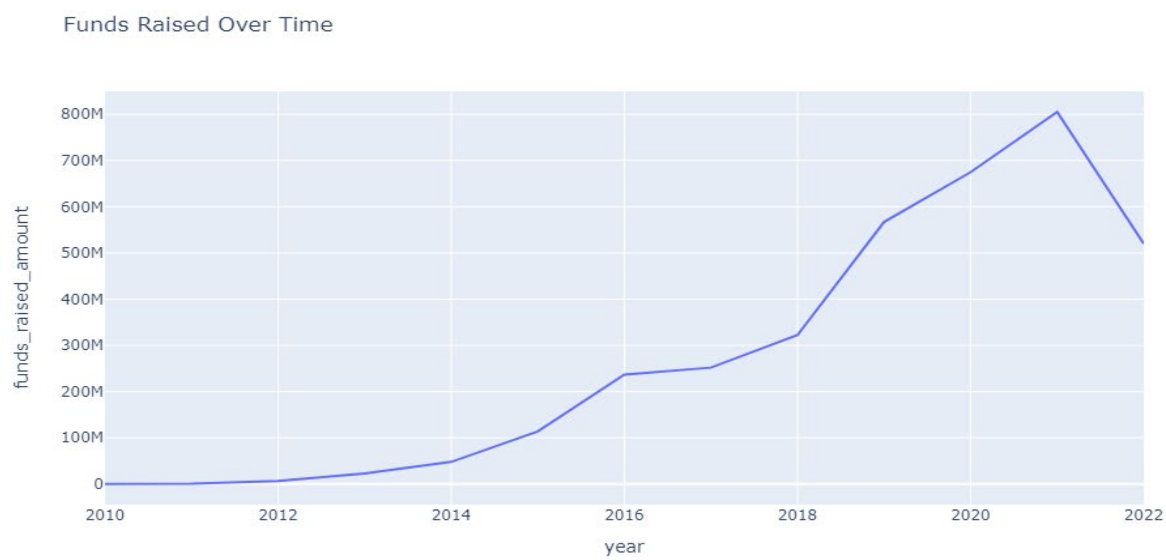
Figure 32. Distribution of funds raised.



The graph shows the amount of money raised in crowdfunding campaigns from 2010 to 2020. Each year is represented by a distinct colour, and numerical annotations indicate the annual increase in funding.

Furthermore, the line chart presented in Figure 33 further supports these findings by demonstrating a steady increase in the amount of funding raised between 2010 and 2022. Notably, 2021 emerges as the peak year in terms of funding, reflecting the culmination of the upward trajectory observed in the data. These findings highlight the remarkable growth and increasing support for Indiegogo campaigns, particularly in recent years.

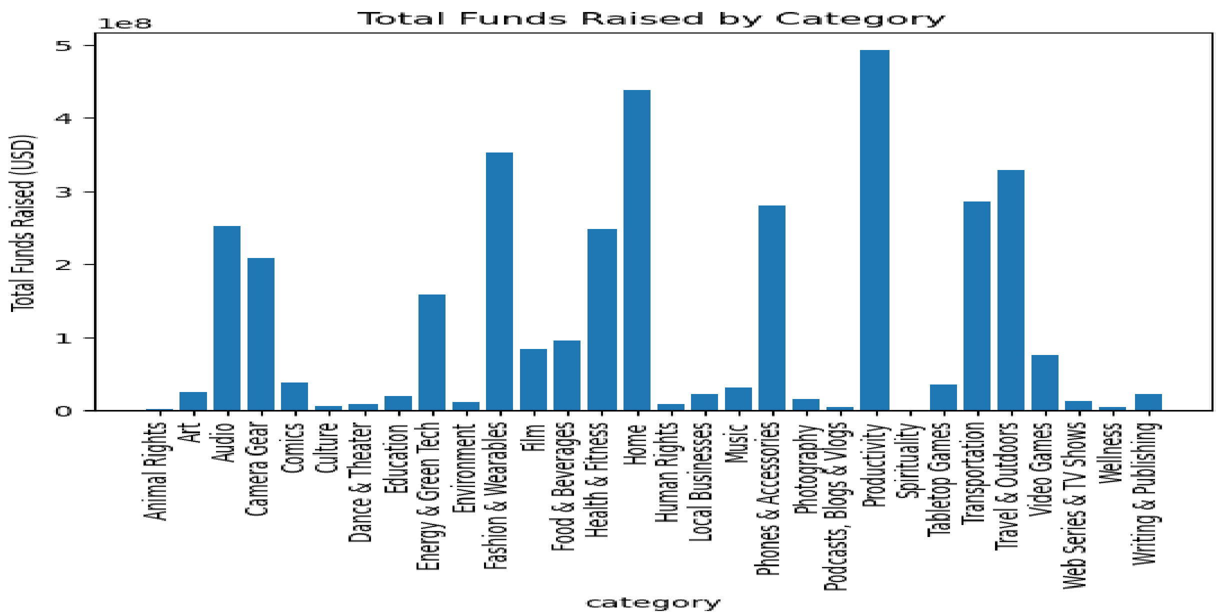
Figure 33. The amount of funds raised over the years.



The line chart displays the amount of money raised in millions, along with the corresponding year for each collected sum between 2010 and 2022.

Figure 34 presents the distribution of funds raised across different categories. Among the categories, Productivity, Home, Fashion & Wearables, Travel & Outdoors, Phones & Accessories, Transportation, Health & Fitness, Audio, Camera Gear, and Energy & Green Tech stand out as the top-performing categories, accumulating the highest amnt funds raised. Conversely, the remaining categories show relatively lower amounts of funds raised. One notable finding is the category of Film, which exhibits a higher number of campaigns, but a comparatively lower amount of funds raised. This observation may be seen as unexpected, considering the popularity and widespread appeal of film-related projects.

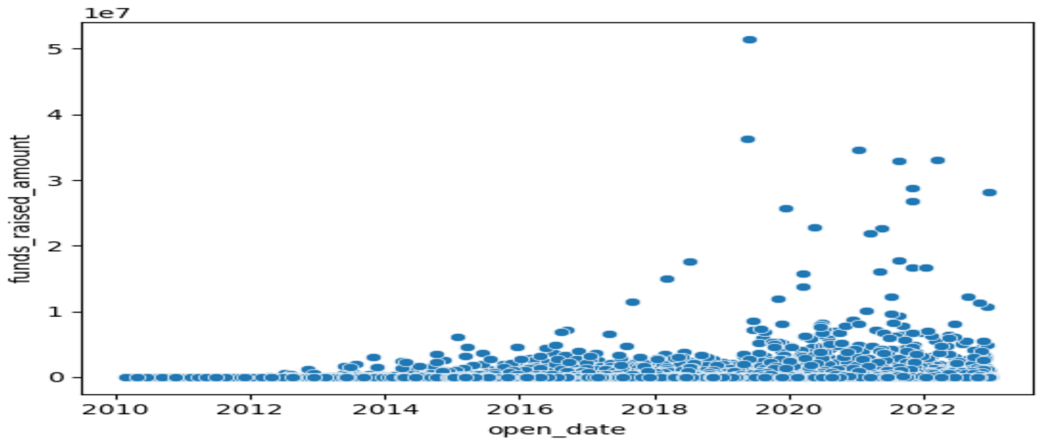
Figure 34. The amount of funds raised by category.



The figure displays campaigns in various categories, such as productivity, home, fashion and wearables, travel and outdoors, phones and accessories, transportation, audio, camera gear, and energy and green tech, along with the total funds raised for each category.

The scatter plot, labeled as Figure 35, showcases a correlation between the length of the fundraising period and the corresponding amount of money gathered. The plot distinctly illustrates a consistent upward trend in the funds collected annually, indicating a positive correlation between the passage of time and the raised funds. This finding underscores a positive growth trajectory, where the amount of funds collected increases steadily as each year unfolds. The results shed light on the success of fundraising endeavours over the years and provide valuable insights into the patterns and dynamics of financial contributions in the studied context.

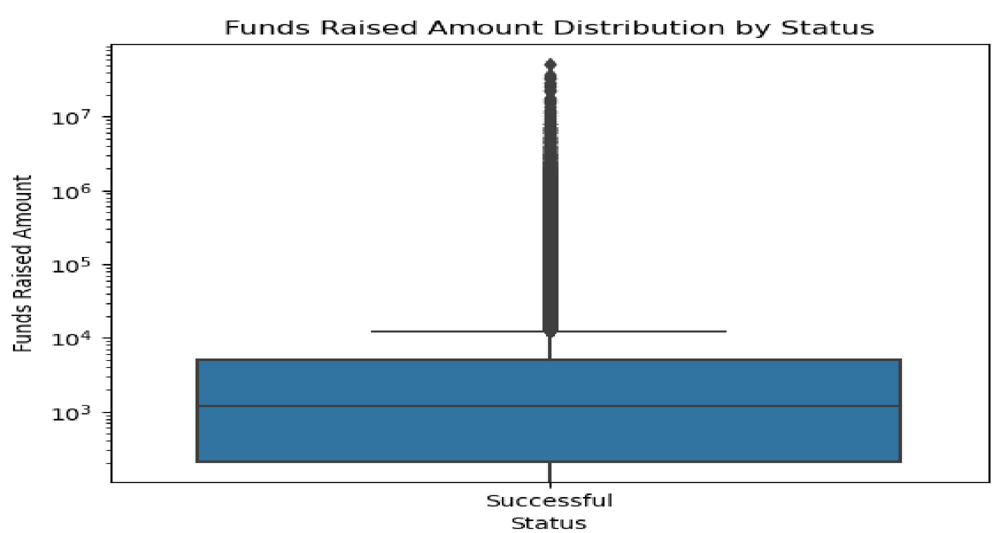
Figure 35. The total amount raised with duration.



A scatter plot illustrating the correlation between fundraising duration from 2010 to 2022 and the amount of money collected during this period.

A boxplot is presented in Figure 36. It can be observed that successful campaigns tend to have a significantly higher amount of money raised. This indicates that successful campaigns have been able to attract significantly more financial support.

Figure 36. Distribution of funds raised for successful campaigns.

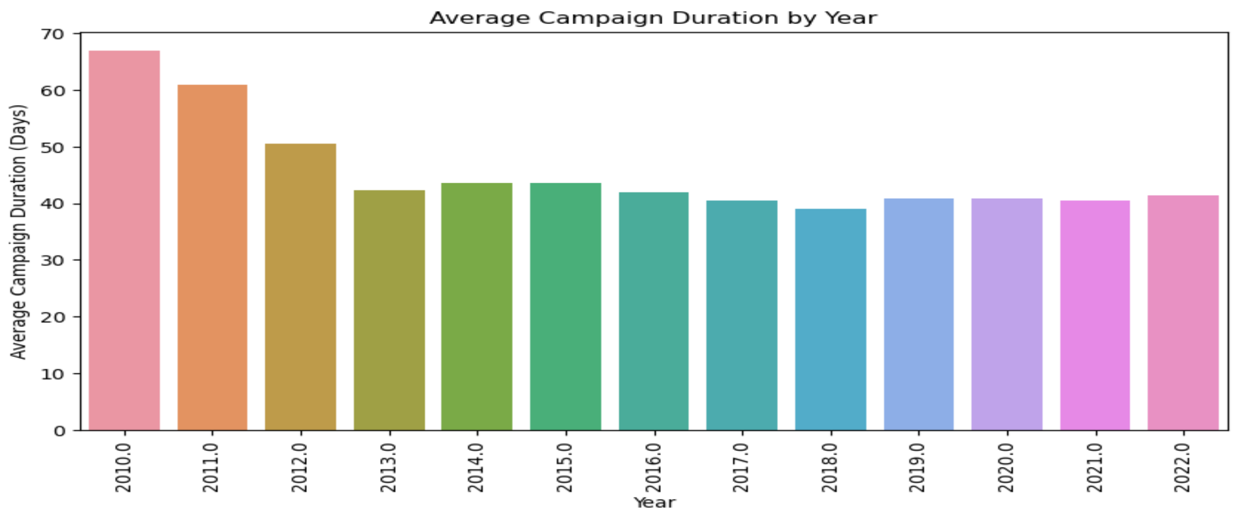


The figure displays the amount of money raised for successful campaigns status from 2010 to 2022.

C. The duration of campaigns

Figure 37 presents valuable insights regarding the average duration of funding campaigns spanning from 2010 to 2022. The graph reveals a notable trend wherein the cam dur experienced a consistent decline from 2010 to 2013. During this period, the average duration decreased significantly from over 60 days to approximately 40 days.

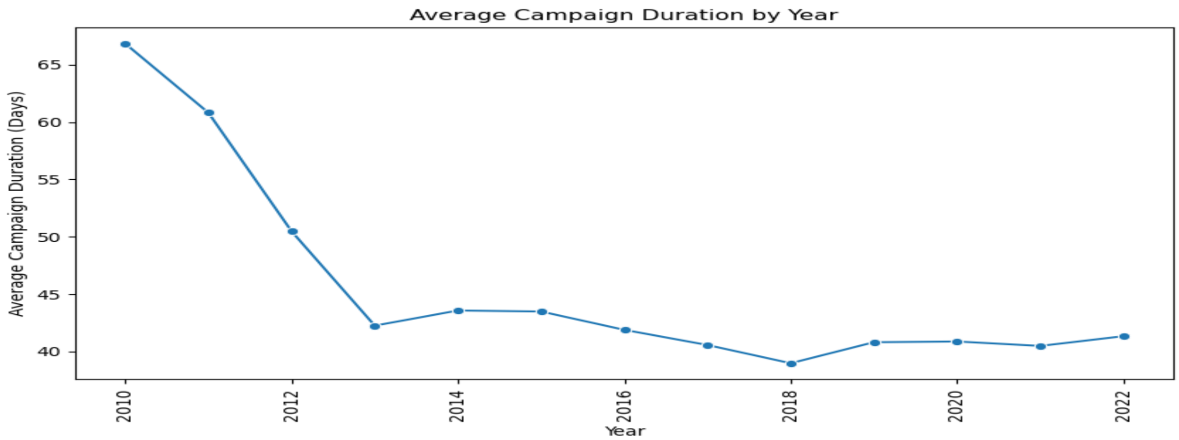
Figure 37. Average duration of funding campaign.



The bar plot displays the average campaign funding duration, including the corresponding years from 2010 to 2022, where each year's average campaign duration is represented.

However, starting from 2013, the average cam dur stabilized, remaining relatively constant throughout the subsequent years until 2022, maintaining an average duration of around 41 days. Furthermore, in Figure 38, the line chart provides additional support for our findings. It shows that, initially, the average duration of funding campaigns exceeded 60 days and gradually decreased to around 40 days by 2013. After 2013, the average duration remained relatively consistent in the subsequent years.

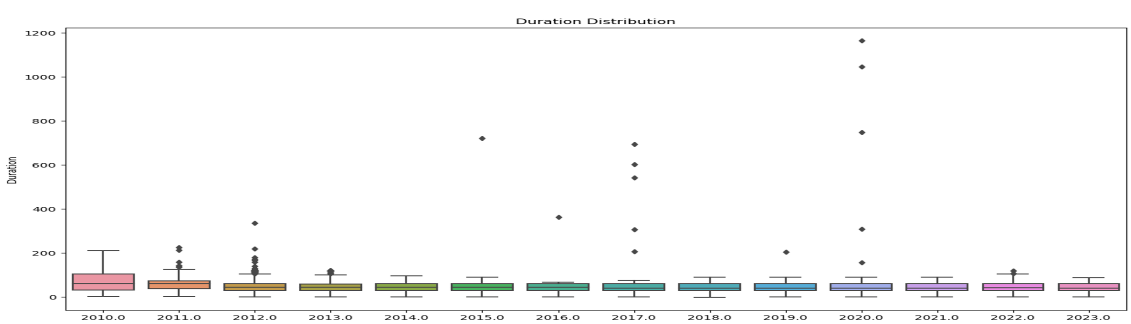
Figure 38. Average campaign duration in years.



The line chart presents the average campaign duration of funding, along with the years that represent the average campaign duration for each year between 2010 and 2022.

Upon examining Figure 39, the boxplot presented significant insights into the average duration of funding campaigns spanning the period from 2010 to 2022. The graph highlights a noteworthy trend, indicating a consistent decline in campaign duration during the initial years. Starting at over 60 days in 2010, the average campaign duration gradually decreased over the next three years, reaching approximately 40 days by 2013. Subsequently, from 2013 onwards until 2022, the average campaign duration remained relatively stable.

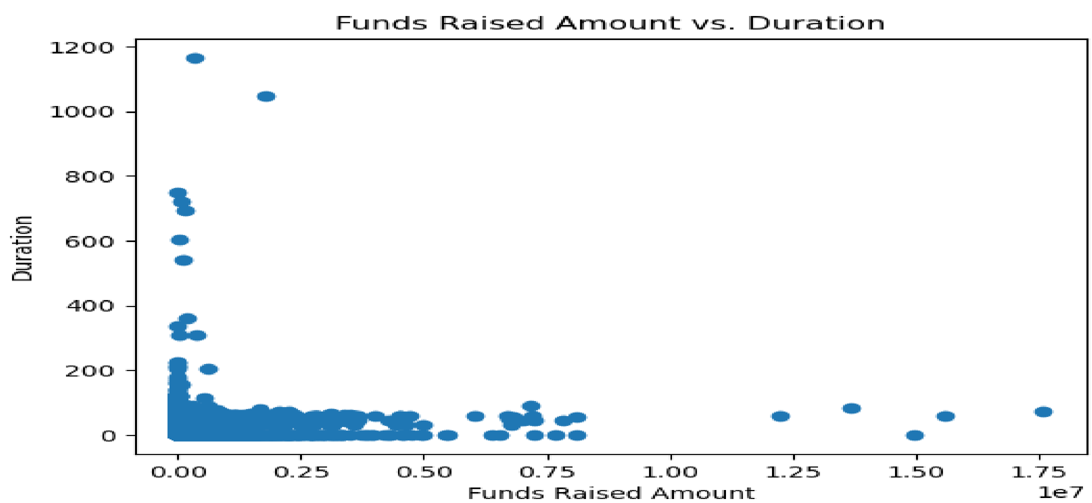
Figure 39. A box Plot for the Average Campaign Durations.



A box plot for the average campaign duration in funding, and the years that represent the average campaign duration for each year between 2010 and 2022.

The scatter plot in Figure 40 depicts the relationship between the average duration of campaigns and the corresponding amount of money raised. It shows that there is no positive or negative correlation between the amount of money raised and the campaign duration. However, there are a few cases where a longer campaign duration is associated with a higher amount of funds collected. Consequently, it can be inferred that campaigns requiring a greater amount of time to reach their funding goals tend to attract more financial support.

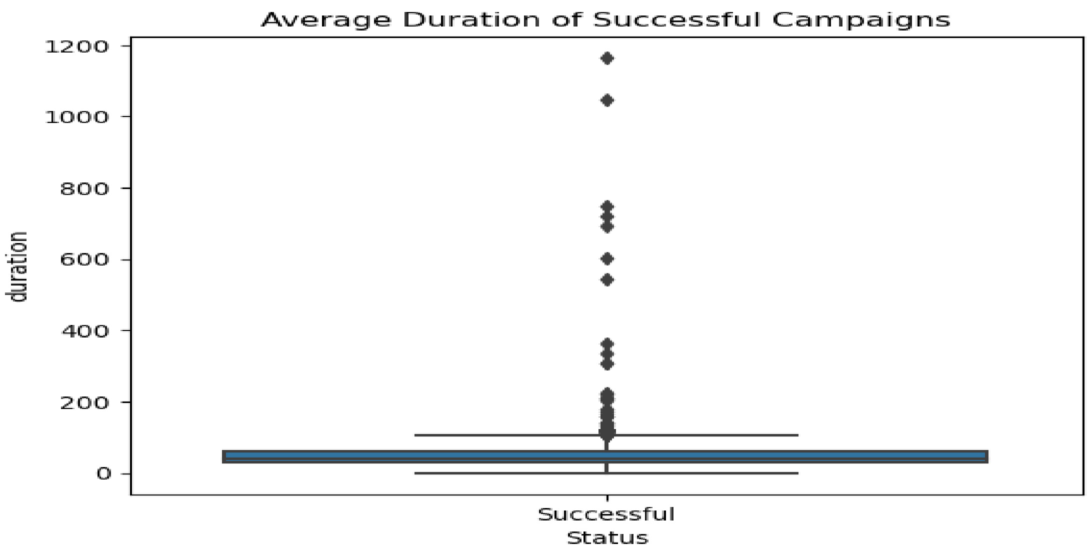
Figure 40. The amount of Funds raised over the duration.



The boxplot shows a correlation between the amount of money raised and the campaign duration between 2010 and 2022.

Figure 41 presents the box plot of the average duration of successful campaigns. Although a few successful campaigns exhibit longer durations, reaching approximately 1200 days, the majority of campaigns display relatively short average durations, with less than 50 days. These findings indicate that while some successful campaigns may require an extended time frame to achieve their goals, most successful campaigns tend to have shorter durations. This information provides valuable guidance for campaign planning and suggests that a concise timeframe may contribute to campaign success.

Figure 41. Average duration of successful campaigns.



The graph shows the average duration of successful campaign statuses between 2010 and 2022.

4.2 Equity-based crowdfunding

Equity crowdfunding platforms have become increasingly popular in recent years, offering investors the opportunity to purchase equity in startups and early-stage companies in exchange for a stake in the company. Several popular equity crowdfunding platforms operate in the US, including Wefunder, Fundable, StartEngine, and Republic. Wefunder is an equity crowdfunding platform that allows both accredited and non-accredited investors to invest in startups. According to their website, Wefunder has helped fund over 1,300 companies, raising over $200 million (Wefunder, 2023). Fundable is another platform that allows startups to raise funds through equity crowdfunding, as well as through traditional fundraising methods. Fundable has helped fund over

1,100 companies, raising over $500 million (Fundable, 2023). StartEngine is a platform founded in 2015 that allows both accredited and non-accredited investors to invest in early-stage startups. StartEngine has helped fund over 800 companies, raising over $300 million (StartEngine, 2023). Republic is a platform that allows both accredited and non-accredited investors to invest in startups, offering a range of investment opportunities from traditional equity offerings to revenue-sharing and debt offerings. Republic has helped fund over 700 companies, raising over $400 million (Republic, 2023).

Overall, equity crowdfunding has provided startups with a new way to raise funds and has allowed investors to invest in high-risk, high-potential startups. According to a report by Crowdfund Capital Advisors, equity crowdfunding in the US raised $1.3 billion in 2020, with an average deal size of $443,000 (Crowdfund Capital Advisors, 2021). As the equity crowdfunding industry continues to grow, it is likely that more platforms will emerge, providing even greater investment opportunities for both startups and investors.

Data Collection and Pre-processing

The dataset for equity-based platforms was created by aggregating and preprocessing data from monthly datasets obtained from www.KingCrowd.com. Regarding the preprocessing stage of our thesis dataset, we employed several steps to ensure data cleanliness and organization. Initially, we dropped seventy-two columns that included redundant and unwanted data because they will be irrelevant for the analysis, such as cik, jurisdiction_of_incorporation, industry, raises_state_abbr, companies_url, blog, and staff_pick. Second, we eliminated 78 columns that contained only words which are 'Null', 'Niche', 'Wide', 'Yes' and 'No' (Not a Number), such as crowdfunding_type_2_id, accelerator_program_name, market_at_round_market_regulation, rega_financials_total_asset, and price_per_share, or consisted entirely of zero values, such as rev_share_return_multiple and debt_interest_rate. Two columns remain: "the number of funders" and the "pledge amount". We also removed several campaigns with very large pledge amounts, resulting in 2,262 campaigns. A new column, called "duration," was introduced, which is calculated as the number of days between the start_date and close_date of the campaign, and the original columns were dropped. Furthermore, a few PGMs containing "background checks," "financial information," "social media," "cookies," "Google Analytics," and "third-party verification" were added to the dataset. Lastly, columns representing "success" and "COVID-19" were added to the dataset. All these steps were done to ensure the resulting dataset is accurate, relevant and free of defects or inconsistencies. The final dataset contains twelve features, which are outlined in Appendix D.

Platforms' governance mechanisms PGMs

Equity platforms, unlike reward crowdfunding platforms, are subject to more regulation and oversight. Many equity platforms are registered under the supervision of the US Securities and Exchange Commission (SEC) and are members of the Financial Industry Regulatory Authority (FINRA), see Table 12. These platforms collect various types of information from users, including personal details such as name, age, email address, gender, and address. They also collect financial information like credit card and bank account details. The information collected by equity platforms is used to comply with federal, state, and local laws, and any SEC and FINRA regulations. The platforms employ different methods to collect information. Firstly, users are typically required to fill out a form when opening an account on the platform, providing the necessary personal and financial information. Secondly, platforms such as Wefunder, StartEngine and Republic use cookies, Google Analytics, and social media integrations to gather additional information about users' interactions with the platform and their online behaviour.

To ensure the security and integrity of their services, equity platforms often rely on third-party services for identity verification and payment processing. For example, the Wefunder platform uses services like Blockscore, LexisNexis, and Onfido to verify user identities. The collected information serves multiple purposes. It enables platforms to enhance the user experience. Additionally, the information is used to prevent fraud or the recurrence of fraudulent activities, protecting both the platform and its users from potential risks.

It's important to note that equity platforms do not verify the adequacy, accuracy, or completeness of the information provided by entrepreneurs on their platforms. They do not provide any warranty, express or implied, regarding the adequacy, accuracy, or completeness of the information on their sites or the use of that information. Equity platforms do not offer recommendations on the suitability of specific investment opportunities for individual investors. They are not investment advisors. Ultimately, funders are responsible for making their own investment decisions, either independently or with the assistance of their personal advisors. Some platforms, such as Title3Funds, specifically state that funders are responsible for conducting their own due diligence or seeking guidance from their professional investors.

To evaluate the effectiveness of PGMs, the data available for equity platforms beginning in 2018 rendering any mechanisms implemented prior to that year non-testable. Conversely, there's a chance that many platforms adopted new mechanisms after 2016, and we can use these for our tests. We're also planning to assess these PGMs across different types of platforms, including equity and reward-based ones. As of now, we have collected PGM data for a few equity platforms, and we're actively researching the rest.

Table 12. Information details about PGMs for multiple equity platforms.

PGMs Applied	Platform name						
	Wefunder						
	2012	2015	2016	2017	2018	2020	2021
Background check	✓	✓	✓	✓	✓	✓	✓
Financial information	✓	✓	✓	✓	✓	✓	✓
Social media	-	-	-	✓	✓	✓	✓
Cookies	✓	✓	✓	✓	✓	✓	✓
Google analytics	-	-	-	✓	✓	✓	✓
Third-party verification	-	✓	✓	✓	✓	✓	✓

PGMs Applied	Platform name				
	SeedInvest				
	2012	2013	2019	2021	2022
Background check	✓	✓	✓	✓	✓
Financial information	✓	✓	✓	✓	✓
Social media	-	✓	✓	✓	✓
Cookies	-	✓	✓	✓	✓
Google analytics	-	✓	✓	✓	✓
Third-party verification	-	✓	✓	✓	✓

PGMs Applied	Platform name							
	StartEngine							
	2011	2015	2017	2018	2019	2020	2021	2022
Background check	✓	✓	✓	✓	✓	✓	✓	✓
Financial information	✓	✓	✓	✓	✓	✓	✓	✓
Social media	-	✓	✓	✓	✓	✓	✓	✓
Cookies	✓	✓	✓	✓	✓	✓	✓	✓
Google analytics	-	✓	✓	✓	✓	✓	✓	✓
Third-party verification	-	✓	✓	✓	✓	✓	✓	✓

PGMs Applied	Platform name		
	Netcapital		
	2016	2018	2022
Background check	✓	✓	✓
Financial information	✓	✓	✓
Social media	-	-	-
Cookies	✓	✓	✓
Google analytics	-	-	-
Third-party verification	✓	✓	✓

PGMs Applied	Platform name	
	TruCrowd	
	2016	2022
Background check	✓	✓
Financial information	✓	✓
Social media	-	-
Cookies	✓	✓
Google analytics	-	-
Third-party verification	✓	✓

PGMs Applied	Platform name	
	MainVest	
	2019	2023
Background check	✓	✓
Financial information	✓	✓
Social media	-	-
Cookies	✓	✓
Google analytics	✓	✓
Third-party verification	✓	✓

PGMs Applied	Platform name	
	SMBX	
	2020	2022
Background check	✓	✓
Financial information	✓	✓
Social media	✓	✓
Cookies	✓	✓
Google analytics	✓	✓
Third-party verification	✓	✓

Exploratory Data Analysis

EDA is a fundamental approach in understanding the dataset used in this thesis. It plays a critical role in identifying patterns, relationships, and potential anomalies within the data. This analysis involves a thorough examination of the data, accompanied by visualizations in the form of tables, which provide essential statistics for each feature. Two tables present a key statistic such as the mean, standard deviation, minimum value, quartiles (25%, 50%, 75%), maximum, uniqueness, the most frequent value, and count.

Table 13 provides a comprehensive statistical overview of crowdfunding campaign performance. It consists of three key metrics: 'Amount pledged' indicates an average campaign funding of around $257,482.7 with a standard deviation of $545,327.9, ranging from unfunded campaigns of $0.00 to $5 million. 'Number of investors' shows an average of 268 investors per campaign, with a notable standard deviation of 645 and a wide range from 0 to an impressive 8,653 investors. The 'Duration of campaign' metric reveals an average campaign length of 131 days, with a standard deviation of 105.40 days, varying from 0 to a maximum of 1,073 days. These insights, derived from an analysis of 2,262 campaigns, provide valuable information about crowdfunding fundraising levels, investor participation, and campaign durations.

Table 13. Descriptive statistics of numerical features for equity platforms.

Statistic	Mean	Std	Min	25%	50%	75%	Max	Count
The number of investors	268.16	645.1	0.00	0.00	40.0	185.0	8,653	2262
Pledged amount	257,482.7	545,327.9	0.00	2,583.43	60,994.5	256,541.8	5,000,000	2262
Duration	131.25	105.40	0.00	63.0	94.0	171.0	1073.0	2262

The table presents numerical features for three variables: 'the number of funders,' 'the amount of money raised,' and 'duration time.' The table includes the mean, standard deviation, minimum, %25, median (%50), %75, maximum, and count for the whole variables, offering a holistic view of campaign performance.

Table 14 provides statistics related to the "Raise status" mechanism. It was used 2,273 times, with "Successful" as the unique status, and it appeared most frequently, 3,170 times. The EDA focuses on four key indicators that are collected and expected to provide insights into the impact of PGMs on the success of crowdfunding campaigns across different platforms. The data we have includes all indicators except suspended campaigns. These indicators are the number of funded campaigns, the number of funders, the amount of money raised, and the duration of the campaigns. By thoroughly examining the available indicators, we can gain a comprehensive understanding of the relationship between PGMs and the success of crowdfunding campaigns.

Table 14. Descriptive statistics of non-numerical features.

Statistic	Freq	Unique	Top	Count
Raise status	2248	Successful	3	2262

The table presents a summary statistic for an indicator that encompasses non-numeric attributes. The variable 'Raise status' offers a succinct description of the campaign's current state, indicating whether it has been successful, canceled, or not funded.

A. Number of funded campaigns

Table 15 presents an insightful overview of the campaign distribution across thirty-two platforms operating in the USA. The data reveals that a few platforms have launched over a hundred campaigns between 2018 and 2021; these platforms have experienced growth and are gaining traction among crowdfunding participants. In contrast, the remaining platforms have a relatively smaller number of campaigns attributed to them. This suggests that a select few platforms have been more active in hosting crowdfunding campaigns. The table also includes information on the campaign statuses, categorizing them as successful, cancelled, or not funded. It is noteworthy that the percentage of successful campaigns is significantly higher when compared to the combined percentage of cancelled and not funded campaigns. This finding underscores the overall success rate of campaigns across the platforms, indicating that a substantial number of campaigns have achieved their funding goals.

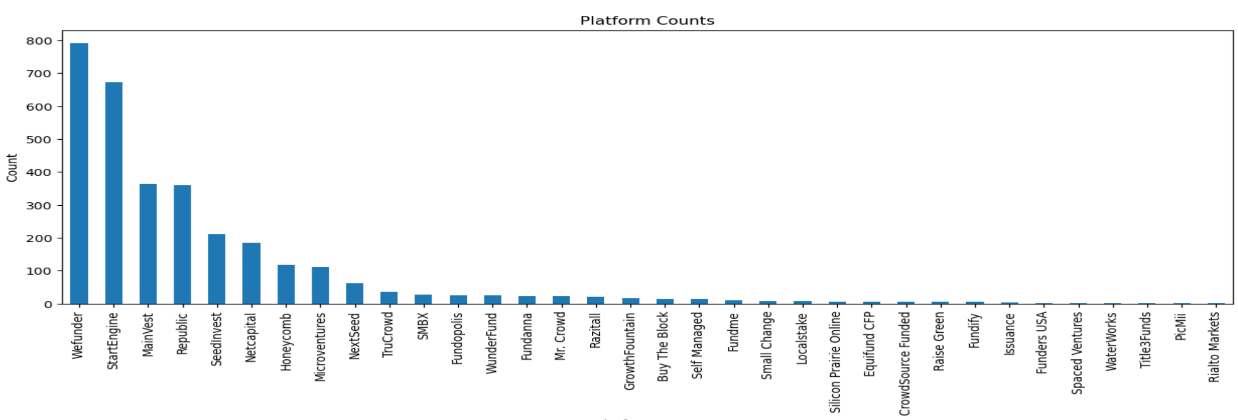
Table 15. Number of campaigns for each platform and their status.

Platform name	Campaign number	Campaign status		
		Successful	Not funded	Cancelled
Wefunder	791	634	80	77
StartEngine	672	476	8	188
MainVest	365	163	182	20
Republic	359	324	32	3
SeedInvest	210	112	8	90
Netcapital	186	158	28	0
Honeycomb	119	98	16	5
Microventures	111	90	12	2
NextSeed	63	53	4	6
TruCrowd	36	25	7	4
SMBX	27	24	2	1
Fundopolis	25	13	11	1
WunderFund	25	12	2	11
Fundanna	24	19	3	5
Mr. Crowd	23	6	4	13
Razitall	22	1	32	14
GrowthFountain	17	2	9	6
Buy The Block	15	11	4	0
Self-Managed	15	15	0	0
Fundme	11	3	4	4
Small Change	8	5	3	0
Localstake	8	6	0	2
Silicon Prairie Online	6	3	3	0
Equifund CFP	6	6	0	0
CrowdSource Funded	5	1	1	3
Raise Green	5	4	0	1
Fundify	5	4	1	0
Issuance	3	3	0	0
Funders USA	2	0	1	1
Spaced Ventures	2	2	0	0
WaterWorks	1	0	1	0
Title3Funds	1	1	0	0
PicMii	1	0	1	0
Rialto Markets	1	1	0	0

This table contains three columns, which list 32 equity-based crowdfunding platforms. It offers information about the number of campaigns conducted by each platform between January 2018 and June 2021, along with the current status of these campaigns on each platform.

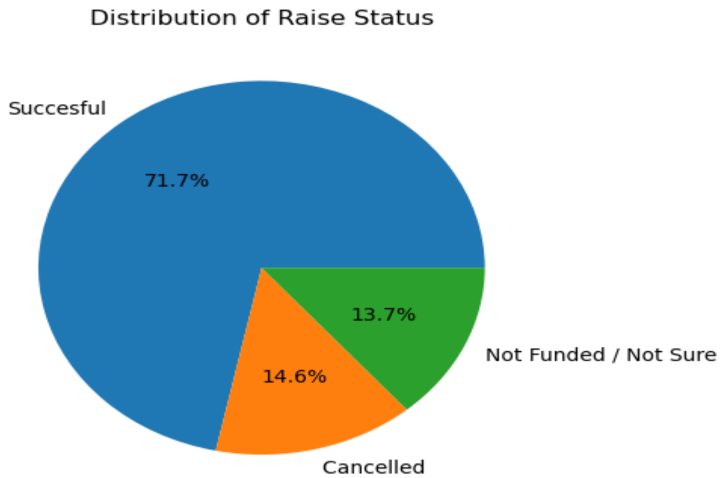
Figure 42 presents a comprehensive overview of the distribution of campaigns across different equity platforms. The graph reveals that Wefunder and StartEngine are the two platforms with the highest number of campaigns, having 791 and 672 campaigns, respectively. Following closely are Mainvest and Republic, with 365 and 359 campaigns, respectively. Additionally, SeedInvest, Netcapital and Micro ventures are shown to have 210, 186 and 111 campaigns, respectively. The rest of the platforms have less than 70 campaigns between 2018 and 2021. It is worth noting that the remaining platforms have fewer than 70 campaigns during the period from 2018 to June 2021. It shows that Wefunder and StartEngine are serving as the top choices for campaign creators. Meanwhile, Mainvest, Republic, SeedInvest, and Netcapital also establish themselves as platforms with significant campaign presence.

Figure 42. The number of campaigns on 32 equity-based platforms.



The table shows the performance of 32 equity-based platforms, including Wefunder and Rialto Market. It provides a detailed breakdown of the number of campaigns conducted on each platform during this time frame.

Figure 43. Distribution of campaign status.

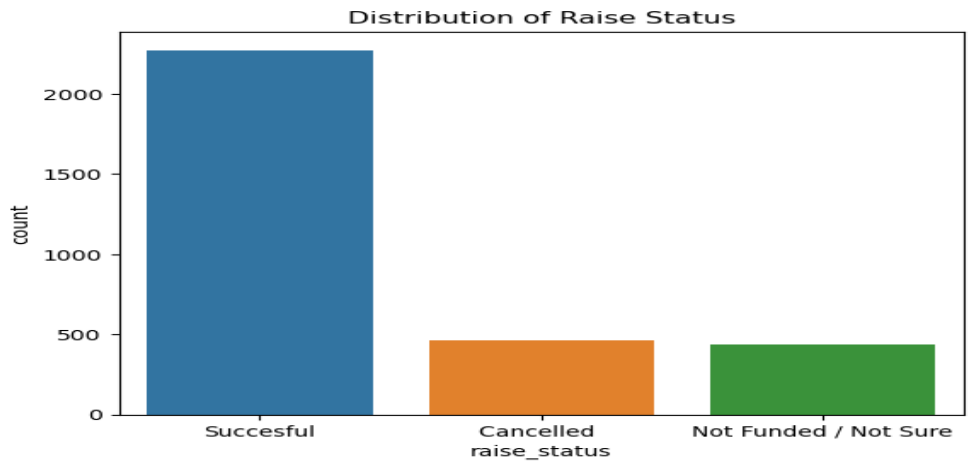


The graph represents three different statuses: successful, not funded, and cancelled campaigns, along with numerical values indicating the size of each status category.

Figure 43 presents a comprehensive analysis of campaign statuses across various equity platforms. The data reveals a significant dominance of successful campaigns, accounting for over 71% of all campaigns conducted between 2018 and 2021. In contrast, the number of cancelled and not funded campaigns is relatively lower, representing approximately 28% of the total. These findings highlight the prevalence of successful campaigns in the equity crowdfunding landscape and emphasize the importance of distinguishing them from the comparatively smaller proportions of cancelled and not funded campaigns.

Figure 44 provides a visual representation of the number of successful, cancelled, and not funded campaigns. The bar plot clearly shows that successful campaigns significantly outnumber cancelled and not funded campaigns. Specifically, the plot indicates that there are more than 2000 successful campaigns, whereas both cancelled and not funded campaigns have approximately 500 instances each. This observation highlights the disparity in outcomes among these campaign categories, suggesting that a substantial number of campaigns achieve success, while a smaller proportion are either cancelled or fail to secure funding.

Figure 44. A Bar Chart of campaign status.



The bar chart displays the outcomes of various campaigns' status, including successful, cancelled, and unfunded campaigns, along with the number of campaigns associated with each status.

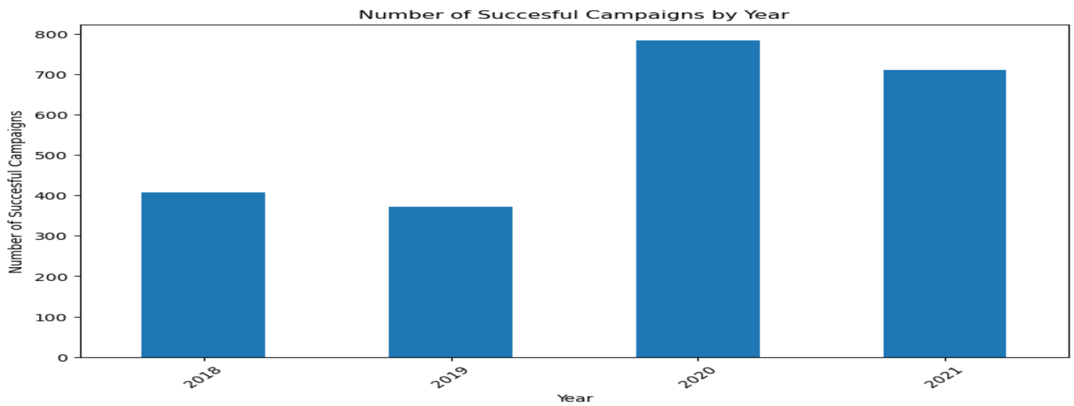
To conduct a deeper analysis of the campaign states, we used the provided labels to generate bar plots categorized by campaign type. Additionally, we focused on the top platforms, determined by the number of campaigns, as depicted in Figure 45. The bar plots revealed intriguing insights. Firstly, it was observed that Wefunder emerged as the top category, displaying the highest number of campaigns overall, with a noteworthy count of 634 successful campaigns. However, when considering the not funded campaigns, the Mainvest category stood out, encompassing 182 campaigns that did not meet their funding goals. On the other hand, StartEngine exhibited a significant number of cancelled campaigns, totalling 188. These findings shed light on the distribution of campaign outcomes across different categories and platforms, providing valuable information for further analysis and understanding of the crowdfunding landscape.

Figure 45. The status of campaigns of all equity-based platforms.

The figure displays four graphs illustrating the distribution of campaign statuses, including successful, not funded, and cancelled campaigns. Furthermore, there is a graph representing all equity platforms. Next to each graph, the number of campaigns for each platform is provided.

According to the bar plot in Figure 46, the num fun campaigns expressed a substantial growth pattern, doubling over the years analyzed. Specifically, the count of funded campaigns escalated from approximately 400 in both 2018 and 2019 to approximately 800 in 2020. This upward trajectory indicates a significant increase in the successful outcome of crowdfunding campaigns during the period under consideration.

Figure 46. The number of successful campaigns.

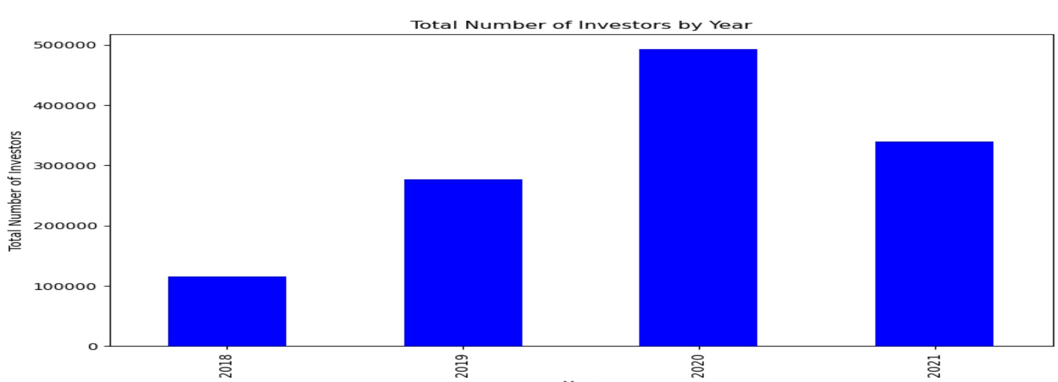


The chart displays the years of successful campaigns across all platforms, accompanied by the respective number of successful campaigns for each year.

B. Number of Funders

The bar plot labeled as 47 provides insights into the number of funders who participated in supporting crowdfunding projects from January 2018 to June 2021. By analyzing the plot, it becomes clear that the number of funders steadily increased between 2018 and 2020. However, in 2021, there was a noticeable drop in the number of funders. It is important to note that the data in the plot is limited to June 2021 and, therefore, does not encompass the entirety of the year.

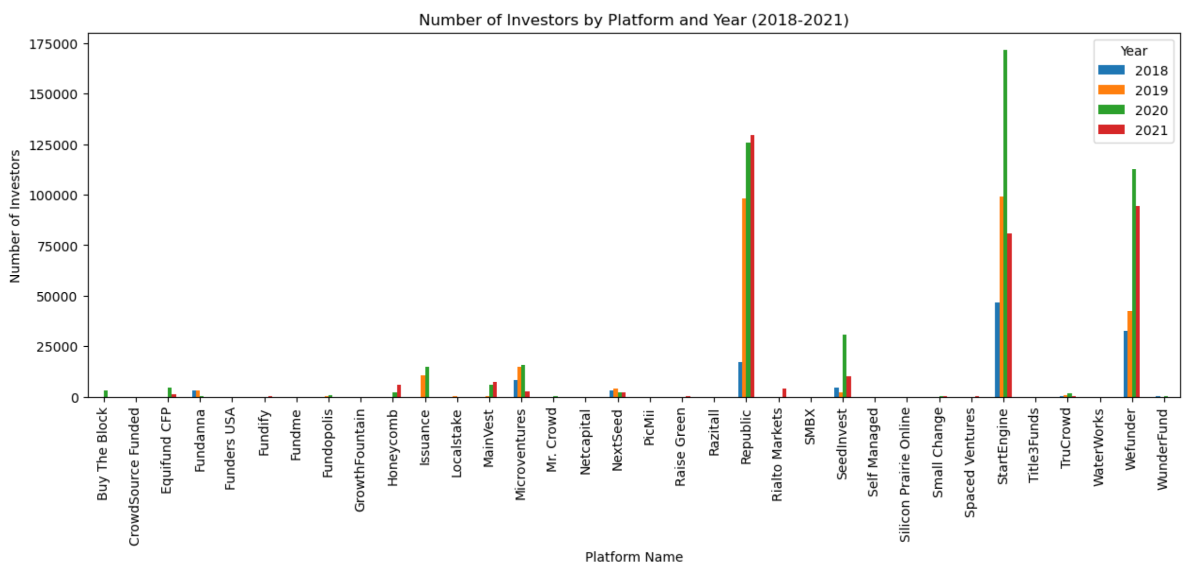
Figure 47. Total number of investors participating in the campaigns.



The figure displays the total number of funders who participated in equity campaigns between January 2018 and June 2021.

Bar plot 48, which shows certain crowdfunding platforms, namely StartEngine, Wefunder, Republic, Microventures, SeedInvest, NextSeed, and Fundanna, consistently attract a substantial number of funders each year, reaching into the thousands. In contrast, other platforms generally experience a lower number of investors, occasionally falling below a thousand in certain years and occasionally surpassing that threshold in subsequent years. For instance, TruCrowd had 191 investors in 2018, followed by a significant increase to 1,854 investors in 2020, and then a decrease to 179 investors in 2021. This fluctuation in investor participation emphasizes the varying levels of interest and engagement across different crowdfunding platforms

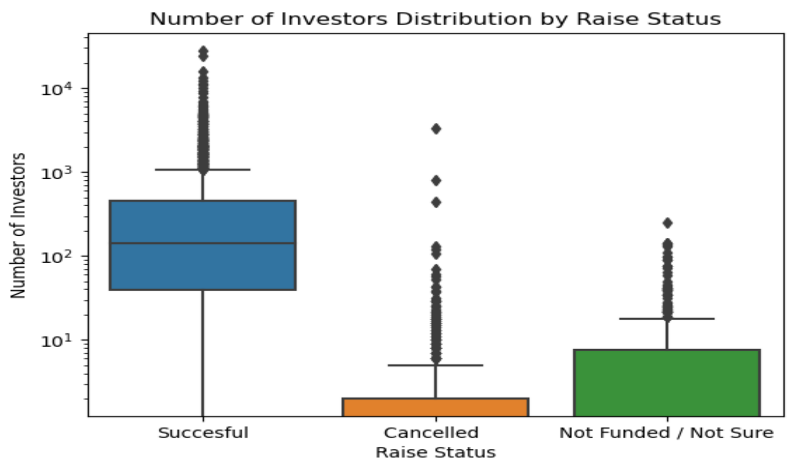
Figure 48. Total number of investors by year.



The number of investors in crowdfunding campaigns across all equity platforms, such as StartEngine, Wefunder, Republic, Microventures, SeedInvest, NextSeed, and Fundanna, is represented by different colours for each year.

In Figure 49, we can see a clear pattern when we look at the relationship between a campaign's outcome and the number of people who supported it. The graph reveals that successful campaigns consistently have more supporters, while cancelled and unsuccessful campaigns tend to have fewer funders. This suggests that the number of funders plays a crucial role in determining the success or failure of a campaign.

Figure 49. Campaign status and participating funders.

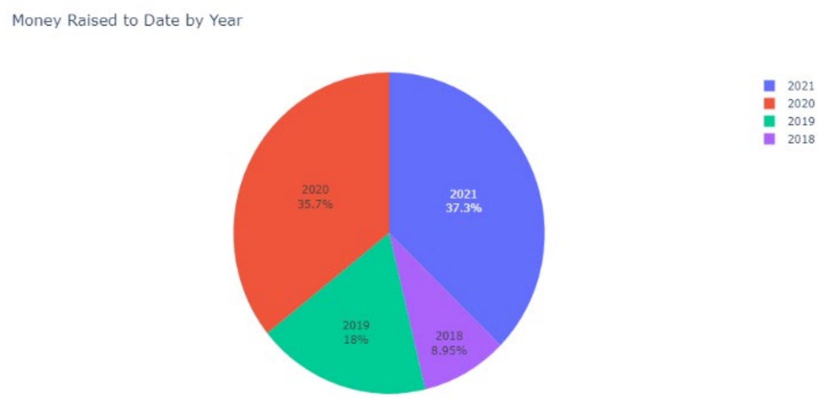


The figure shows the campaign status for successful, not funded, canceled, and campaigns, along with the number of funders who participated for each status.

C. Amount of money raised.

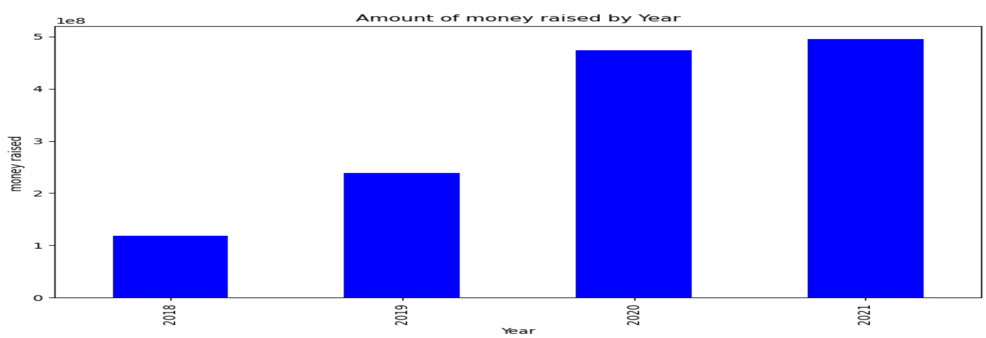
Figures 50 and 51 provide an overview of the funds raised across 32 platforms during a three-year period. The data indicates a gradual increase in the amnt mon raised over time. Notably, the pie chart further reinforces this trend, showing a significant increase in the percentage of funds raised, rising from 18% in 2019 to 35.7% in 2020 and further to 37.3% in 2021. These findings suggest a positive growth trajectory in the total funds raised, with 2021 standing out as a particularly successful year in terms of financial contributions.

Figure 50. Distribution of funds raised.



The graph shows the amount of money raised in crowdfunding campaigns from 2018 to 2021. Each year is represented by a distinct colour, and numerical annotations indicate the annual increase in funding.

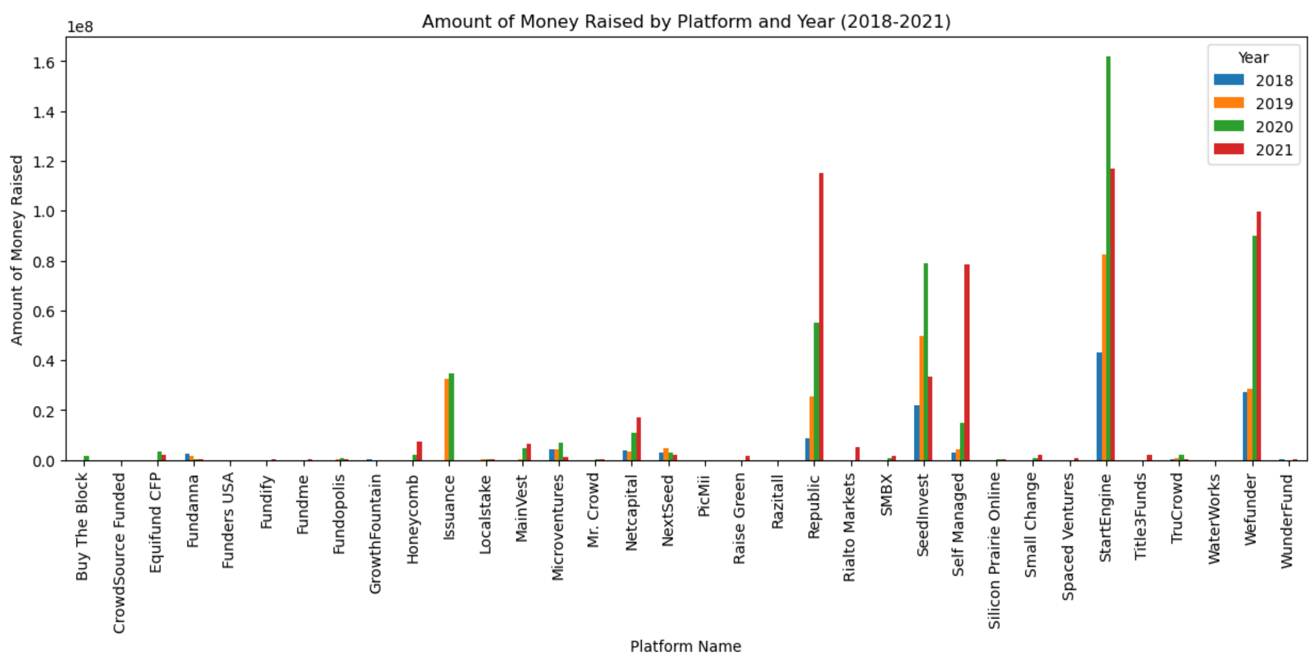
Figure 51. The amount of funds raised by year.



The line chart displays the amount of money raised for all platforms, along with the corresponding year for each collected sum between 2018 and 2021.

In Figure 52 shows a notable correlation between the annual increase in funds raised and the years spanning from 2018 to 2021. During this period, certain platforms emerged as dominant players, including StartEngine, Wefunder, Republic, Microventures, SeedInvest, NextSeed, and Fundanna. These platforms have consistently attracted substantial amounts of funding, surpassing other platforms in terms of monetary contributions. This trend is further supported by the number of investors involved in supporting projects. It is obvious that platforms with a larger investor base tend to generate higher funding outcomes. These findings highlight the significance of investor participation in driving funding success, as platforms with greater investor engagement tend to achieve more substantial financial results.

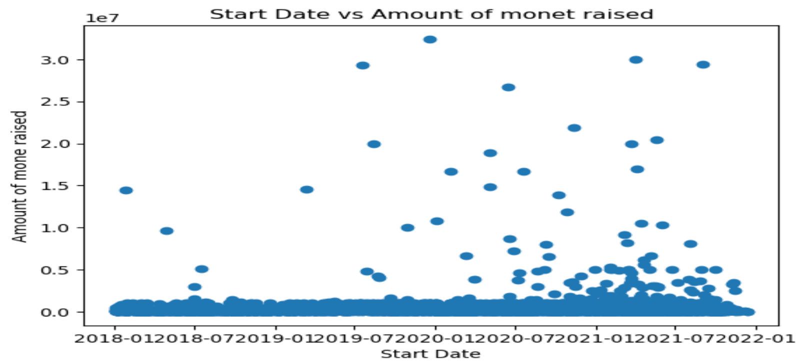
Figure 52. The amount of funds raised by the platform



The figure displays the amount of money raised by all equity crowdfunding platforms, ranging from Wefunder to Buy the Block, during the years 2018 to 2021, each year represented by a different colour.

Scatter plot 53 exhibits that there is a correlation between the length of the period and the amount of money gathered. The plot clearly indicates a consistent increase in the funds collected each year, with a positive correlation between the years and the amount of money raised. This suggests a positive growth trajectory, with a higher amount of funds being collected as each year progresses. These findings highlight the successful fundraising efforts over the years.

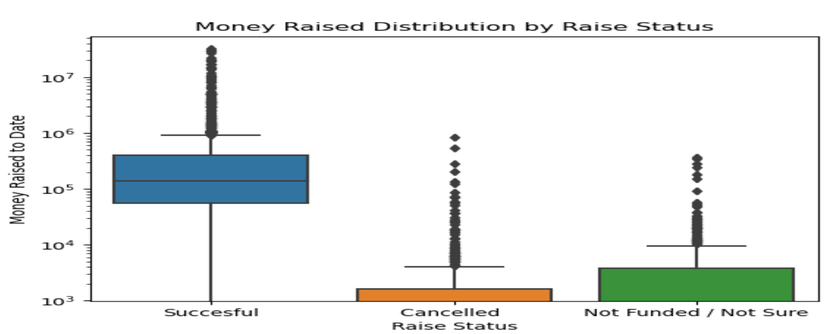
Figure 53. Distribution of funds raised by year.



The graph displays the years between 2018 and 2021, along with the total amount of money raised by all platforms during this period.

Figure 54 highlights a significant trend regarding the pledged amount in relation to the state of crowdfunding campaigns. Notably, it is obvious that cancelled campaigns or those that did not receive funding generally raised a relatively small amount of money compared to successful campaigns. This suggests that successful campaigns are more effective in generating greater financial support from funders.

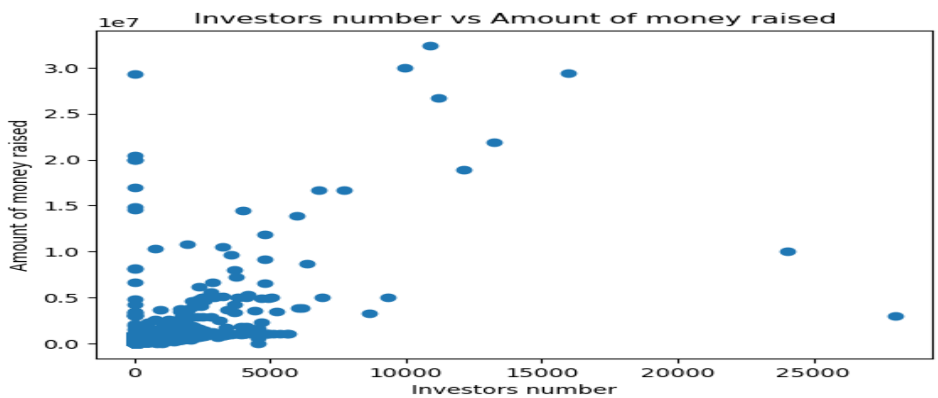
Figure 54. The amount of funds raised by the status.



The figure displays campaign statuses: successful, not funded, and cancelled campaigns, along with the amount of money raised for each status.

Figure 55, a scatter plot, depicts the relationship between the number of investors and the amount of money raised. The data clearly reveals a positive correlation, indicating that as the number of investors increases, the amount of money raised also tends to increase. This finding underscores the notion that a larger base of funders is associated with higher levels of money raised. Consequently, it suggests that attracting more investors can be instrumental in achieving greater fundraising success.

Figure 55. The number of investors and the amount of funds raised.

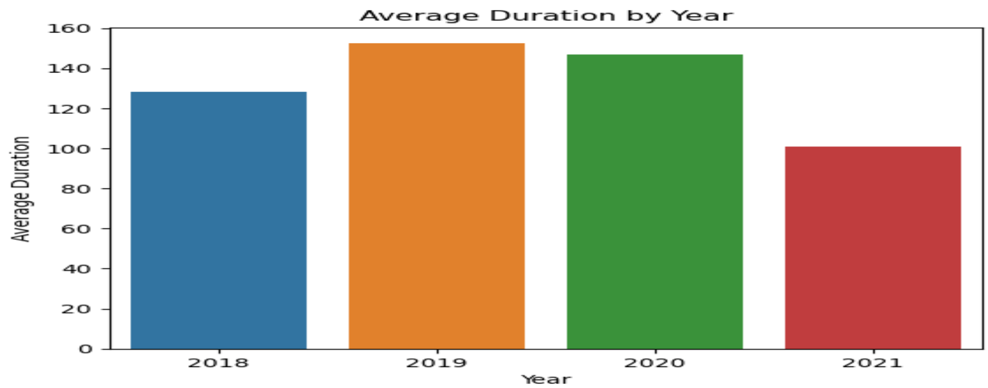


The figure displays the correlation between the number of participating investors and the amount of money raised in funding campaigns.

D. Campaigns duration

Figure 56 presents insightful information on the average duration of funding campaigns from 2018 to 2021. The graph demonstrates a clear pattern of campaign durations over this period. In 2018, the average campaign duration exceeded 120 days, indicating a significant timeframe for fundraising efforts. Subsequently, in both 2019 and 2020, the average campaign duration extended further to over 140 days, suggesting a trend of campaigns lasting even longer. However, there is a notable departure from this pattern in 2021, as the average campaign duration reduced to approximately 100 days, representing a considerable decrease compared to previous years.

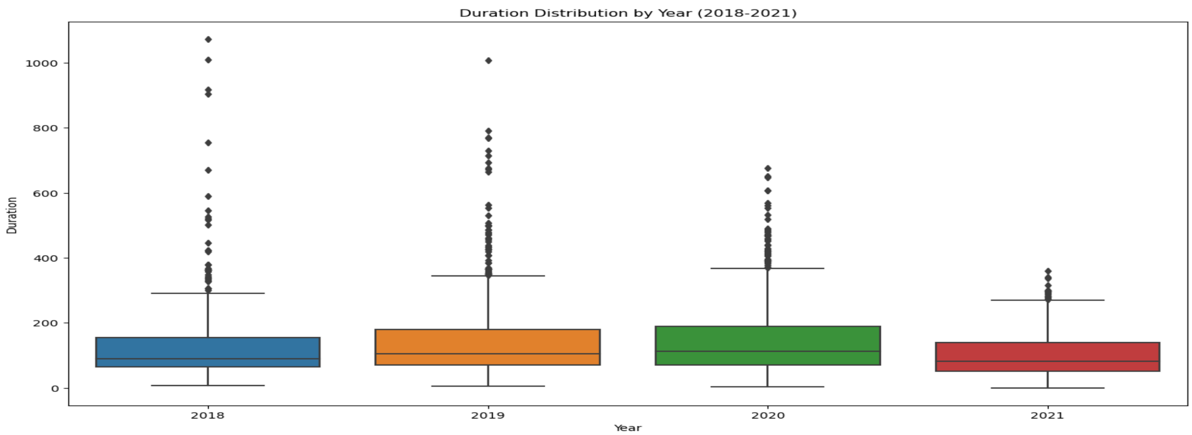
Figure 56. Average duration of campaigns.



The bar plot displays the average campaign funding duration for the years 2018 to 2021, representing the average duration for each of these years.

Similarly, Figure 57 provides additional confirmation of the average duration of funding campaigns across multiple years. The data reveals a consistent trend of fluctuating campaign durations. In 2018, the average campaign duration was approximately 128 days, which notably increased to 150 days in 2019. While 2020 saw a slight decrease to 145 days, 2021 witnessed a more substantial reduction to 100 days, reflecting the shortest average duration among the analyzed periods. This change may reflect adaptations to evolving donor preferences or improved methods for engaging potential funders.

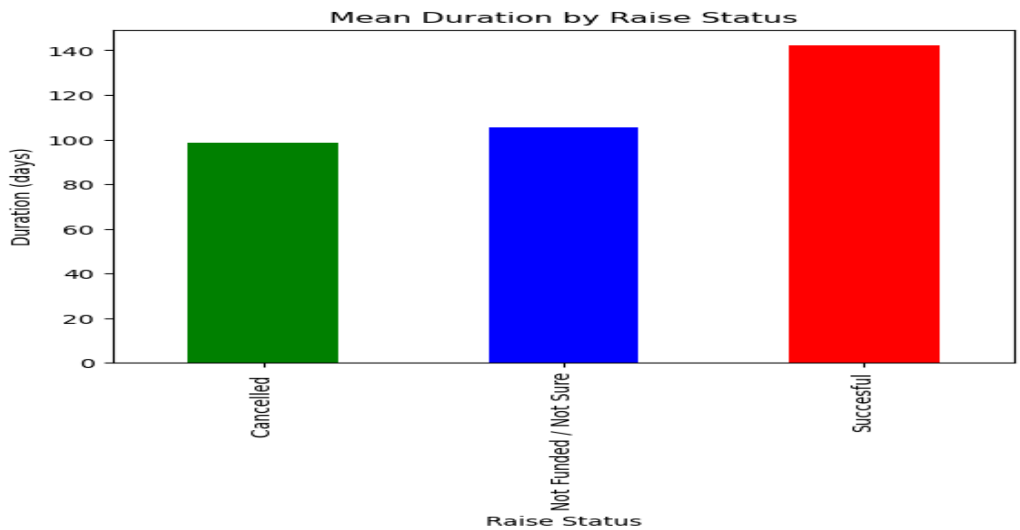
Figure 57. Variation in campaign duration over the years.



The figure displays the campaign duration years between 2018 and 2021, along with the average campaign duration.

Figures 58 and 59, a bar plot, offer valuable insights into the average duration of campaigns based on their status. The data analysis indicates that successful campaigns generally have a longer average duration, spanning approximately 140 days. In contrast, cancelled and not funded campaigns tend to have shorter durations, averaging around 100 days. This finding suggests that successful campaigns often require a more extended period to secure the desired funding compared to campaigns that are cancelled or fail to receive adequate funding.

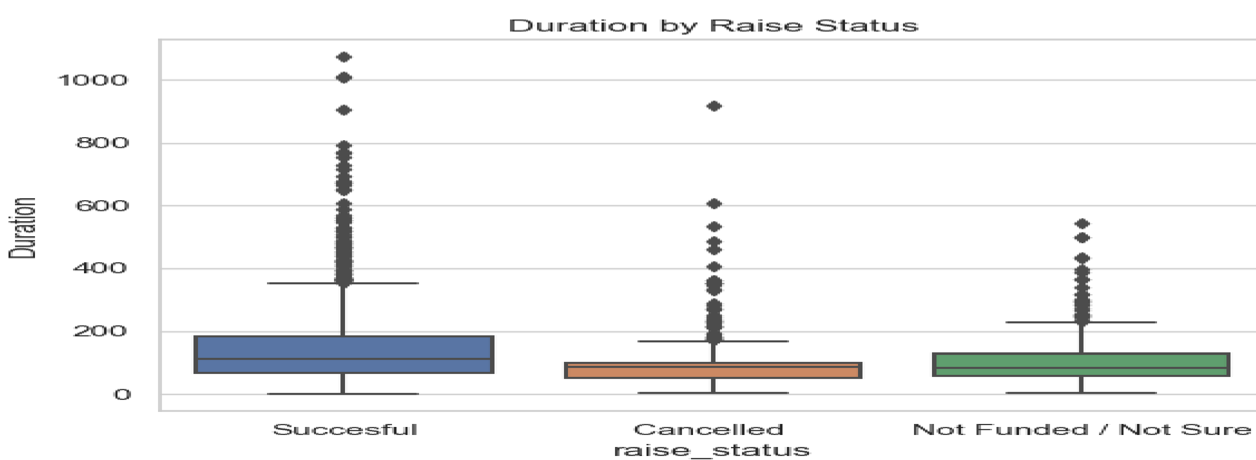
Figure 58. Average duration and campaign status.



A bar plot displays campaign statuses: successful, not funded, and cancelled campaigns, along with the average campaign duration for each status.

Not funded campaigns also display a duration between 100 and 150 days, while cancelled campaigns show the shortest duration, typically less than 100 days.

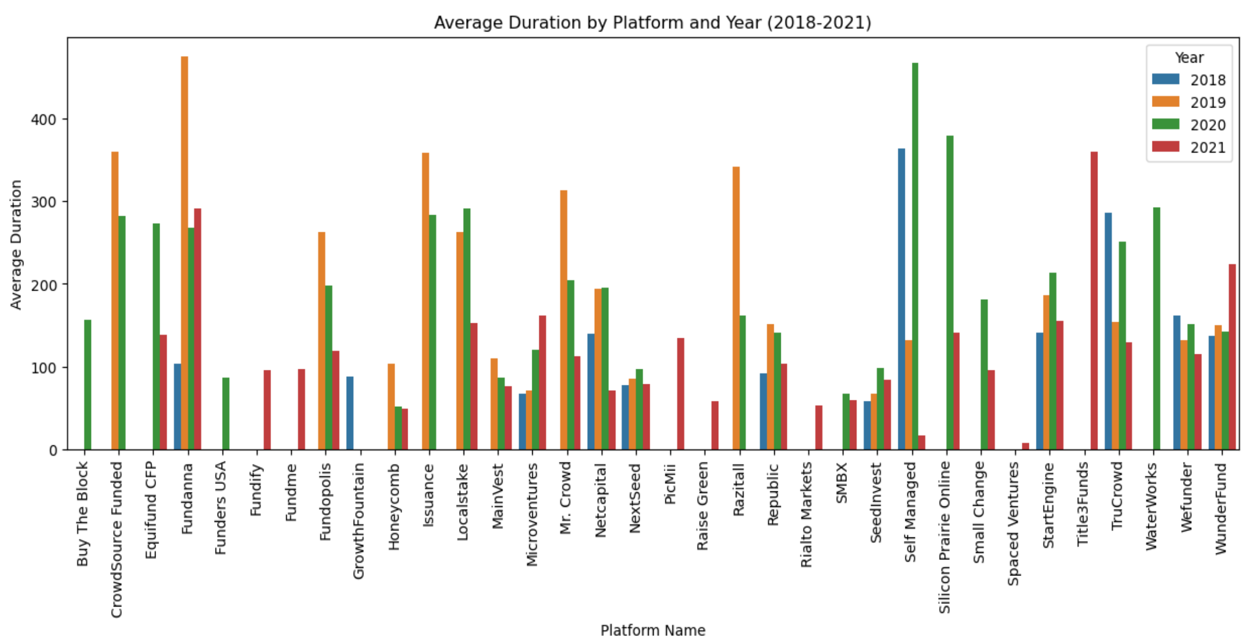
Figure 59. Average duration with respect to status.



The figure shows campaign statuses: successful, not funded, and cancelled campaigns, along with the number of campaign durations for each status.

Figure 60, an analysis of average campaign durations across various platforms, is presented. The data highlights notable variations in average durations, with some platforms exhibiting significantly longer durations exceeding 600 days. Specifically, platforms like Fundanna, Self Managed, Razitall, and Mr. Crowd have average durations surpassing 600 days, indicating a lengthier period for campaigns to reach their funding goals. On the other hand, despite Wefunder and StartEngine having the highest number of campaigns, their average durations are relatively shorter. Wefunder boasts an average duration of less than 200 days, while StartEngine follows closely with an average duration of approximately 300 days. These findings suggest that campaigns on these platforms tend to achieve their funding targets within a comparatively shorter timeframe.

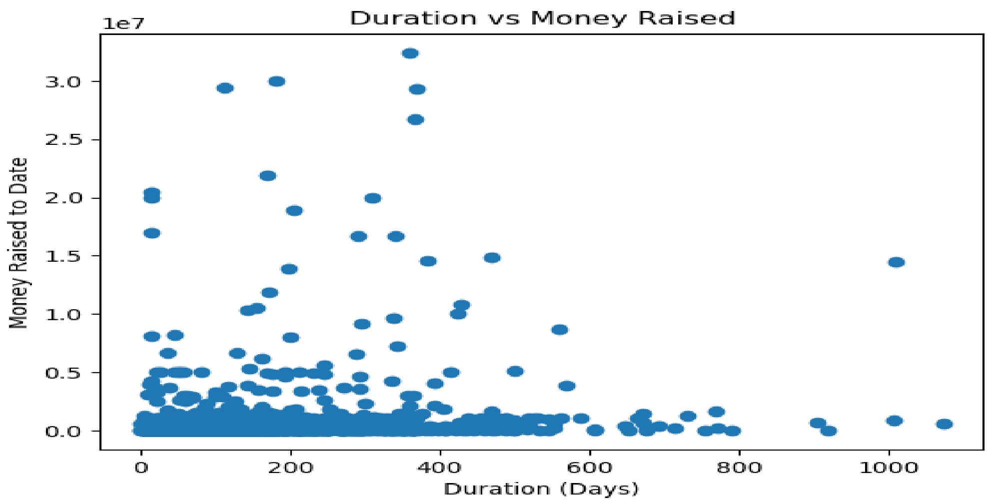
Figure 60. Average duration by platform.



The figure presents the average campaign duration across all equity crowdfunding platforms, spanning from Wefunder to Buy the Block. This data covers the years from 2018 to 2021, with each year represented by a distinct colour.

Scatter plot 61 presents that there is a correlation between the length of the period and the amount of money gathered. The plot clearly indicates a consistent increase in the funds collected each year, with a positive correlation between the years and the amount of money raised. This suggests a positive growth trajectory, with a higher amount of funds being collected as each year progresses. These findings highlight the successful fundraising efforts over the years.

Figure 61. A scatter plot of duration with funds raised.



A scatter plot shows a correlation between average campaign duration and the amount of funds raised.

In this data, the duration of campaigns is a bit higher than in the other dataset. One reason could be that, in order to finance various projects in terms of equity raising, it takes more time, and we see that the box plots show the duration to be less than 200 days.

4.3 Conclusion

4.3.1 Reward-based crowdfunding

The data on PGMs was collected through the Wayback Machine and Time Travel, revealing significant changes in the mechanisms employed by the Kickstarter platform from 2012 to 2022, as shown in Table 6. Initially, during the period from 2012 to 2018, Kickstarter's approach revolved around background checks and financial information to verify creators' identities and assess their financial credibility, thereby ensuring the integrity of campaigns and protecting funders. As Kickstarter expanded and encountered new challenges, it augmented its risk management strategies, adding Third-party providers between 2018 and 2022. These additional measures are likely aimed at enhancing fraud detection and bolstering platform security. Furthermore, in response to the evolving technological landscape, Kickstarter integrated digital tools into its mechanisms from 2018 to 2022, including Social Media and cookies, as well as Google Analytics, to gain insights into user behaviour and interactions. These data-driven approaches likely enabled Kickstarter to improve campaign recommendations and enhance the overall user experience. This dynamic evolution reflects Kickstarter's proactive efforts to adapt to the changing needs and challenges of its crowdfunding ecosystem.

On the other side, the five indicators that have been analyzed show noteworthy results. An analysis of Figures 1 and 2 reveals that suspended campaigns, which are associated with fraudulent activities, make up a very small percentage, specifically 0.25% of the total campaigns, suggesting trust in the Kickstarter platform. Figures 4 and 5 emphasize the relatively small representation of fraudulent incidents and potential fraud cases compared to the vast majority of non-fraudulent cases, which account for less than 1% of the total. Remarkably, Figure 11 depicts a dominating proportion of successful campaigns, accounting for approximately 60% of the total, while failed campaigns constitute over 35%, indicating a significant portion of campaigns that fell short of their goals. Interestingly, a small percentage of campaigns, roughly 5%, were either canceled or suspended. Moreover, Figures 18 and 21 highlight a notable disparity in the number of funders and the amount of money between successful and unsuccessful campaigns, with the former garnering a significantly higher number of funders and raised funds. Over the years, the number of suspended cases has declined (Figure 3), while the number of funders and the amount of money raised have increased (Figures 19 and 23, respectively) for successful campaigns. Additionally, the duration of campaigns tends to be shorter for successful campaigns compared to failed, canceled, and suspended campaigns, typically spanning 30 days.

The Indiegogo Platform has undergone a progressive evolution of PGMs employed between 2011 and 2023. In its initial phase in 2011, Indiegogo relied on a combination of background checks and financial information. Then, in 2014, it introduced additional mechanisms, including social media and cookies, to ensure campaign integrity and verify the credibility of project users. During this time, it also began leveraging data from third-party providers. As the platform experienced and responded to emerging challenges, it implemented further PGMs, such as Google Analytics in 2016, and by 2018, (as shown in Table 9). These new mechanisms were likely implemented to enhance fraud detection and improve user interaction.

The analysis of Indiegogo data reveals a remarkable growth in successful campaigns over the period of 2010 to 2022, as exemplified in Figure 30. The number of successful campaigns experienced a substantial increase, starting from just a few hundred in 2010 and reaching approximately 10,000 in 2020. This trend highlights the growing popularity and effectiveness of crowdfunding as a means of raising funds for various projects and ventures. Furthermore, the analysis demonstrates a steady increase in the amount of money raised through Indiegogo campaigns during the same period, as depicted in Figure 34. This consistent upward trajectory signifies the growing confidence and trust among funders, as well as the increasing recognition of crowdfunding as a viable funding option. Another notable finding is the significant reduction in the average duration of campaigns, from over 60 days in 2010 to approximately 40 days in 2020. This trend is supported by Figure 38, which indicates that while some successful campaigns still opt for longer durations, the majority of campaigns now tend to have shorter durations. This shift suggests that crowdfunding campaigns are becoming more streamlined and efficient, enabling project creators to achieve their funding goals in a shorter timeframe.

4.3.2 Equity-based crowdfunding

The PGMs for equity crowdfunding were also collected through the Wayback Machine and Time Travel, including Wefunder, StartEngine, SeedInvest, Netcapital, TruCrowd and Mainvest. The data reveal a distinct evolution in the mechanisms employed by these platforms over time. During their early years, these crowdfunding platforms primarily relied on two essential mechanisms: Background checks and Financial information verification, aimed at ensuring the legitimacy of campaigns and assessing the financial credibility of project initiators. However, as the crowdfunding landscape evolved, the platforms adapted by incorporating a more diverse set of PGMs in recent years. The data reveals a shift towards more PGMs. Table 12 provides a comprehensive overview of how various platforms have evolved their mechanisms for user identification and fraud detection over the years. This tabulated data underscores the continuous improvements made by equity-crowdfunding platforms in their proactive pursuit of enhancing risk management and user protection measures over time.

On the other side, the initial analysis of the indicators has yielded intriguing findings. Notably, a significant majority (approximately 71%) of the campaigns achieved success, surpassing the count of 2000, as shown in Figure 43. Moreover, there has been a noticeable upward trajectory in the success of campaigns, with the number doubling from approximately 400 in both 2018 and 2019 to around 800 funded campaigns in 2020, as shown in Figure 46. Conversely, the number of cancelled and not funded campaigns remained relatively lower, comprising approximately 23% of the total, with each category accounting for nearly 500 campaigns. This information is visually represented in Figure 45. Further examination, utilizing histograms, has uncovered valuable insights. Wefunder emerges as the leading category, boasting the highest overall number of campaigns, specifically 634 successful campaigns, as shown in Figure 46. However, when considering campaigns that did not meet their funding goals, the Mainvest category stands out with 182 campaigns falling into this category. StartEngine, on the other hand, demonstrates a significant number of cancelled campaigns, totaling 188, as presented in Figure 45. Additionally, the number of funders participating in crowdfunding projects has steadily increased over time, as presented in Figure 49, with successful campaigns attracting a higher number of funders compared to cancelled and unfunded campaigns, as shown in Figure 49. The total amount of funds raised has also doubled over the three-year period, as shown in Figures 50 and 51. It is worth noting that there is a confirmed correlation between the increase in the number of investors and the amount of funds raised during the same period, as shown in Figure 55. Moreover, there has been a noticeable decrease in the average duration of funding campaigns, potentially reflecting the increased amount of funds raised within the same time frame, as depicted in Figure 56. Overall, these findings provide important insights into the crowdfunding ecosystem, offering valuable data for research and analysis in this field.

Chapter Five: Evaluating Platforms Governance Mechanisms PGMs

5. Evaluating Platform Governance Mechanisms Efficacy Through Logistic Regression

Logistic regression is a statistical technique generally used to predict binary responses; therefore used in modelling binary variables that have two states, 1/0, and can be labelled as success and failure (Hilbe, 2015). The logistic regression model can be used to examine how different variables influence various crowdfunding campaigns. In order to confirm their contributions to campaign success and lower fraud, the model analyzes the impact of several campaign features, such as backer count, pledged amount, and duration. It also evaluates the effects of PGMs like social media, Google Analytics, and third-party verification to verify their roles in increasing success and reducing fraud in the campaigns.

In our analysis, logistic regression aims to evaluate the efficacy of PGMs applied. We thus centred our attention on two main tasks: success and fraud in the logistic regression model. The success model attempts to identify the extent of PGMs' contribution to increase campaign success, while the fraud model aims to identify the extent of PGMs' effect on reducing fraudulent campaigns. Furthermore, we implemented this approach in two steps. The first step involves using data that represents reward-based crowdfunding (e.g., Kickstarter, IndieGoGo) and data that represents equity-based crowdfunding platforms, which will be specified later. The second step involves merging all data platforms into a single dataset and performing analysis using the logistic regression model.

The data gathered and cleaned using the Python programming language will be examined in this chapter. We will provide details on when PGMs were applied, along with descriptive statistics, correlation coefficients, and univariate tests, followed by the logistic regression results.

5.1 Reward-based crowdfunding

First, we examine reward-based crowdfunding datasets that represent the Kickstarter and Indiegogo platforms. This analysis aims to demonstrate the effectiveness of PGMs in enhancing campaign success and reducing fraud. Thus, the results display the logistic regression success model.

5.1.1 Success model

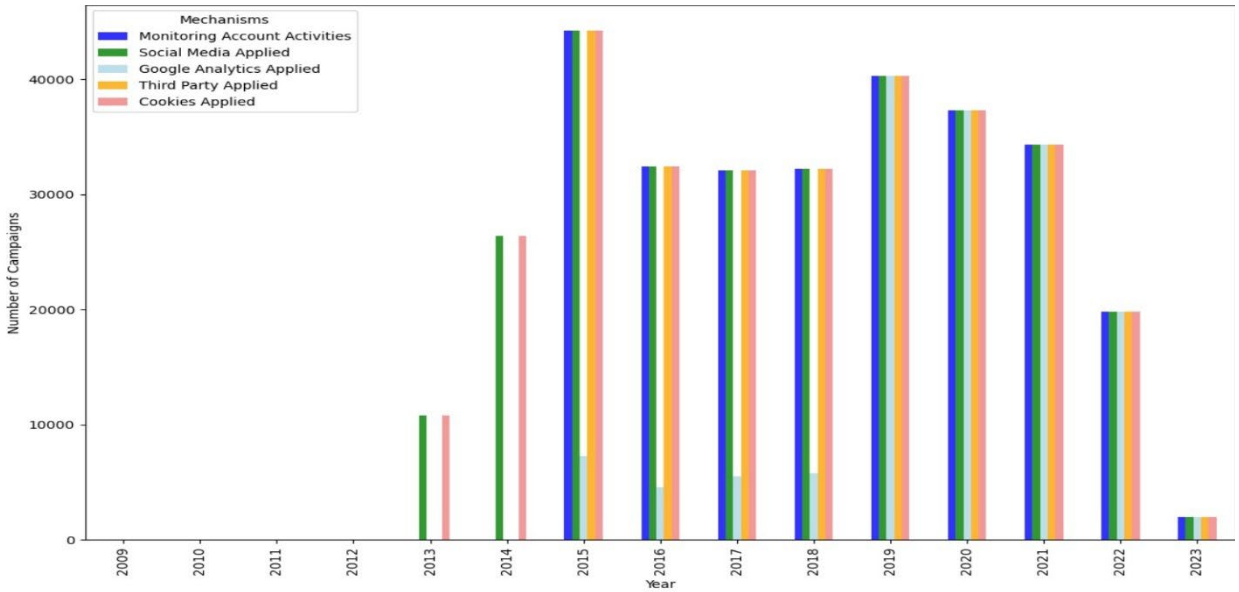
5.1.1.1 PGMs applied

The reward-based crowdfunding has implemented several PGMs aimed at improving service quality and verifying users. Two types of PGMs are excluded, as they have been in use since the platform was founded and thus will not affect our analysis. These excluded PGMs are background checks and credit checks, and the other two PGMs have been excluded due to their high correlation, which is cookies. Conversely, the PGMs retained for our analysis are social media, Google Analytics, and third-party verification, as shown in Figure 62. In this regard, these PGMs will be given either '1' if they are applied or '0' if they are not. The following figure provides information about when the platform started using each PGM.

5.1.1.2 Descriptive statistics

Table 16 provides descriptive statistics for several variables associated with reward-based campaigns. The dataset shows the number of campaigns that were present between 2009 and 2023. The number of funders varies notably, from campaigns with no funders at all to one with up to 73,206 funders. The pledged amount also varies significantly from campaigns that receive no

Figure 62. Distribution of campaigns by year for reward-based crowdfunding.



This figure depicts the distribution of the campaigns and the use of PGMs on reward-based crowdfunding by year. The PGMs include social media and cookies (starting in 2012), Google Analytics, monitoring account activities and third-party verification (starting in 2014).

money to a maximum pledge of $4,979,652. Both variables, the number of funders and pledged, show a wide range and significant variability between campaigns. As for duration, despite the average campaign duration being 34 days, the analysis shows a wide range, from a minimum of 0 days to a maximum of 1165 days. Regarding PGMs, reward platforms have applied social media and cookies for most campaigns. Meanwhile, Google Analytics covers less than half of the campaigns. As for fraud cases, the average number of fraud cases is around 55 cases; the range varies from zero cases in some years to 306 cases in other years. Lastly, the campaign's success rate indicates that approximately two-thirds of the campaigns reached their funding goals.

5.1.1.3 Spearman correlation coefficients

A correlation coefficient is a statistical tool that presents a structured representation of the relationship between multiple variables. The purpose is to assess the strength of the association and identify patterns in those associations. Given the characteristics of the dataset, the Spearman correlation method (Astivia and Zumbo, 2017; Winter et al., 2016) is employed over the other types of methods. In particular, the technique is used to accommodate the presence of binary variables, such as campaign success or unsuccessful categories, as well as variables with a non-linear relationship. It also considers the presence of outlier data, making Spearman correlation estimates more accurate.

Table 17 presents the Spearman correlation coefficients between several variables. The number of funders shows a positive and significant correlation with the pledged amount and success, indicating that more funders tend to raise more funds and increase the success probability. Meanwhile, it shows a negative and significant correlation with duration, indicating that with more days, fewer investors participate in campaigns. At the same time, social media, Google Analytics and third-party mechanisms also show a negative correlation with funders, suggesting that these mechanisms do not impact attracting more funders. In contrast, the pledged amount strongly correlates with PGMs, indicating that these mechanisms tend to raise more funds and increase the campaign's success rate. For duration, social media generally has less impact on longer campaigns but a greater impact on shorter campaigns. In contrast, Google Analytics and third-party verification are generally more effective in longer campaigns, whereas they have less impact on shorter ones. As for fraud cases, they have a positive and significant correlation with Google Analytics and third-party verification, but a negative correlation with social media and cookies.

Table 16. Descriptive statistics.

Variable	Mean	Std	Min	25%	50%	75%	max	Number of observations
The number of funders	135.80	804.63	0	0	12	73	73,206	332809
Pledged amount	25,562.7	166,172.4	0	171.0	1,625.0	7,325.0	4,979,652.0	332809
Duration	34.02	15.36	0	30	30	40	1165	332809
Social media	0.935	0.245	0	1	1	1	1	332809
Cookies	0.935	0.245	0	1	1	1	1	332809
Google analytics	0.470	0.499	0	0	0	1	1	332809
Third-party identity verification	0.824	0.380	0	1	1	1	1	332809
Fraud cases	55.60	82.463	0	0	50	65	306	332809
success	0.684	0.465	0	0	1	1	1	332809

This table presents the descriptive statistics for variables applied, including the mean, standard deviation (std), minimum (min), quartiles (%25, %50, %75), and maximum (max) value. The variables are defined in (Appendix B). The sample covers the period 2009 to 2023.

Table 17. Spearman correlation coefficients.

Variable	Number of funders	Pledged amount	Duration	Social media	Cookies	Google analytics	Monitoring account activities	Third party verification	Fraud cases
Pledged amount	0.628***								
Duration	-0.177***	-0.047***							
Social media	0.040***	0.004**	-0.064***						
Cookies	0.040***	0.004**	-0.064***	1.00***					
Google analytics	-0.167***	0.145***	0.106***	0.247***	0.247***				
Third party verification	-0.060***	0.024***	0.018***	0.567***	0.567***	0.435***	1.00***		
Fraud cases	0.351***	-0.053***	-0.157***	0.210***	0.210***	-0.450***	0.415***	0.415***	
success	0.260***	0.576***	0.025***	-0.090***	-0.090***	0.313***	0.006***	0.006***	-0.332***

This table presents the Spearman correlation matrix between the variables in our model. The significance levels are *** for 1%, ** for 5% and * for 10%.

5.1.1.4 Univariate analysis

A univariate test is a statistical technique used to analyze each variable in a dataset individually, emphasizing describing the variables' characteristics, like the mean and median. Table 18 represents a comparison between the means and the medians of successful and unsuccessful campaigns. The analysis shows that the difference in the mean and median of the number of funders is highly significant, indicating that successful campaigns had more funders. In addition, the mean and median of the amount pledged are significantly higher for campaigns that reach their goals, indicating that they collect significantly higher funds. As for duration, the mean difference is significant, indicating that successful campaigns tend to be longer. However, the median difference is '0', indicating that there is no variation between successful and unsuccessful campaigns.

In contrast, the mean and the median differences in social media and third-party are significant between their means and medians, implying that they influence campaign success. While Google Analytics shows a high significance in means and medians, this suggests that using Google Analytics contributes to success. Such preliminary findings suggest that the number of funders, the amount pledged, the duration of the campaign, and PGMs are significant in determining campaign success.

5.1.1.5 Success model for reward-based crowdfunding

The logistic regression model provides estimated coefficients to understand the relationship between predictors and success. Our analysis covers many aspects, including a logistic regression model for success and a model evaluation that includes a confusion matrix and classification report. These methods are aimed at evaluating the effect of a predictor variable on the success of

Table 18. Univariate analysis.

		Successful campaigns			Unsuccessful Campaigns			Differences		
Variables	N	Mean	Median	N	Mean	Median	Mean	t-test	Median	z-test
The number of funders	227,486	192.6	35.00	105,320	13.12	3.00	179.48	88.783***	32	12.630***
Pledged amount	227,728	36,361	3,636	105,320	2,338	70.00	34,023	78.906***	35,66	6.599***
Duration	227,728	34.3	30.00	105,320	33.50	30.00	0.8	14.258***	0.0	0.0
Fraud cases	227,728	41.400	5.00	105,320	86.2	65.00	-44.8	-144.198***	-60	-154.1***
Social media	227,728	0.921	1.00	105,320	0.968	1.00	-0.047	-60.164***	0.0	0.0
Cookies	227,728	0.921	1.00	105,320	0.968	1.00	-0.047	-60.164***	0.0	0.0
Google Analytics	227,728	0.577	1.00	105,320	0.241	0.00	0.336	200.402***	1.0	475.9***
Third-party verification	227,728	0.826	1.00	105,320	0.821	1.00	0.005	3.515***	0.0	0.0

The table presents the mean and median differences between successful and unsuccessful campaigns, along with the results of t-tests and z-tests. The significance levels are *** for 1%, ** for 5%, and * for 10%.

the campaigns. Accordingly, the dataset was split into an 80% training and 20% test dataset. 80% of the training data is used to train the model, while the remaining 20% is used to evaluate the model's performance on unseen data, and the data selection is random.

Table 19 presents the results of a logistic regression for the success model, based on a total of 266,440 observations. The model explains 29.65% of the variance in the probability of success, which does not seem high. The value of the log-likelihood is higher than the value of the null model. This indicates that the model fits the data substantially better than the null model. In addition, the intercept has a positive coefficient, representing the baseline of the log odds of success. The low standard error indicates the accuracy of the estimate, as well as the statistically significant p-value. The analysis indicates that the probability of success is high even without considering other predictors.

The coefficient of the number of funders is positive; this implies that the more funders who participated in campaigns, the more likely the campaign's success becomes. The small standard error indicates a very reliable coefficient estimate, and the low p-value confirms a strong statistical significance result. The analysis indicates that funders enhance a campaign's chances of success, and with each new funder, the probability of success also increases. The pledged amount has a positive coefficient as well, indicating that it is likely to improve the campaign's success. The small standard error reflects a highly precise coefficient estimate, and the low p-value shows a statistically significant result. The study shows that high pledge values also have a positive effect on success, but within limited boundaries, because most campaigns are given little amounts of funds. Additionally, the duration has a positive coefficient, indicating that longer campaigns enhance the likelihood of success. The low standard error confirms that the coefficient estimate is very precise, and the low p-value demonstrates high statistical significance. The analysis shows that shorter campaign durations have a lower success rate. Compared to these, longer campaigns have a higher success rate because extended periods often reduce the sense of urgency. This could be due to the fact that funders want to know more about the projects and the entrepreneurs.

Table 19. Success model for reward-based crowdfunding.

No. Observations:	266440
Df Residuals:	266432
Pseudo R-squ.:	0.2965
Log-Likelihood:	-1.1699e+05
LL-Null:	-1.6630e+05
LLR p-value:	0.00

Variables	Coef	Std err	Z
Intercept	1.006 ***	0.026	39.171
The number of funders	0.028 ***	0.00	140.549
Pledged amount	8.648e-06 ***	3.67e-07	23.591
Duration	0.002 ***	0.00	5.893
Social media	-1.880 ***	0.026	-72.130
Google analytics	2.202 ***	0.012	181.601
Third-party verification	-0.390 ***	0.016	-24.413

This table presents the results of the logistic regression for model 1. The dependent variable is success, and the independent variables are defined in (Appendix B). The sample covers the period of 2009 to 2023. The significance levels are *** for 1%, ** for 5% and * for 10%.

Regarding PGMs, the analysis shows that social media has a negative coefficient, which implies that it decreases the probability of campaign success. This result rejects the hypothesis (H1). The data reveals that platforms that used social media, social media campaigns also attracted more funders and received higher pledge amounts. However, prior studies indicate that social media presence is not necessarily a trustworthy signal. Mollick (2014) demonstrates that entrepreneurs' Facebook friends do signify network size but not effectiveness, signalling that having many friends on social media is not conclusive proof of crowdfunding success. In addition, the number of these accounts is likely inactive or fake. Dong et al. (2018) and Cumming (2016) indicate that fraudsters are inactive or have no presence on social media. On the other hand, the analysis shows that Google Analytics has a positive coefficient, indicating that implementing the Google Analytics mechanism increases the probability of campaign success, which supports hypothesis (H1). With a low standard error, indicating an accuracy estimate of the coefficient, along with a low p-value, suggesting that it is statistically significant.

For the third-party identity verification, we hypothesized that it increases the probability of success and reduces fraud. However, the analysis shows that the third-party has a negative coefficient, indicating it reduces the probability of success. The high standard error indicates that the coefficient estimate is unreliable, but the low p-value confirms its statistical significance. The analysis shows that the majority of campaigns used the third-party mechanism, compared to those that did not. Although more funders are participating, which is reflected in the large amounts of money contributed, this has not had a positive impact on the role of the third-party mechanism in increasing successful campaigns.

Reward platforms may require verification for campaigns in specific high-risk categories or industrial (e.g., finance, tech, or projects with significant funding goals). These campaigns tend to be more intricate to execute successfully, owing to the complexity of the offering and the higher financial requirements.

Model evaluation

To enhance and validate the results of the logistic regression for the success model, additional evaluation techniques can be applied to assess performance and reliability. One such technique is the confusion matrix analysis, which provides insights into the model's classification accuracy by providing statistical details about true positives (TP) which refer to the number of cases that were correctly predicted as positive, false positives (FP) that denote the number of cases that were incorrectly predicted as positive, true negatives (TN) that represent the number of cases that were correctly predicted as negative, and false negatives (FN) that signify the number of cases that were incorrectly predicted as negative. Additionally, the classification reports include precision, recall, F1-score, support, and accuracy, as well as macro average and weighted average.

A. Confusion matrix.

A confusion matrix is a method for evaluating the effectiveness of a predictive model, especially in classification tasks. It compares the actual and predicted values to show how the model performs across categories. The matrix compares (TP), (TN), (FP), and (FN) for each class as shown in Table 20.

In this context, campaigns that are unsuccessful (TN) are denoted by '0' while successful campaigns (TP) are denoted by '1'. Therefore, predicting the classifications in the test dataset and creating a confusion matrix is the following step.

Table 20 presents a confusion matrix where the true negative (TN) class '0' (unsuccessful) shows 14,237 cases, which the model correctly predicted as class '0'. The true positive (TP) class '1' (successful) shows 40,885 cases, which were accurately identified as class '1'. The false negative (FN) shows 4,713 cases, where the model incorrectly predicted class '0' instead of class '1'. The false positive (FP) shows 6,775 cases, where the model incorrectly predicted class '1' instead of class '0'.

Table 20. A confusion matrix.

	Predict			
	Predicted	0	1	All
True	0	14237	6775	21012
	1	4713	40885	45598
	All	18950	47660	66610

This table shows the confusion matrix of the model, where the rows indicate the actual classifications while the columns indicate the predicted classifications. '0' denotes failed campaigns, while '1' denotes successful campaigns.

B. Classification Report.

The classification report provides a comprehensive view of how the model performs, and it presents key metrics for each class within the model, including precision, which measures the accuracy of true positives to the total number of positive predictions. Recall represents the capability to identify all true positives. The F1-score is the harmonic mean of precision and recall, demonstrating the balance between the two categories. Support indicates the number of actual cases for each class in the dataset. In addition, the accuracy indicates how precise the model is.

Table 21 presents the classification report; the precision for class '0' (unsuccessful) shows the model correctly predicted 73% of the actual cases that were predicted to be failed. For class '1' (successful), the model correctly predicted 86% of actual cases that were predicted to be successful. The model is more reliable at predicting class '1' than class '0' due to its higher value. Similarly, the recall for class '0' indicates that the model correctly identified 68% of true negatives, while for class '1', it correctly identified 90% of true positives. This indicates that the model can identify most of class '1'. In addition, for class '0', the f1-score is 0.71, which is lower than for class '1'. This suggests that the model struggles to balance precision and recall for class '0'.

Table 21. Classification Report.

	precision	recall	f1-score	support
0	0.75	0.68	0.71	21012
1	0.86	0.90	0.88	45598
Accuracy			0.83	66610
Macro avg	0.80	0.79	0.79	66610
Weighted avg	0.82	0.83	0.82	66610

This table presents the classification report, which includes precision, recall, f1-score, and support for successful and unsuccessful campaigns supported by statistics. Also, the macro and weighted average.

In comparison, class '1' has an of 0.88, demonstrating stronger, yet still imperfect, performance. The macro average values for these metrics are approximately 0.82, reflecting the model's performance, and the weighted average values indicate that the model performs well for both classes. The classification accuracy shows that it is acceptable.

5.1.1.6 Interaction effects on crowdfunding outcomes: Kickstarter vs Indiegogo platform

In this stage, we seek to determine whether the impact of the PGMs on campaigns differs according to the platform employed. Consequently, a new dummy variable, "Kickstarter," has been introduced to compare the effectiveness of the PGMs across the Kickstarter and Indiegogo platforms, as detailed in Table 22. This variable is coded as '1' for Kickstarter campaigns and as '0' for Indiegogo campaigns.

The analysis indicates the presence of perfect multicollinearity error; this is because a variable perfectly predicts the outcome. This issue arises due to several mechanisms that share identical values, making the model unable to estimate effects reliably. Consequently, we relied on a single mechanism that does not share, which is third-party verification, to test whether the PGMs have a different (perhaps stronger) effect on any given platform.

Table 22 displays the interaction between Kickstarter and third-party verification. The mechanism alone contributes positively to campaign success. In contrast, the interaction with Kickstarter produces a negative and significant coefficient. The findings demonstrate that the mechanism has a greater impact on campaign success for Indiegogo compared to its interaction with the Kickstarter platform. Both Kickstarter and Indiegogo are highly rated among other platforms, according to Strip (2025).

Table 22. Comparative analysis of interaction effects on Kickstarter vs the Indiegogo platform.

No. Observations:	266440
Df Residuals:	266431
Pseudo R- squared:	0.4896
Log-Likelihood:	-84884
LL-Null:	-1.6630e+05
LLR p-value:	0.00

Variables	coef	std err	z
Intercept	6.601 ***	0.216	30.496
The number of funders	0.044 ***	0.000	174.844
Pledged amount	1.235e-07	1.37e-07	0.903
Duration	-0.019 ***	0.00	-42.930
Social media	-0.894 ***	0.030	-30.144
Google analytics	0.678 ***	0.014	49.067
Third-party verification	1.903 ***	0.281	6.762
Kickstarter	-6.305 ***	0.217	-29.100
Kickstarter x third-party verification	-2.263 ***	0.281	-8.059

This table presents the results of the logistic regression with the Kickstarter interaction model 2. The dependent variable is success, and the independent and control variables are defined in (Appendix B). The sample covers the period of 2009 to 2023. The significance levels are *** for 1%, ** for 5% and * for 10%.

Kickstarter, though, uses a fixed 'all or nothing' funding model, which means funders will only receive their funds back if the campaign does not reach its funding goal. This provides strong reassurance to funders. Indiegogo, on the other hand, uses a flexible 'keep it all' and 'all or nothing' funding model, allowing entrepreneurs to keep the funds even if the campaign does not meet its target. Hence, additional verification is required to enhance the credibility and build trust, which explains the greater influence of third-party on Indiegogo campaigns.

5.1.2 Fraud model

5.1.2.1 Fraud model for reward-based crowdfunding

Table 23 provides the results of a logistic regression for the fraud model, powered by a total of 266,440 observations. The pseudo-R-squared shows that the model explains 29.87% of the variance in fraud probability, which is relatively low. The log-likelihood is -2591.1, markedly higher and substantially more favourable than the null model's -3695.1. In addition, the intercept has a negative coefficient; the model indicates that the likelihood of fraud is generally low (negative baseline log odds) when no other factors exist. In other words, the majority of campaigns are not fraudulent by default. This finding aligns with Mollick's (2014) study of reward-based crowdfunding on the Kickstarter platform, which also found that fraudulent campaigns are rare. The low standard error, meaning the estimates are precise, along with a low p-value, indicates statistical significance.

The low positive coefficient of the number of funders suggests that there is no significant relationship between the number of funders and the probability of fraudulent activity. The low standard error indicates that the estimate is precise, but a high p-value indicates statistical insignificance. This shows that the number of funders has no effect on the likelihood of fraudulent campaigns. For pledged, the small negative coefficient shows that the pledged amount does not effectively distinguish between fraudulent and non-fraudulent campaigns; fraudulent activity occurs in campaigns with varying funding amounts. With a large standard error, the estimate is unreliable, and a high p-value indicates that it is statistically insignificant. As for duration, the coefficient shows a negative effect on campaigns. Therefore, longer campaign durations are associated with a lower likelihood of fraud. The very low p-value suggests that this association is statistically significant. The analysis shows that shorter campaigns are more likely to be associated with fraudulent activity, as opposed to longer campaigns, which may not be associated with fraudulent activity. This may be due to longer campaigns allowing for more scrutiny and thus giving funders more time to evaluate the projects.

Table 23. Fraud model for reward-based crowdfunding.

No. Observations:	266440		
Df Residuals:	266432		
Pseudo R- squared:	0.3011		
Log-Likelihood:	-2582.6		
LL-Null:	-3695.1		
LLR p-value:	0.00		
Variables	coef	std err	z
Intercept	-4.130 ***	0.026	39.171
The number of funders	4.091e-05	0.00	0.243
Pledged amount	-1.449e-06	9.44e-07	-1.535
Duration	-0.166 ***	0.005	-35.450
Previou**s** fraud cases	-0.0024 ***	0.001	-4.005
Social media	1.593 ***	0.426	3.740
Google analytics	-2.870 ***	0.177	-16.191
Third-party identity	0.737 ***	0.146	5.045

This table presents the results of the logistic regression for model 3. The dependent variable is fraud, and the independent and control variables are defined in (Appendix B). The sample covers the period of 2009 to 2023. The significance levels are *** for 1%, ** for 5% and * for 10%.

In addition, the coefficient for previous fraud cases is negative, indicating that previous fraud cases can help predict future fraud. The very low p-value suggests that this association is statistically significant. The analysis suggests that, based on the past patterns of fraud cases, the predictor is more likely to make better predictions in future.

Regarding PGMs, the coefficient on social media is positive, indicating that social media increases the likelihood of fraudulent activities in campaigns. The low standard error reflects the precision in the estimate, and the p-value is statistically significant. The result shows that the social media mechanism contradicts the initial hypothesis (H1). Although social media was thought to increase campaign success and mitigate fraud, this result reinforces evidence that poor or fake social media signals reduce campaign performance. In the same vein, Wessel et al., (2016) illustrates that suspicious or fraudulent social networking activity can lead to donor distrust over time, thus reducing participation. These findings imply that the efficacy of social media as a mechanism depends crucially on the quality and credence of intrinsic signals. While the coefficient of Google Analytics is negative, indicating that campaigns that have implemented a certain mechanism are less likely to be fraudulent. The p-value is statistically significant. The analysis demonstrates that campaigns using Google Analytics significantly reduce the probability of fraudulent activity. This finding supports the hypothesis (H2) that this mechanism contributes to a lower likelihood of fraud.

Lastly, the coefficient on third-party verification is positive, indicating that campaigns that use a third party increase fraudulent activity, contrary to the hypothesis (H4). The low standard error indicates that precision is reliable, and the low p-value indicates statistical significance. The analysis shows that since platforms began employing third-party verification, more funders have participated and more funds have been raised. The study also shows that campaigns have shorter durations but are more likely to be associated with fraud. In contrast, campaigns that do not implement third-party verification demonstrate significantly lower fraud rates, which might suggest inconsistency in their implementation. A possible explanation is that the third-party verification indicates that the platform imposes these requirements as part of its verification process for high-risk campaigns, supporting its diagnostic rather than preventative role.

5.1.2.2 Conclusion

The findings of the success model reveal that pledge amounts increase the likelihood of campaign success, as the number of funders participating increases, the total funding for each campaign increases. As for campaign duration, the study finds that longer campaigns tend to have higher chances of success, thereby attracting more funders, while shorter durations are less effective because it's challenging to get attention before time runs out. Regarding PGMs, the study finds that using Google Analytics is associated with a higher likelihood of campaign success. In contrast, mechanisms such as social media and third-party verification are associated with a decrease in the probability of success in these campaigns.

Regarding the fraud model, the study indicates that the number of funders does not have a significant positive or negative effect on fraud, nor does the amount pledged predict fraud well, since fraud also happens for projects that have different levels of funding. While shorter-duration campaigns are more likely to be associated with fraud, longer-duration campaigns are associated with a low fraud rate. Regarding PGMs, the findings demonstrate that campaigns employing Google Analytics are significantly less likely to experience fraud. Conversely, the use of social media and third-party identity verification mechanisms increases fraudulent activity and is associated with a greater likelihood of fraud. The mechanisms are ineffective at preventing fraud.

On the other hand, third-party interaction with Kickstarter appears to decrease the chance of success. At the same time, the mechanism alone indicates an increase in the impact on campaign success. This suggests that the mechanism plays a more significant role on Indiegogo than on Kickstarter.

5.2 Equity-based crowdfunding

In this section, we will present seven platforms out of 31, which are Wefunder, StartEngine, Mainvest, SeedInvest, Netcapital, TruCrowd, and SMBX. These platforms represent two-thirds of the campaigns. We choose to rely on these platforms because they have data on PGMs applied, unlike those that lack data, which we cannot include in our analysis. Equity platforms differ from reward platforms because they are more regulated, and this is because they are registered with the US Securities and Exchange Commission (SEC), as well as members of the Financial Industry Regulatory Authority (FINRA) and Securities Investor Protection Corporation (SIPC).

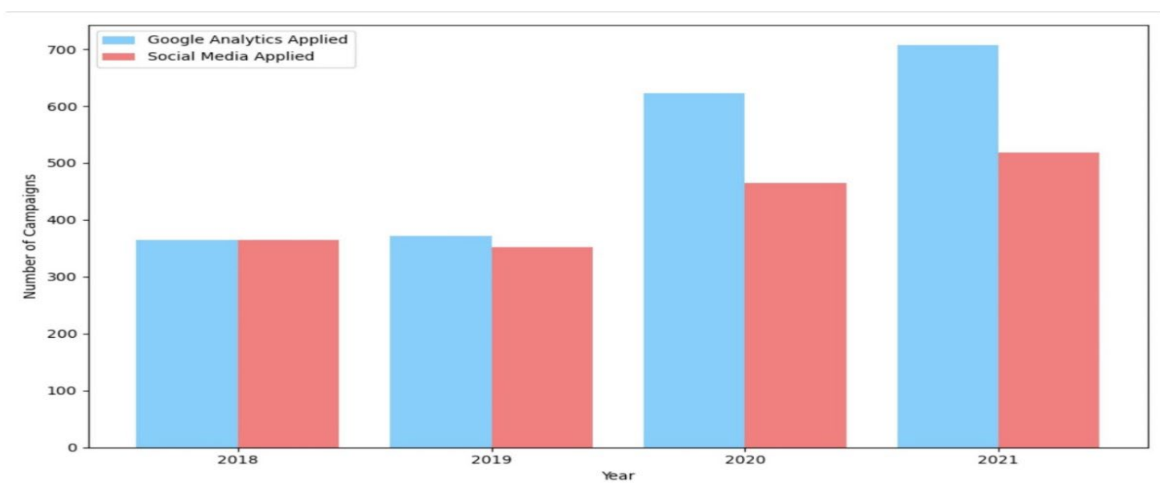
5.2.1 PGMs applied

The equity-based crowdfunding platforms have implemented several PGMs to improve service quality and verify users. Five types of PGMs are excluded, as they have been in use since the platforms were initiated and thus will not affect our analysis. These include background checks, credit checks, cookies, monitoring account activities, and third-party verification. Conversely, the PGMs retained for our analysis are social media and Google Analytics, as indicated in Figure 63. In this context, these PGMs will be assigned a value of '1' if they are implemented, and '0' if they are not. The following figure shows information about PGMs and their implementation annually.

5.2.2 Descriptive statistics

Descriptive statistics for campaigns of equity-based crowdfunding-related variables are reported in Table 24. To be clear, this data displays campaigns throughout 2018 and 2021. The variance in the number of funders is very high, which represents a large difference between campaigns with no funders and those with up to 8,653 funders. The pledged amount also varies widely, from unfunded campaigns to the highest pledge of $5 million. From campaign durations, the findings show that the number of funders, the amount pledged, and the duration have a wide range of values and imply a large variation in funded campaigns. The duration of the campaigns ranges from a low of '0' days to a high of 1073 days and implies that some campaigns run for a very long time.

Figure 63. Distribution of campaigns by year for equity-based crowdfunding.



This figure shows the distribution of the campaigns and the use of PGMs on equity platforms by year. The PGMs include Google Analytics (starting in 2018) and social media (starting in 2018).

Regarding PGMs, approximately 74.1% and 90.2% campaigns have used social media and Google Analytics, respectively. Lastly, the campaign's success rate is 69.3%, indicating that approximately two-thirds of the campaigns reached their funding goals, as shown in the table.

Table 24. Descriptive statistics.

Variable	Mean	Std	Min	25%	50%	75%	max	Number of observations
The number of investors	268.16	645.10	0.00	0.00	40.00	185.0	8,653	2,262
Pledged amount	257,482	545,327	0.00	2,853.4	60,994.5	256,541.8	5,000,000	2,262
Duration	131.22	105.40	0.00	63.0	94.0	171.0	1073	2,262
Social media	0.741	0.438	0.00	0.00	1.00	1.00	1.00	2,262
Cookies	1.00	0.00	1.00	1.00	1.00	1.00	1.00	2,262
Google analytics	0.902	0.297	0.00	1.00	1.00	1.00	1.00	2,262
Third-party verification	1.00	0.00	1.00	1.00	1.00	1.00	1.00	2,262
success	0.693	0.461	0.00	0.00	1.00	1.00	1.00	2,262

This table presents the descriptive statistics for variables applied, including the mean, standard deviation (std), minimum (min), quartiles (%25, %50, %75), and maximum (max) value. The variables are defined in (Appendix B). The sample covers the period from 2018 to 2021.

5.2.3 Spearman correlation coefficients

Table 25 presents the correlation coefficients for all variables incorporated in equity-based crowdfunding. The number of funders is strongly correlated with the amount pledged, duration, social media, and Google Analytics.

Similarly, there is a positive and significant correlation between the amount pledged, the duration, social media, and Google Analytics. In addition, there is a significant correlation between duration and social media, but a negative relationship with Google Analytics. Regarding PGMs, social media has a significant positive correlation with Google Analytics and success, while Google Analytics has a significant negative correlation with success.

Table 25. Spearman correlation coefficients.

Variable	Number of investors	Pledged amount	Duration	Social media	Google analytics
Pledged amount	0.751 ***				
Duration	0.404 ***	0.355 ***			
Social media	0.341 ***	0.287 ***	0.195 ***		
Google analytics	0.339 ***	0.086 ***	-0.022	0.558 ***	
success	0.588 ***	0.749 ***	0.298 ***	0.136 ***	-0.091 ***

This table presents the Spearman correlation matrix between the variables in our model. The significance levels are *** for 1%, ** for 5% and * for 10%.

5.2.4 Univariate analysis

Table 26 compares the means and medians of all successful and unsuccessful campaigns across various variables. The number of funders has a substantial difference between the mean and median, which indicates that successful campaigns attract more funders than unsuccessful. Average pledges were also much higher for successful campaigns than for unsuccessful ones, indicating that many campaigns reached their funding goal. As for duration, successful campaigns tend to have longer durations, and non-successful campaigns tend to have shorter durations. Results indicate that there is no effect of duration on success. For PGMs, the mean for social media is statistically significant. However, the median is not, indicating a slight variation between successful and unsuccessful campaigns, indicating that social media increases the success rate. The mean and median for Google Analytics are significant; the analysis shows that unsuccessful campaigns use Google Analytics more, while successful campaigns use it slightly less.

5.2.5 Success model for equity-based crowdfunding

Table 27 presents the results of the logistic regression for the success model with 1,829 total observations. The pseudo-R-squared indicates that the model explains 65.02% of the variance in the success probability, which seems high. The log-likelihood value is higher than that of the null model, indicating that the model fits the data much better than the null model. In addition, the intercept has a positive coefficient, representing the baseline of the log odds of success. The low standard error indicates the accuracy of the estimate, as well as the statistically significant p-value. The analysis indicates that the probability of success is high even without considering other predictors.

The positive coefficient of the funders indicates that the more funders the campaigns have, the higher the chances of the campaigns being successful. The low standard error and the low p-value demonstrate a high level of statistical significance. This indicates that funders contribute to increasing success rates because each additional funder slightly raises the probability of success. The coefficient of the pledged amount is positive, indicating that a slight increase in the pledged sum is associated with a campaign's success rate. The low standard error indicates a precise estimate, and along with the low p-value, confirms its significance. The analysis finds that campaigns that raise more funds are more likely to succeed. In contrast, campaign duration has a negative coefficient, which indicates that the success rate decreases with each additional day of an increase in campaigns. The low standard error indicates an inaccurate estimate, whereas the p-value reflects statistical significance. Therefore, shorter campaign durations are associated with the likelihood of success; however, longer campaign duration is associated with a decrease in success, which, in turn, may diminish the interest of funders.

Table 26. Univariate analysis.

	Successful campaigns			Unsuccessful Campaigns			Differences			
Variables	N	Mean	Median	N	Mean	Median	Mean	t-test	Median	z-test
The number of investors	1567	381.9	105	695	11.6	0.0	370.3	19.097***	105	4.321***
Pledged amount	1567	368,374	132,385	695	7,459	0.0	360,915	22.786***	132,385	6.70***
duration	1567	149,4	120	695	90.2	79.0	1,403.8	15.758***	41.0	8.708***
social media	1567	0.779	1.00	695	0.653	1.0	0.126	6.035***	0.0	0.0
Google analytics	1567	0.883	1.00	695	0.944	1.0	-0.061	-5.119***	0.0	0.0

The table presents the mean and median differences between successful and unsuccessful campaigns, along with the results of t-tests and z-tests. The significance levels are *** for 1%, ** for 5% and * for 10%.

Regarding PGMs, the analysis shows that the social media mechanism has a positive coefficient, which implies that social media increases the probability of campaign success, which aligns with the hypothesis (H1). A low standard error indicates the reliability of the estimate, and a p-value indicates statistical significance. The evidence demonstrates that the high usage of social media within campaigns had a positive impact on increasing success rates. As for google analytics, the hypothesis (H2) suggests that the mechanism increases the success rate. Contrary to our hypothesis, the analysis shows that the coefficient is negative, indicating that this mechanism decreases the probability of success. Existing studies indicate that equity platforms predominantly use pre-screening and due diligence (e.g., identity verification, background checks, regulatory compliance) to ensure the credibility of the campaigns(Ahlers et al., 2015; Hornuf and Schwienbacher, 2017; Cumming et al., 2019). This may explain the negative effect of Google Analytics.

Table 27. Success model for equity-based crowdfunding.

No. Observations:	1829
Df Residuals:	1823
Pseudo R-squ.:	0.6502
Log-Likelihood:	-392.63
LL-Null:	-1122.6
LLR p-value:	0.00

Variables	coef	std err	z
Intercept	0.970 ***	0.266	3.641
The number of investors	0.076 ***	0.006	11.798
Pledged amount	2.78e-05 ***	3.48e-06	7.995
Duration	-0.0028 ***	0.001	-2.257
Social media	0.734 ***	0.245	2.998
Google analytics	-3.604 ***	0.339	-10.647

This table presents the results of the logistic regression for model 4. The dependent variable is success, and the independent variables are defined in (Appendix B). The sample covers the period of 2009 to 2023. The significance levels are *** for 1%, ** for 5% and * for 10%.

Model evaluation

A. *Confusion matrix*

Table 28 presents a confusion matrix where the TN class '0' (unsuccessful) shows that the model correctly predicts all classes as class '0'. The TP class '1' (successful) shows that the model accurately predicts all cases as class '1'. Conversely, the FN shows that the model incorrectly predicts a negative class '0' instead of class '1'. The FP shows that the model incorrectly predicts class '1' instead of ‘0'. The findings show that the model performs well with class '1', but poorly with class '0'.

Table 28. A confusion matrix.

		Predicted		
		0	1	All
True	0	125	15	140
	1	15	303	318
	All	140	318	458

This table shows the confusion matrix of the model, where the rows indicate the actual classifications while the columns indicate the predicted classifications. '0' denotes failed campaigns, while '1' denotes successful campaigns.

B. Classification report.

Table 29 presents the classification report; the precision for class '0' (unsuccessful) indicates that 89% of the actual cases were correctly predicted as failed. For class '1' (successful): the model correctly predicted 95% of the actual that were predicted to be successful. The model is more accurate in class '1' prediction than class '0'. Similarly, for recall of class '0', the model predicted 89% of TN, while for class '1', 95% of TP was predicted. This indicates that the model detects TP along with a few FN. Further, for class '0', the f1-score is 0.89, which is lower than that for class '1'. This shows that the model struggles to balance recall and precision for class '0'. The macro average values of such measures are approximately 0.92, which reflects the performance of the model well, and the weighted average values show that the model performs well for both classes. The accuracy of 0.93 means that 93% of its predictions are correct.

Table 29. Classification Report.

	precision	recall	f1-score	support
0	0.89	0.89	0.89	140
1	0.95	0.95	0.95	318
Accuracy			0.93	51711
Macro avg	0.92	0.92	0.92	51711
Weighted avg	0.93	0.93	0.93	51711

This table presents the classification report, which includes precision, recall, f1-score, and support for successful and unsuccessful campaigns supported by statistics.

5.2.6 Conclusion

The findings show that the number of funders and the pledged amount are associated with an increase in the success rate. The more funders involved per campaign, the more likely the campaigns are to be successful; similarly, the higher the funding received, the higher the chance of success. As for duration, the study finds that shorter campaign durations are more likely to succeed, whereas longer campaign durations are less likely to succeed. For PGMs, the findings show that social media is a crucial mechanism that serves a great purpose in enhancing the campaigns' chances of being successful. Meanwhile, Google Analytics reduces the campaign's success.

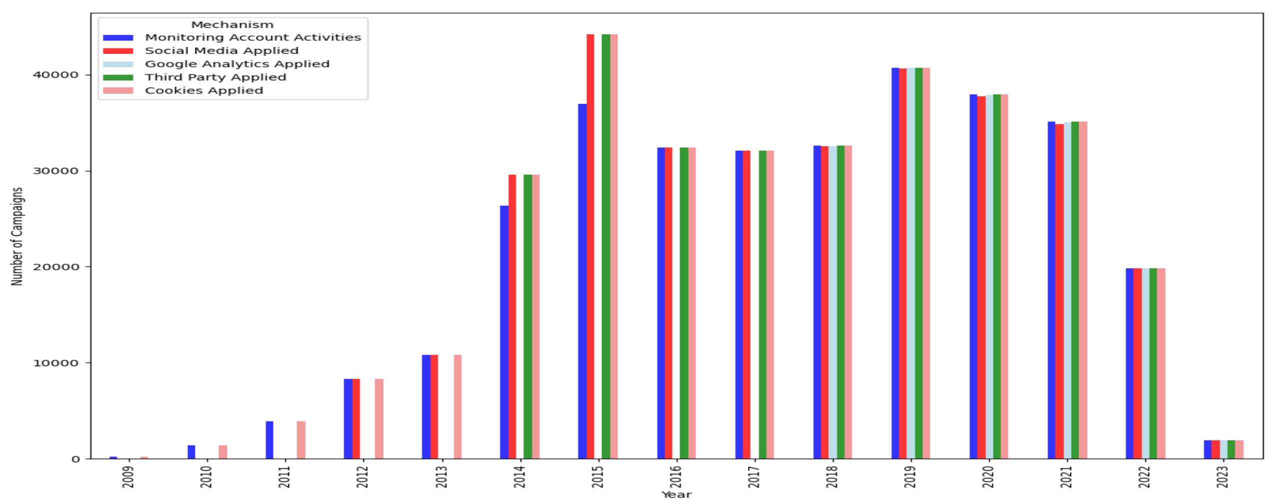
5.3 Combined dataset of reward-based and equity-based crowdfunding

This section combines all data that represents reward-based and equity-based crowdfunding. We analyze this data collectively, as we did earlier separately, to assess the results and determine whether the PGMs have improved and enhanced campaign success rates, as well as reduced fraudulent activity.

5.3.1 PGMs applied

In this stage, two different PGMs are excluded, as they have been in use since the platforms were initiated and thus will not affect our analysis.

Figure 64. Distribution of campaigns by year for all crowdfunding platforms.



This figure depicts the distribution of the campaigns and the use of PGMs on all platforms by year. The PGMs include social media and cookies (starting in 2012), Google Analytics, monitoring account activities and third-party verification (starting in 2014).

These include background checks and credit checks. Conversely, the PGMs retained for our analysis are social media, cookies, Google Analytics, third-party verification, and monitoring account activities (see Figure 64). In this context, these PGMs will be assigned a value of '1' if they are implemented, and '0' if they are not. The following figure shows information about PGMs and their implementation annually.

5.3.2 Descriptive statistics.

Table 30 shows descriptive statistics for various variables associated with reward-based and equity-based crowdfunding. The number of funders varies significantly, ranging from campaigns that had no funders participating at all to having up to 73,206 funders. The amount pledged varies widely, from campaigns that receive no funds at all to a maximum of $5 million, which reflects a high variability among successful campaigns. The average campaign duration is 34 days; analysis shows that the range of campaigns is from 0 days to 1,165 days, reflecting that some campaigns took much longer than others. When it comes to PGMs, most campaigns have implemented mechanisms such as social media, cookies, monitoring account activities, and third-party verification. However, google analytics was employed in half of the campaigns. The analysis also shows that about two-thirds of these campaigns have reached their funding goals.

5.3.3 Spearman correlation coefficients

Table 31 presents variables and mechanisms that were used in the regression model, along with their correlation coefficients. The pledged amount is positively correlated with the number of funders, and both are strongly correlated with success, indicating that the more funders involved, the higher the probability of success. While duration is negatively correlated with pledged amount and the number of funders, i.e., the longer the duration, the less interested investors become, but positively correlated with success.

Table 30. Descriptive statistics.

Variable	Mean	Std	Min	25%	50%	75%	max	Number of observations
Number of funders	136.04	797.70	0.0	0.0	12.0	73.0	73,206	335071
Pledged amount	27,128.08	172,392.6	0.0	172.0	1,645.0	7,505	5,000,000	335071
Duration	34.7	19.30	0.0	30.0	30.0	42.0	1165	335071
Social media	0.935	0.247	0.0	1.0	1.0	1.0	1.0	335071
Cookies	0.935	0.245	0.0	1.0	0.0	1.0	1.0	335071
Google analytics	0.474	0.500	0.0	0.0	1.0	1.0	1.0	335071
Third-party identity verification	0.830	0.380	0.0	1.0	1.0	1.0	1.0	335071
Success	0.683	0.465	0.0	00	1.0	1.0	1.0	335071

This table presents the descriptive statistics for variables applied, including the mean, standard deviation (std), minimum (min), quartiles (%25, %50, %75), and maximum (max) value. The variables are defined in (Appendix B). The sample covers the period 2009 to 2023.

Regarding PGMs, social media, cookies, and google analytics correlate positively with funders, meaning that these mechanisms positively influence the number of funders. While third-party verification has a negative correlation with funders, suggesting that these mechanisms do not help in increasing the number of funders. Success also has a negative and significant correlation with social media, cookies, monitoring account activities and third-party verification, implying these mechanisms do not significantly help in campaign success. However, campaign success is positively and significantly correlated with Google Analytics, indicating that it contributes to campaign success.

Table 31. Spearman correlation coefficients.

Variable	Number of funders	Pledged amount	Duration	Social media	Cookies	Google analytics	Third party Verification	Monitoring Account activities
Pledged	0.628***							
Duration	-0.171***	-0.037***						
Social media	0.042***	0.002	-0.071***					
Cookies	0.042***	0.004**	-0.065***	0.991***				
Google analytics	-0.162***	0.149***	0.115***	0.237***	0.244***			
Third party Verification	-0.058***	0.026***	0.016***	0.557***	0.563***	0.437***		
success	0.263***	0.577***	0.025***	-0.087***	-0.090***	0.311***	0.006***	0.006***

This table presents the Spearman correlation matrix between the variables in our model. The significance levels are *** for 1%, ** 5% for, and * for 10%.

5.3.4 Univariate analysis

Table 32 compares the means and medians of successful and unsuccessful campaigns. The number of funders shows that the mean and median for successful campaigns are higher than those for unsuccessful campaigns, which implies that successful campaigns have a higher number of funders. The mean and median pledges are much higher for successful campaigns, suggesting that they collect considerably more funds. For duration, longer campaigns are more likely to increase the success probability; however, shorter campaigns are less likely to increase the success probability. Regarding PGMs, social media, cookies, third-party verification, and monitoring account activities show a negative mean and are statistically significant, suggesting that these mechanisms decrease the probability of success. In contrast, Google Analytics shows a statistically significant and positive mean, indicating that the mechanism increases the likelihood of success.

5.3.5 Success model for reward-based and equity-based crowdfunding

Table 33 presents the results of the logistic regression for the success model, based on all data with a total of 268,269 observations, are included. The pseudo-R-squared demonstrates that the model explains approximately 29.23% of the variance. The log-likelihood is -118,490, compared to -167,440 for the null model. The higher log-likelihood indicates the model fits the data much better than the null model. In addition, the model shows that the intercept has a positive coefficient and is statistically significant, indicating that the probability of success is high even without considering other predictors.

The number of funders has a positive coefficient, which implies that the more funders a campaign has, the greater the likelihood of success. The low standard error, along with the p-value, proves a high level of statistical significance. The pledged amount also has a positive coefficient,

Table 32. Univariate analysis.

	Successful campaigns			Unsuccessful Campaigns		Differences			
Variables	N	Mean	Median	N	Mean	Median	Mean	t-test	Median	z-test
Funders	229053	193.876	36.0	106018	13.14	2.00	180.736	89.621***	34	13.452***
Pledged	229053	39,380.66	4,012	106018	1042.52	125.0	38,338.14	85.115***	3887	6.885***
duration	229053	34.64	30.0	106018	34.76	30.00	-0.12	-1.652*	0	0.00
social media	229053	0.978	1.00	106018	0.948	1.00	0.03	40.164***	0	0.00
Google Analytics	229053	0.536	1.00	106018	0.422	0.00	0.114	61.926***	1	433.425***
Cookies	229053	0.993	1.00	106018	0.973	1.00	0.02	37.958***	0	0.00
Third-party verification	229053	0.922	1.00	106018	0.895	1.00	0.027	24.681***	0	0.00

The table presents the mean and median differences between successful and unsuccessful campaigns, along with the results of t-tests and z-tests. The significance levels are *** for 1%, ** for 5%, and * for 10%.

indicating that the more money received by funders, the more successful the campaigns are. The low standard error implies the accuracy of the estimate, and the p-value confirms statistical significance. The analysis indicates that the more funders participated in the campaigns, the more funds were collected, and the higher the success rate.

In addition, the duration has a negative coefficient; this means that the shorter the campaigns last, the higher the chances of success. The high standard error indicates that the estimate of the precision is unreliable, and the high p-value suggests statistical insignificance. The analysis indicates that neither longer nor shorter duration has any influence on campaign success.

Table 33. Success model for reward-based and equity-based crowdfunding.

No. Observations:	268269
Df Residuals:	268262
Pseudo R-squ.:	0.2923
Log-Likelihood:	-1.1849e+05
LL-Null:	-1.6744e+05
LLR p-value:	0.00

Variable	coef	std err	z
Intercept	1.019 ***	0.025	41.027
The number of funders	0.0273 ***	0.000	140.236
Pledged amount	8.285e-06 ***	3.53e-07	23.491
Duration	-0.0004	0.000	-1.370
Social media	-1.773 ***	0.026	-69.523
Google analytics	2.183 ***	0.012	180.984
Third-party verification	-0.421 ***	0.016	-26.476

This table presents the results of the logistic regression for model 5. The dependent variable is success, and the independent variables are defined in (Appendix B). The sample covers the period of 2009 to 2023. The significance levels are *** for 1%, ** for 5% and * for 10%.

Regarding the PGMs, Google Analytics shows a positive coefficient, indicating that the mechanisms increase the probability of campaign success rates, which align with the hypothesis (H2). The low standard error indicates that the estimate of the precision is reliable, and the p-value is statistically significant. The analysis shows that the mechanism can significantly increase the campaigns' likelihood of success.

In contrast, social media and third-party verification show a negative coefficient, implying that both mechanisms decrease the probability of success. The low standard error indicates that the estimate of the precision is reliable, and the low p-value indicates statistical significance. The findings suggest that social media appears to be ineffective, with no impact on success; therefore, it has no effect on the likelihood of success. Regarding the third-party verification, which is a credible and effective mechanism employed by most platforms to verify investors, the analysis indicates that it also has no impact on increasing campaign success.

Model evaluation

A. Confusion matrix

Table 34 presents a confusion matrix, in which the TN class '0' (unsuccessful) indicates that all cases were correctly identified. The TP class '1' (successful) indicates that it correctly identified all cases. Conversely, the FN shows that the model incorrectly predicts a negative class '0' instead of class '1'. Similarly, the FP shows that the model falsely predicts class '1' instead of class '0'. The study finds that the model performs very well for both categories.

Table 34. A confusion matrix.

		Predicted		
		0	1	All
True	0	14265	6864	21129
	1	4579	41360	45939
	All	18844	48224	67068

This table shows the confusion matrix of the model, where the rows indicate the actual classifications while the columns indicate the predicted classifications. '0' denotes failed campaigns, while '1' denotes successful campaigns.

B. Classification report

Table 35 presents the classification report; the precision for class '0' (unsuccessful) shows that the model correctly predicted 76% of the actual cases. For class '1' (successful): the model correctly predicted 86% of the actual that were predicted to be successful.

The model is more accurate in class '1' prediction than class '0' due to its higher value. Similarly, for recall of class '0', the mode predicted 68% of TN, while for class '1', 90% of TP was predicted. This indicates that the model detects TP along with a few FN. Further, for class '0', the f1-score is 0.71, which is lower than that for class '1'. This shows that the model struggles to balance recall and precision for class '0'. The macro average values of such measures are approximately 0.80, which reflects the performance of the model well, and the weighted average values show that the model performs well for both classes. The accuracy of 0.83 means that 83% of its predictions are correct.

Table 35. Classification Report.

	precision	recall	F1-score	support
0	0.76	0.68	0.71	21129
1	0.86	0.90	0.88	45939
Accuracy			0.83	67068
Macro avg	0.81	0.79	0.80	67068
Weighted avg	0.83	0.83	0.83	67068

This table presents the classification report, which includes precision, recall, f1-score, and support for successful and unsuccessful campaigns supported by statistics.

5.3.6 Interaction effects on crowdfunding outcomes: reward-based vs equity-based crowdfunding

At this phase, we aim to determine whether the effect of the PGMs on campaigns differs depending on the platform used. Consequently, a new dummy variable, "equity," has been introduced to compare the PGMs' efficacy across all reward-based crowdfunding and equity-based crowdfunding, as outlined in Table 38. This variable is coded as '1' for equity-based campaigns and as '0' for reward-based campaigns.

The analysis has a perfect multicollinearity problem, where one or more combinations of variables perfectly predict the outcome or lack sufficient variation that effects cannot be estimated by the model reliably. In our study, there are several mechanisms that share the same value, which limits the precision of effect estimation. Consequently, we relied on one mechanism, which is third-party verification, to test whether the PGMs have a different (possibly stronger) effect for any given platform.

Table 36 displays the interaction between the equity-based variable and the third-party verification mechanism. The mechanism alone has a significant negative effect on campaign success. In contrast, the interaction with equity produces a significant positive coefficient, suggesting that third-party verification is more effective in equity-based crowdfunding compared to reward-based crowdfunding. Given that reward-based crowdfunding relies on a fixed all-or-nothing funding model, which reduces the risk. In contrast, equity platforms use a different funding model, which may require additional verification. Additionally, funders who participated in reward-based crowdfunding campaigns do not expect to receive a refund for their contribution. On the other hand, investors in equity-based crowdfunding are expected to become shareholders in startups, which puts more pressure on platforms to verify users.

Table 36. Comparative analysis of interaction effects on equity-based vs reward-based crowdfunding.

No. Observations:	268269		
Df Residuals:	268260		
Pseudo R-squ.:	0.4856		
Log-Likelihood:	-86131		
LL-Null:	-1.6744e+05		
LLR p-value:	0.00		
	coef	std err	z
Intercept	0.131 ***	0.029	4.529
Backers	0.043 ***	0.000	174.809
Pledged	1.331e-06 ***	1.99e-07	6.705
Duration	-0.0134 ***	0.00	-35.981
Social media	-0.900 ***	0.030	-31.029
Google analytics	0.680 ***	0.014	49.459
Third-party verification	-0.356 ***	0.017	-20.740
Equity	6.142 ***	0.215	28.515
Equity x third-party verification	2.290 ***	0.278	8.239

This table presents the results of the logistic regression for model 6. The dependent variable is success, and the independent variables are defined in (Appendix B). The sample covers the period of 2009 to 2023. The significance levels are *** for 1%, ** for 5% and * for 10%.

5.3.7 Conclusion

The study finds that funders enhance success rates with each new funder participating. This can increase the likelihood of attracting the attention of potential funders. This also connects to the pledged amount, which suggests that raising more money leads to increased campaign success. Therefore, the more investors participate, the more funds are raised and then the greater the success rate. When it comes to campaign duration, the analysis shows that the shorter duration campaign is associated with a higher success rate, while a longer duration tends to become less effective due to urgency, which may diminish the interest of the funder.

Regarding PGMs, social media and third-party verification have a negative effect, which decreases the success rate of the campaigns, while google analytics has a positive effect, which leads to an increase in the success rate of the campaigns. On the other hand, the interaction between equity and third-party verification shows that the mechanism itself has a negative effect on the success rate and thus decreases the probability of success. However, when considering their interaction, it has a positive effect, which means it increases the likelihood of campaign success. This indicates that third-party verification is more effective in equity-based crowdfunding compared to reward-based crowdfunding.

5.4 Additional tests 'Robustness'

The effect of COVID-19 on PGMs

To further analyze the effect of the PGMs, we conducted another analysis by further adding another dummy variable, i.e., 'COVID-19'. According to Suligowski (2023), the pandemic period was from March 2020 to May 2022. Thus, a new dummy variable, "COVID-19," has been included in order to compare the performance of the PGMs on all the reward-based as well as equity-based crowdfunding platforms, as shown in Table 39. This variable is coded for campaigns from 2020 to 2022 as '1' and for the remaining campaigns as '0'.

During the analysis of both models' success and fraud for reward-based crowdfunding, we encountered a ‘Singular matrix’ problem. This is because there was a high multicollinearity between COVID-19 and PGMs. The strong correlation between COVID-19 and PGMs makes the model mathematically unstable and will never be able to estimate the interaction accurately. However, we did not encounter the issue with equity-based datasets across all datasets, as shown in Table 37.

Table 37 provides the logistic regression coefficients of success before and during the COVID-19 pandemic. On all platforms, the analysis indicates a significantly negative coefficient for the social media mechanism, which implies that it is less likely to increase the success of the campaign before the pandemic. During COVID-19, the effectiveness of social media turned significantly positive, impacting the campaign's success to a greater extent. This can be attributed to the fact that, during the pandemic, funders spent more time online and engaged more with various digital content than in the pre-pandemic period. This confirms the notion of social media providing support during the pandemic.

For equity platforms, the analysis shows that the social media mechanism prior to the pandemic contributed positively but not significantly to the campaign's success. Although investors spent more time online during the COVID-19 pandemic, the findings indicate that this mechanism did not affect campaign success. A possible reason is that the non-significance can be due to the limited timespan of the dataset (only four years), which limits statistical power and makes it challenging to identify consistent patterns. Moreover, the COVID-19 period covers two years of the dataset, which also does not provide enough stability to capture significant shifts.

Table 37. Success model with the effect of COVID-19 across all platforms.

	All-data platforms	Equity-based crowdfunding
Variables	coef	coef
Intercept	1.075 ***	1,242 ***
The number of funders	0.028 ***	0.080 ***
Pledged amount	8.318e-06 ***	2.585e-05 ***
Duration	-2.538e-05 ***	-0.003 **
Social media	-1.881 ***	0.430
Google analytics	2.401 ***	-3.824 ***
Third-party identity	-0.390 ***	-
COVID-19	-3.821 ***	-0.321
COVID-19 x social media	3.460 ***	0.781
COVID-19 x Google Analytics	-	0.234

This table presents the regression coefficients for three different datasets, along with the subsample used for interaction with COVID-19. The sample covers the period of 2009 to 2023.

Regarding Google Analytics, the analysis shows that before COVID-19, the mechanism had a significant negative impact on success, suggesting that it reduces the probability of success. The negative result may be due to many platforms launching recently, which may not yet have the ability to apply the mechanism effectively. During the pandemic, Google Analytics shows a positive but not a significant effect on success, suggesting that the mechanism did not affect the campaigns success. That is, before and during the pandemic, the mechanism was ineffective in increasing the success.

Chapter Six: Discussion

6.1 The number of funders and pledged amount

The analysis for different datasets shows that funders can predict the success of campaigns; the more funders the campaign has, the greater the chances of the campaign being successful. This is because the probability of success increases with each new funder who participates. In addition, the univariate analysis shows that, on average, successful campaigns have more funders compared to unsuccessful campaigns. However, the fraud model indicates that changes in the number of funders neither enhance nor reduce the probability of fraudulent campaigns. Therefore, it is impossible to determine whether the campaigns involved fraudulent activities solely based on the number of participants.

Similarly, the results for different datasets reveal that the pledged amount also shows a positive relationship with the success of the campaign. Most campaigns have extremely low pledged amounts, indicating limited impact, while some have very high promised amounts. This indicates a wide range of amounts received. Accordingly, campaigns with a large number of funders or significant pledges per funder tend to contribute more to the success rate of campaigns than those with a smaller number of participants or small pledges promised. Furthermore, the univariate analysis indicates that the average amount pledged is higher for successful campaigns that reach their target and receive more funds than unsuccessful campaigns. Regarding the fraud model, the analysis reveals that it was impossible to distinguish between fraudulent and non-fraudulent campaigns because fraud occurs across campaigns with varying funding levels.

6.2 Campaign duration

As for duration, the analysis of reward-based platforms within the success model shows that longer durations are associated with a high probability of success, indicating that longer duration campaigns are generally more effective because extended periods often reduce the sense of urgency. A shorter duration is associated with a lower success rate. Besides, the univariate analysis also indicates that the successful campaigns tend to have longer durations, and unsuccessful campaigns tend to have shorter durations. This could be due to funders wanting to know more about the projects and the entrepreneurs. As for the fraud model, the analysis reveals it resembles the success model; longer campaign durations are associated with a reduced likelihood of fraud, whereas shorter-duration campaigns are more likely to be associated with fraudulent activities. This may be due to longer campaigns allowing for more scrutiny and thus giving funders more time to evaluate the projects. In contrast, the equity-based crowdfunding shows that the success rate decreases with each additional day of an increase in campaigns. This demonstrates that shorter campaign durations are associated with the likelihood of success. Yet, a longer campaign duration is associated with a decrease in success, which, in turn, may diminish the interest of funders. However, the univariate analysis for the equity-based platforms indicates that longer campaigns tend to last longer, and shorter campaigns are less likely to increase the likelihood of success. These different conclusions highlight that the univariate tests compare the average between successful and unsuccessful campaigns, while logistic regression considers multiple variables simultaneously, offering a more detailed perspective.

6.3 Social media

Regarding PGMs, platforms that rely on reward-based and equity-based crowdfunding use the mechanism to verify users and promote their campaigns simultaneously. The analysis reveals that the majority of campaigns employed social media mechanism; therefore, the campaigns attracted more funders and received higher pledge amounts. However, the analysis for reward-based crowdfunding shows that social media decreases the probability of campaign success. This suggests that many of these accounts may be inactive or fake, since fraud leaders are not always active on social media, as indicated by Dong et al., (2018). In addition, the univariate analysis also indicates that, on average, successful campaigns used fewer social media mechanism compared to unsuccessful campaigns. In addition, the social media mechanism does not make any contribution toward detecting or preventing fraudulent activities. Social media can attract many curious funders, but they might not convert into pledges, which can lower success rates. Others might see it as a marketing gimmick that raises doubts about the project's seriousness. In contrast, equity-based crowdfunding is quite the opposite; social media significantly increases the campaigns' likelihood of success. Further, the univariate analysis also shows that, on average, successful campaigns used more social media mechanism compared to unsuccessful campaigns. This suggests that funders or investors expect a return on their investment. Consequently, they often have a strong network that can assist in securing their investment. Others view it as a due diligence tool that complements financial analysis.

6.4 Google Analytics

As for Google Analytics, the analysis of reward-based crowdfunding shows that it increases the probability of campaign success, suggesting the effectiveness of this mechanism. The univariate analysis also indicates that the average of employing the mechanism is higher for successful campaigns compared to unsuccessful ones. At the same time, this mechanism is associated with a lower risk of fraud, which ultimately helps prevent it. As for equity-based crowdfunding, it shows a decrease in the likelihood of success in Google Analytics. The data shows that most platforms employed Google Analytics, while a few did not. The results show that it reduces the probability of success. Consequently, the Google Analytics mechanism is less apparent to investors who participated in campaigns; thus, it functions as a backend traffic tracking tool for platforms rather than a means of verifying the identity or credibility of investors.

6.5 Third-party identity verification

Third-party identity verification reduces the probability of success for both types of crowdfunding. Although it may seem counterintuitive, as verification is generally viewed as a reliable and effective mechanism and platforms widely use it. Analysis shows that the majority of campaigns employed the third-party mechanism compared to those that did not. Additionally, a greater number of funders are involved, which is reflected in the substantial amounts of money contributed; however, this has not had a positive impact on the role of the third-party verification in increasing successful campaigns. Possible explanations for the negative impact include applying third-party verification to certain campaigns, especially those considered higher risk, such as those with significant funding goals or businesses subject to stricter regulations and rules. In addition, most funders or investors who participated may not know that campaigns have undergone third-party verification, thus it does not directly influence more funders or lead to higher pledges. However, the univariate analysis indicates that the average of successful campaigns is slightly higher compared to unsuccessful ones. The different conclusions demonstrate that the logistic regression model considers multiple variables simultaneously, providing a more detailed perspective, while univariate tests compare the averages between successful and unsuccessful campaigns.

6.6 Comparative analysis of interaction effects

The interaction between Kickstarter and the third-party verification mechanism of reward-based crowdfunding reveals that the mechanism has no significant impact on the probability of campaign success. The third-party alone mechanism contributes positively to campaign success, indicating that it has a significant impact on the probability of campaign success. In contrast, the interaction with Kickstarter has a negative impact on campaign success. The findings demonstrate that the third-party verification has a more substantial impact on campaign success for the IndieGoGo platform compared to its interaction with the Kickstarter platform. This can be explained by showing the difference in the funding model. Kickstarter uses a fixed 'all or nothing' funding model, which means funders will only receive their funds back if a campaign fails to meet its funding goal. This provides significant reassurance to funders. Indiegogo, on the other hand, uses a flexible 'keep it all' and 'all or nothing' funding model, allowing entrepreneurs to keep the funds even if the campaign does not meet its target. Hence, additional verification is required to enhance the credibility and build trust, which explains the greater influence of third-party on Indiegogo campaigns.

Regarding the combined dataset, the interaction between the equity-based and the third-party verification shows a positive effect on campaign success. While the mechanism alone shows a negative effect on campaign success, it does not increase the success rate. In contrast, the interaction with equity produces a positive coefficient; the mechanism increases the probability of campaign success. The findings demonstrate that the third-party verification is more effective in equity-based crowdfunding compared to reward-based crowdfunding. This can be illustrated by the differences in the funding models and funders' approaches to expectations. Reward-based crowdfunding relies on a fixed ‘all-or-nothing’ funding model, which reduces the risk. In contrast, equity uses a different funding models, which may require additional verification. Additionally, funders who participated in reward-based crowdfunding campaigns do not expect to receive a refund for their contribution. On the other hand, investors in equity-based crowdfunding are expected to become shareholders in startups and thus receive financial return, which puts more pressure on equity-based platforms to verify users.

6.7 The effect of COVID-19

The effect of COVID-19 on PGMS for equity-based platforms is analyzed, showing that the social media mechanism prior to the pandemic contributed positively but not significantly to the campaign's success. During the pandemic, the social media mechanism showed a positive effect, but not a significant one. The analysis shows that social media is not significant before and during COVID-19. Although investors spent more time online during the COVID-19 pandemic, the findings suggest that this shift did not impact campaign success. A possible reason is that the non-significance can be due to the limited timespan of the dataset (only four years), which limits statistical power and makes it challenging to identify consistent patterns. Moreover, the COVID-19 period covers two years of the dataset, which also does not provide enough stability to capture significant shifts.

Regarding Google Analytics, the analysis finds that prior to COVID-19, the mechanism had a significant negative impact on success, suggesting that it reduces the probability of success. The negative result may be due to many platforms launching recently, which may not yet have the ability to apply the mechanism effectively. During the pandemic, Google Analytics shows a positive but not statistically significant effect on success, suggesting that the mechanism did not affect the campaigns success. That is, before and after the pandemic, the mechanism was ineffective.

Regarding all platforms, the analysis indicates a significantly negative coefficient for the social media mechanism, which implies that it is less likely to increase the success of the campaign before the pandemic. During COVID-19, the effectiveness of social media turned significantly positive, impacting the campaign's success to a greater extent. This can be attributed to the fact that during the pandemic, the funders were more online and engaged more with various digital content compared to the pre-pandemic period. This confirms the notion of social media providing support during the pandemic.

6.8 Contributions of the study

1. Creation of a novel, publicly available dataset.

The biggest challenge for my research was the lack of data for crowdfunding studies. As a result, the most important contribution of this study is the preparation of a new, well-organized database of crowdfunding campaigns. It provides accurate data on campaign characteristics, including successful, unsuccessful, suspended and cancelled campaigns. This enables researchers to expand the scope of future studies on campaign success and fraud prevention. Additionally, the study verifies both suspended and cancelled campaigns to determine whether these campaigns are fraudulent or not, and this verification is conducted through social media platforms such as Reddit.

2. **Identifying PGMs applied in crowdfunding.**

This study contributes to the literature on crowdfunding platforms by introducing the PGMs. By systematically classifying various PGMs, such as social media integration, cookies, Google Analytics, monitoring account activities, and third-party identity verification, the study presents a more accurate categorization that minimizes conceptual overlap. The study shows how governance principles work in the online crowdfunding space. Thus, the findings highlight that PGMs in crowdfunding are multidimensional. The research hence expands the theoretical scope of PGMs research by illustrating how mechanism frameworks can be used in crowdfunding platforms where trustworthiness, transparency, and investor protection become determining attributes to shape the outcome.

3. **Evidence-based guidance for policy recommendations on PGMs**

This study provides a practical contribution to platform policy by identifying the PGMs that have the most influence on campaign success and those that do not reduce fraud. The empirical evidence classifies mechanisms that provide measurable benefits and those with limited impact. By estimating the relative contribution of each mechanism, the study provides platform managers with an evidence-based foundation to make informed decisions about the PGMs. For example, the social media mechanism is likely to increase the success rate, but does not necessarily reduce fraudulent activities, while the third-party verification mechanism demonstrates direct ways for building trust. Such highlights provide broader policy recommendations to platform managers, allowing them to concentrate on internal policies, improve or eliminate those that are ineffective, and strike the ideal balance between enhancing campaign success and reducing fraudulent activities.

Chapter Seven: Conclusion and Future Research

7.1 Limitations

Acknowledging the study's limitations is fundamental for maintaining scientific integrity and opens the door for further research to address these issues (Price and Murnan, 2004). This approach provides a comprehensive framework for the potential success of these studies by enabling future research to build upon the discoveries offered in the existing findin8gs. Such a strategy can ensure that the expected benefits are achieved and have a significant impact on the study that is undertaken. Study limitations are described.

First: Sample size and generalizability. Given that this is a case study covering a limited number of fraud cases across specific platforms. Although the data provided significantly contributed to providing in-depth insights, it may not be representative of all fraud cases due to its limited scope. Consequently, determining the effectiveness of PGMs in reducing fraud risk might not be generalizable in some platforms. In the same vein, some data are only available for a limited number of years, such as equity-based platforms. Although the study used a dataset from multiple platforms that provided valuable insights, the research findings are difficult to generalize to a great extent across multiple platforms. Future studies need to improve the sample size to capture the diversity of cases more effectively and extend the timeframe to improve the generalizability of the results.

Second: PGMs applied. The limitation relates to measuring the effectiveness of platform governance mechanisms (PGMs). Some mechanisms were in place since the platform's establishment; hence, it is difficult to assess their effectiveness in campaigns because there is no baseline metric from before implementation to compare, such as comparing the years before applying the mechanism to the years after its use. Furthermore, certain mechanisms also capture similar values to other mechanisms because both were implemented in the same year, leading to multicollinearity in the dataset. In such cases, some mechanisms were excluded to reduce multicollinearity and improve the model's interpretability. However, this exclusion prevents the possibility of determining the effectiveness of excluded mechanisms, and their non-inclusion may have impacted the outcomes.

Third: Narrow focus. Crowdfunding has four types; two types are the focus of our research: reward-based and equity-based crowdfunding, which are the most common, according to Stripe (2025). Loan-based and donation-based crowdfunding are not considered in this study. Although the researcher believes that there is enough evidence to prove the findings, the selective data can cause bias because the platforms that have been examined might not be representative of all crowdfunding types. The results may be over- or underestimates of the effect of PGMs on improving the success rate and reducing fraud if excluded platforms are likely to be different in their behavior. Thus, this is a limitation to the generalizability of the results.

7.2 Conclusion

During the financial crisis in 2008, banks and financial institutions reduced their willingness to lend, and simultaneously, trust in banks declined, leading to increased demand for funds from startups (Mónika and Madarász, 2014). To cover this gap, crowdfunding platforms serve as alternative sources of funding for many innovative ideas. Yet, crowdfunding faces various challenges, such as the risk of fraud and improving the success rate of campaigns. Given the cost of due diligence compared to the low return on investment, information asymmetry related to the campaign, and the inability of funders to evaluate projects, there is an increased likelihood of fraud.

With a focus on different variables and the PGMs, we analyze the number of funders, pledged amount, and campaign duration as control variables, as well as mechanisms that include social media, cookies, Google Analytics, monitoring account activities, and third-party verification. The study clarifies the role of platforms in protecting funders and crowdfunding platforms.

Our study emphasizes several mechanisms that platforms implement to verify users and promote the campaign, which may be a significant opportunity to reduce fraud and improve the campaign's success. The findings confirm that the number of funders and the amount pledged are the strongest predictors of a campaign's success. The more funders that participate in the campaign, and the higher the amount pledged received, the more campaigns gain credibility and legitimacy among new potential investors and funders, and they become more effective. This, in turn, enhances confidence and increases participation in new campaigns. Conversely, neither of these predictors can identify or distinguish fraudulent campaigns from non-fraudulent ones, as fraudulent activities occur at different levels within campaigns.

The duration of the campaign, however, shows variation in results across the crowdfunding platforms studied. Longer campaigns provide the chance to secure higher funding while enabling funders to carefully assess the project and uncover fraudulent activity. Our findings show that in reward-based platforms, the successful campaigns tend to have longer duration, which is associated with a higher likelihood of success, suggesting that extended campaigns are generally more effective because longer durations often lower the sense of urgency, while shorter durations are associated with lower success. In contrast, equity-based crowdfunding shows that shorter campaign durations are associated with the likelihood of success, confirming that the success rate declined with each additional day as campaign duration increased. This variation in results highlights the importance of considering the type of crowdfunding platform and how duration interacts with the behaviour of funders and investors, as well as platform dynamics.

Studies show that social media has emerged as a primary mechanism for promoting campaign success. Our research indicates that, on equity-based platforms, social media has proven effective and thus capable of increasing the likelihood of campaign success. In contrast, reward-based crowdfunding shows that social media has had no effect in increasing campaign success; on the contrary, it has decreased the probability of campaign success. A major reason for this is that many of these accounts are either inactive or fake. Regarding fraud detection, the mechanism does not contribute to detecting or preventing fraudulent activities.

Crowdfunding platforms share information with third parties to verify users, a crucial mechanism for platforms aiming to balance growth with integrity. The findings indicate that although there are mechanisms that contribute positively to success by increasing campaign success and reducing fraud, a third-party verification mechanism, by contrast, is not as strongly associated with enhancing campaign success rate or preventing or reducing fraudulent activities. These findings raise interesting inquiries about what could become a future question regarding third-party verification. Such research would shed light on a deeper understanding of how the third-party mechanism operates.

In brief, this study highlights the dual role of PGMs that platforms implemented in different campaigns. Mechanisms such as social media and Google Analytics have proven their effectiveness in campaign success and in reducing fraud. In contrast, other mechanisms, like third-party verification, have shown no effectiveness in campaign success. By exploring these effects, the study contributes to an improved knowledge of what platforms can do to protect investors.

7.3 Future Research

On considering the limitations of the research, some of the problems were identified that could be addressed in future studies, including those that would be useful in addressing the problem of the crowdfunding industry and protecting both entrepreneurs and funders. These results, therefore, provide pathways for further research to address the problem of the mechanisms applied by platforms and their potential to increase campaign success and reduce fraud.

The researcher proposed to expand the dataset by encompassing all four of the major types of crowdfunding, i.e., reward-based, equity-based, donation-based, and lending-based crowdfunding, as well as including multiple platforms within each type. Such a design would provide a richer and comparative characterization of the impact of different mechanisms of governance on success and fraud across various types of crowdfunding. Moreover, the collection of data over a more extended period, ideally covering many years per platform, enables researchers to observe how the platform implements the mechanisms and assess whether the effectiveness of mechanisms is invariant or shifts with time. Such a larger dataset would not only render findings better established externally, but would allow comparison across types and platforms, providing richer information on whether mechanisms effective in one configuration, say, reward-based, can be translated into another, say, equity-based or donation-based.

Given that some mechanisms have been shown not to impact campaigns, future research could explore some qualitative aspects that will provide a more comprehensive view of the PGMs. The study could complement the current dataset by gathering primary data collected directly from platforms using systematic surveys. This would enable researchers to monitor platforms' adherence to due diligence in campaign verification, ensure the implementation of mechanisms across all campaigns without exception, and observe differences in how they are applied across platforms. Whereas secondary campaign-level data can only inform on measurable outcomes, platform-level data can inform on the internal governance practices underlying such outcomes. With the inclusion of multiple platforms, future research would be better served in establishing whether higher rates of success and lower rates of fraud are systematically connected with stronger due diligence mechanisms and allow for meaningful cross-platform comparison, thereby driving enforcement and effectiveness differences.

Future research should address the third-party verification, which our findings show has a negative impact on either campaign success or fraud reduction. This raises an inquiry into whether the mechanism's design or implementation influences its effectiveness. As well, explore how platforms communicate with third-party verification, and whether this difference impacts their effectiveness, as well as the conditions under which users become trusted to participate in campaigns. Understanding how the third-party verification operates can enhance credibility and build trust between entrepreneurs and funders. Future studies can inform platforms' strategies to improve crowdfunding governance and performance by identifying how this mechanism can be effective in campaigns.

References

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some Simple Economics of Crowdfunding. The National Bureau of Economic Research, 14, 63–97. https://doi.org/10.1086/674021

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions. Journal of Economics & Management Strategy, 24(2), 253–274. https://doi.org/10.1111/0022-1082.00201

Ahlers, G. K. C., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. Entrepreneurship Theory and Practice, 39(4), 955–980. https://doi.org/10.1111/etap.12157

Aidoo, S. (2025). Customer due diligence (CDD) and know your customer (KYC). Research Gate.

Ang, J. S., Cole, R. A., & Lin, J. W. (2000). Agency costs and ownership structure. the Journal of Finance, 55(1), 81-106. https://onlinelibrary.wiley.com/doi/abs/10.1111/0022-1082.00201

Astivia, O. L. O., & Zumbo, B. D. (2017). Population models and simulation methods: The case of the Spearman rank correlation. British Journal of Mathematical and Statistical Psychology, 70(3), 347–367. https://doi.org/10.1111/bmsp.12085

Baucus, M. S., & Mitteness, C. R. (2016). Crowdfrauding: Avoiding Ponzi entrepreneurs when investing in new ventures. Business Horizons, 59(1), 37–50. https://doi.org/10.1016/j.bushor.2015.08.003

Barth, A. (2011). HTTP state management mechanism (RFC 6265). Internet Engineering Task Force *(IETF)*. https://www.rfc-editor.org/rfc/rfc6265

Belavina, E., Marinesi, S., & Tsoukalas, G. (2019). Rethinking Crowdfunding Platform Design: Mechanisms to Deter Misconduct and Improve Efficiency. Management Science, 66(11), 4980–4997. https://doi.org/10.1287/mnsc.2019.3482

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. Journal of Business Venturing, 29(5), 585–609. https://doi.org/10.1016/j.jbusvent.2013.07.003

Belleflamme, P., Omrani, N., Peitz, M., & Institute, I. (2016). Understanding the Strategies of Crowdfunding Platforms. Ifo DICE Report, Ifo Institut – Leibniz-Institut Für Wirtschaftsforschung an Der Universität München, 14(2), 6–10.

Bordo, M., & Landon-Lane, J. (2010). The Global Financial Crisis of 2007-08: Is it Unprecedented? (No. w16589; p. w16589). National Bureau of Economic Research. https://doi.org/10.3386/w16589

Blohm, I., Zogaj, S., Bretschneider, U., & Leimeister, J. M. (2018). How to manage crowdsourcing platforms effectively?. California Management Review, 60(2), 122-149. https://doi.org/10.1177/0008125617738255

Butticè, V., Orsenigo, C., & Wright, M. (2018). The effect of information asymmetries on seria l crowdfunding and campaign success. Economia e Politica Industriale, 45(2), 143-173. https://doi.org/10.1007/s40812-017-0074-9

Burtch, G., Ghose, A., & Wattal, S. (2014). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. Information Systems Research, 25(3), 472–493. https://doi.org/10.1287/isre.2014.0538

Broere, M., & Christmann, R. (2024). Signaling and Fraud when Crowdfunding Campaigns Compete for Pledges. *MPRA*, 41. https://doi.org/Online at https://mpra.ub.uni-muenchen.de/121784/

Chang, J. (2021, April 19). 80 Crowdfunding Statistics You Must See: & Campaign Data. Financesonline.Com. https://alternatives.financesonline.com/crowdfunding-statistics/

Chen, L., Huang, Z., & Liu, D. (2016). Pure and hybrid crowds in crowdfunding markets. Financial Innovation, 2(1), 19. https://doi.org/10.1186/s40854-016-0038-5

Chen, X., & Ma, L. (2023). Lead investors' insider ownership and crowd investors' agency concerns in investor-led equity crowdfuning Pacific-Basin Finance Journal, 78, 101. https://linkinghub.elsevier.com/retrieve/pii/S0927538X23000446

Crowdfund Capital Advisors. (2021). Crowdfund Capital Advisors. Retrieved from. https://crowdfundcapitaladvisors.com/

Crowdfunding's Potential for the Developing World. 2013. infoDev, Finance and Private Sector Development Department. Washington, DC: World Bank.

Cornelius, P. B., & Gokpinar, B. (2020). The role of customer investor involvement in crowdfunding success. Management Science, 66(1), 452-4725

Colombo, Massimo G., Chiara Franzoni, and Cristina Rossi–Lamastra. 2015. "Internal Social Capital and the Attraction of Early Contributions in Crowdfunding." *Entrepreneurship Theory and Practice* 39(1): 75–100. https://doi:10.1111/etap.12118.

Courtney, C., Dutta, S., & Li, Y. (2017). Resolving Information Asymmetry: Signaling, Endorsement, and Crowdfunding Success. Entrepreneurship Theory and Practice, 41(2), 265–290. https://doi.org/10.1111/etap.12267

Cumming, D. J., Johan, S. A., & Zhang, Y. (2019). The role of due diligence in crowdfunding platforms. Journal of Banking & Finance, 108, 105661. https://doi.org/10.1016/j.jbankfin.2019.105661

Cumming, D. J., & Zambelli, S. (2017). Due Diligence and Investee Performance: Due Diligence and Investee Performance. European Financial Management, 23(2), 211–253. https://doi.org/10.1111/eufm.12100

Cumming, D. J., & Zhang, Y. (2017). Are Crowdfunding Platforms Active and Effective Intermediaries? Social Science Research Network., 1–48.

Cumming, D., & Johan, S. (2019). Crowdfunding and Entrepreneurial Internationalization. In Entrepreneurial Finance: Managerial and Policy Implications. (Vol. 2, pp. 109–126). The World Scientific Publishers. https://doi.org/10.1142/9789813220607_0005

Cumming, D. J., Hornuf, L., Karami, M., & Schweizer, D. (2016). Disentangling Crowdfunding from Fraudfunding. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2828919

Cumming, D., Johan, S., & Schweizer, D. (2017). Information systems, agency problems, and fraud: Special section, information systems frontiers. Information Systems Frontiers, 19, 421-424. http://link.springer.com/10.1007/s10796-017-9761-3

Cumming, D., Meoli, M., & Vismara, S. (2021). Does equity crowdfunding democratize entrepreneurial finance? Small Business Economics, 56(2), 533–552. https://doi.org/10.1007/s11187-019-00239-0

Denis, D. J., Denis, D. K., & Sarin, A. (1999). Agency theory and the influence of equity ownership structure on corporate diversification strategies. Strategic Management Journal, 20(11), 1071–1076. https://doi.org/10.1002/(SICI)1097-0266(199911)20:11<1071::AID- SMJ70>3.0.CO;2-G

De Reuver, M., Sørensen, C., & Basole, R. C. (2018). The digital platform: A research agenda. Journal of Information Technology, 33(2), 124–135 https://doi.org/10.1057/s41265-016-0033-3

Dong, W., Liao, S., & Zhang, Z. (2018). Leveraging Financial Social Media Data for Corporate Fraud Detection. Journal of Management Information Systems, 35(2), 461–487. https://doi.org/10.1080/07421222.2018.1451954

Firoozi, F., Jalilvand, A., & Lien, D. H. D. (2016). Information asymmetry and adverse wealth effects of crowdfunding. The Journal of Entrepreneurial Finance (JEF), 18 (1), 1-8.

Freedman, D. M., & Nutting, M. R. (2015). Equity crowdfunding for investors: A guide to risks, returns, regulations, funding portals, due diligence and deal terms. John Wiley & Sons.

Fundable. (2023, June 5). Fundable. Retrieved from. https://www.fundable.com/

Fundraise Up. (2024). Cookies. Retrieved January 17, 2026, from https://fundraiseup.com/docs/cookies/

Gedda, D., Nilsson, B., Såthén, Z., & Søilen, K. S. (2016). Crowdfunding: Finding the Optimal Platform for Funders and Entrepreneurs. Technology Innovation Management Review, 6(3), 11.

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. ACM Transactions on Computer-Human Interaction (TOCHI), 20(6), 1-32. http://hdl.handle.net/10419/197551

Hainz, C. (2018). Fraudulent Behavior by Entrepreneurs and Borrowers. Cumming & L. Hornuf (Eds.), The Economics of Crowdfunding: Startups, Portals and Investor Behavior (pp. 79–99). Springer International Publishing. https://doi.org/10.1007/978-3-319-66119-3_5

Hamdani, A., & Yafeh, Y. (2013). Institutional investors as minority shareholders. *Review of Finance*, *17*(2), 691-725.

Hervé, F., & Schwienbacher, A. (2018). Crowdfunding and innovation. Contemporary topics in finance: a collection of literature surveys, 331-349.

Hilbe, J. M. (2015). Practical Guide to Logistic Regression (Vol. 1). CRC Press, Taylor & Francis Group. https://www.crcpress.com/9781498709576

Hornuf, Lars, and Armin Schwienbacher. 2017. "Should Securities Regulation Promote Equity Crowdfunding?" Small Business Economics 49(3): 579–93. https://doi:10.1007/s11187-017-9839-9.

Igra, M., Kenworthy, N., Luchsinger, C., & Jung, J.-K. (2021). Crowdfunding as a response to COVID-19: Increasing inequities at a time of crisis. *Social Science & Medicine (1982), 282*, 114105. https://doi.org/10.1016/j.socscimed.2021.114105

Indiegogo. (2023, June 3). Indiegogo. Retrieved from. https://indiegogo.trsnd.co/policies

Ivo, J., Lyman, T., & Nava, A. (2017). Crowdfunding and financial inclusion. CGAP (Consultative Group to Assist the Poor) working paper, 41.

Järvinen, J., & Karjaluoto, H. (2015). The use of web analytics for digital marketing performance measurement. Industrial Marketing Management, 50, 117–127. https://doi.org/10.1016/j.indmarman.2015.04.009

Jensen, C., & Meckling, H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Jensen, M. C. (1996). Agency costs of free cash flow, corporate finance, and takeovers. In J. S. Bhandari & L. A. Weiss (Eds.), Corporate Bankruptcy (1st ed., pp. 11–16). Cambridge University Press. https://doi.org/10.1017/CBO9780511609435.005

Jiang, Cuixia, Ranran Han, and Qifa Xu. 2023. “The Impact of Social Media Input Intensity on Reward-Based Crowdfunding Performance: Evidence from China.” *Electronic Commerce Research* 23(3): 1753–74. https://doi:10.1007/s10660-021-09515-7

Johari, R. J., Zul, N. B., Talib, N., & Hussin, S. A. H. S. (2020). Money Laundering: Customer Due Diligence in the Era of Cryptocurrencies. Proceedings of the 1st International Conference on Accounting, Management and Entrepreneurship (ICAMER 2019). 1st International Conference on Accounting, Management and Entrepreneurship (ICAMER 2019), Cirebon, Indonesia. https://doi.org/10.2991/aebmr.k.200305.033

Kaur, Harmeet, and Jaya Gera. (2017. “Effect of Social Media Connectivity on Success of Crowdfunding Campaigns.” Procedia Computer Science 122: 767–74. https://doi:10.1016/j.procs.2017.11.435.

Kristol, D. M., & Montulli, L. (1997). HTTP state management mechanism (RFC 2109). Internet Engineering Task Force (IETF). https://www.rfc-editor.org/rfc/rfc2109

Kickstarter. (2023, June 3). Kickstarter. Retrieved from. https://www.kickstarter.com/privacy?ref=global-footer

Kuti, M., Bedő, Z., & Geiszl, D. (2017). Equity-based Crowdfunding. Hitelintézeti Szemle, 16(4), 187–200. https://doi.org/10.25201/FER.16.4.187200

Kuti, M., & Madarász, G. (2014). Crowdfunding. Public Finance Quarterly; Budapest, 59(3), 355–366.

Lacan, C., & Desmet, P. (2017). Does the crowdfunding platform matter? Risks of negative attitudes in two-sided markets. Journal of Consumer Marketing, 34(6), 472–479. https://doi.org/10.1108/JCM-03-2017-2126

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (2000). Investor protection and corporate governance. *Journal of financial economics*, *58*(1-2), 3-27.

Lee, S., Shafqat, W., & Kim, H. (2022). Backers Beware: Characteristics and Detection of Fraudulent Crowdfunding Campaigns. *Sensors*, *22*(19), 7677. https://doi.org/10.3390/s22197677

Leela, V. (2016). Crowdfunding: A Study of Risk Factors. South Asian Journal of Management, 25 (4)(3), 24.

Lee, S., Park, H., & Kim, H.-C. (2025). Fraud Detection on Crowdfunding Platforms Using Multiple Feature Selection Methods. *IEEE Access*, *13*, 40133–40148. https://doi.org/10.1109/ACCESS.2025.3547396

Ley, A., & Weaven, S. (2011). Exploring agency dynamics of crowdfunding in start-up capital financing. Academy of Entrepreneurship Journal, 17(1), 85.

Li, Q., & Wang, N. (2024). Fundraiser engagement, third-party endorsement and crowdfunding performance: A configurational theory approach. *PLOS ONE*, *19*(8), e0308717. https://doi.org/10.1371/journal.pone.0308717

Liang, Xiaobei, Xiaojuan Hu, and Jiang Jiang. 2020. "Research on the Effects of Information Description on Crowdfunding Success within a Sustainable Economy—The Perspective of Information Communication." Sustainability 12(2): 650. https://doi:10.3390/su12020650.

Li, T. (2013). Fraud in Crowdfunding and Antifraud Insurance. The George Washington University Law School, 22. https://doi.org/10.2139/ssrn.2273263

Lin, L. (2017). Managing the risks of equity crowdfunding: Lessons from China. *Journal of* Corporate Law Studies, 17(2), 327–366. https://doi.org/10.1080/14735970.2017.1296217

Mamonov, S., & Malaga, R. (2018). Success factors in Title III equity crowdfunding in the

United States. Electronic Commerce Research and Applications, 27, 65–73. https://doi.org/10.1016/j.elerap.2017.12.001

Makina, D. (2017). The role of social media in crowdfunding. In Proceedings of the ECSM 2017 4th European Conference on Social Media (p. 186). Cambridge, MA, USA: Academic Conferences and Publishing Limited.

Marashdeh, Z., Saidat, Z., Alkhodary, D., & Al-Haddad, L. (2021). Agency Theory and the Jordanian Corporate Environment: Why a Single Theory Is Not Enough. Academy of Accounting and Financial Studies Journal, 25(5), 1–15.

Mazur, C. (2022, November 3). 25 Critical Crowdfunding Statistics [2022]: How Many Crowdfunding Platforms Are There – Zippia. https://www.zippia.com/advice/crowdfunding-statistics/

Mayer, J. R., & Mitchell, J. C. (2012). Third-party web tracking: Policy and technology. In Proceedings of the 2012 IEEE Symposium on Security and Privacy (pp. 413–427). IEEE. https://doi.org/10.1109/SP.2012.47

Mohammad, M., & Alabdullah, T. (2016). Agency Cost and Management Behavior: The Role of Performance as a Moderator. International Journal of Science and Research (IJSR), 5(1), 2319–7064. https://doi.org/10.21275/NOV153199

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. Journal of Business Venturing, 29(1), 1–16. https://doi.org/10.1016/j.jbusvent.2013.06.005

Mónika, K., & Madarász, G. (2014). Crowdfunding. Public Finance Quarterly, 59(3), 355–366.

Oberoi, S., Srivastava, S., Gupta, V. K., Joshi, R., & Mehta, A. (2022). Crowd Reactions to Entrepreneurial Failure in Rewards-Based Crowdfunding: A Psychological Contract Theory Perspective. Journal of Risk and Financial Management, 15(7), 300.

https://www.mdpi.com/1911-8074/15/7/300

O'connor, S. M. (2023). Crowdfunding Market Size, Share, Growth, Industry Report 2023-2028. https://www.sec.gov/News/PressRelease/DetailbPress

Parhankangas, A., & Renko, M. (2017). Linguistic style and crowdfunding success among social and commercial entrepreneurs. Journal of business venturing, 32(2), 215-236. https://linkinghub.elsevier.com/retrieve/pii/S0883902616302427

Perez, B., Machado, S. R., Andrews, J. T. A., & Kourtellis, N. (2020). I call BS: Fraud Detection in Crowdfunding Campaigns. ArXiv:2006.16849 [Cs]. http://arxiv.org/abs/2006.16849

Petrov, L. F., & Emelyanova, E. S. (2021). The crowdfunding: Financial flows and risks. 2830, 41–51. Scopus.

Podar, M., & Arenas, A. E. (2015). A Work-System Approach to Classifying Risks in Crowdfunding Platforms: An Exploratory Analysis. 21st Americas Conference on Information Systems, AMCIS, Puerto Rico, 2015, 1–18.

Podar, M., Arenas, A. E., Goh, J. M., & Anand, A. (2018). Reading between the lines: Legal risk mitigation by equity crowdfunding platforms. 26th European Conference on Information Systems: Beyond Digitization - Facets of Socio-Technical Change, ECIS 2018 2018, 17. https://aisel.aisnet.org/ecis2018_rp/119

Porsche, Lukáš, Ladislava Zbiejczuk Suchá, and Jan Martinek. 2022. "The Potential of Google Analytics for Tracking the Reading Behavior in Web Books." *Digital Library Perspectives* 38(4): 532–41. https://doi:10.1108/DLP-03-2022-0021.

Porta, R. L., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (2000). Investor protection and corporate governance☆. Journal of Financial Economics.

Powers, T. V. (2012). SEC Regulation of Crowdfunding Intermediaries Under Title III of the

JOBS Act. Banking & Financial Services Policy Report, 31(10),

Price, J. H., & Murnan, J. (2004). Research limitations and the necessity of reporting them. American Journal of Health Education, 35(2), 66–67. https://doi.org/10.1080/19325037.2004.10603611

Ullah, S., & Zhou, Y. (2020). Gender, anonymity and team: What determines crowdfunding success on Kickstarter. Journal of Risk and Financial Management, 13(4), 80. https://www.mdpi.com/1911-8074/13/4/80

Usman, S. M., Bukhari, F. A. S., Usman, M., Badulescu, D., & Sial, M. S. (2019). Does the role of media and founder's past success mitigate the problem of information asymmetry? Evidence from a UK crowdfunding platform. Sustainability, 11(3), 692 http://www.mdpi.com/2071-1050/11/3/692

Renwick, M. J., & Mossialos, E. (2017). Crowdfunding our health: Economic risks and benefits. Social Science & Medicine, 191, 48–56. https://doi.org/10.1016/j.socscimed.2017.08.035

Republic. (2023, June 5) Republic. Retrieved from. https://www.republic.com/

Robock, Z. (2014). The Risk of Money Laundering Through Crowdfunding: A Funding Portal's Guide to Compliance and Crime Fighting. Michigan Business & Entrepreneurial Law Review, 4(1), 19. https://doi.org/10.3868/s050-004-015-0003-8

Rossi, A., & Vismara, S. (2018). What do crowdfunding platforms do? A comparison between investment-based platforms in Europe. Eurasian Business Review, 8(1), 93–118. https://doi.org/10.1007/s40821-017-0092-6

Schulz, M., & Blohm, I. (2019). The Effectiveness of Governance Mechanisms in Crowdfunding. Fortieth International Conference on Information Systems, 9

Shafqat, W., & Byun, Y. (2019). Identifying Topics: Analysis of Crowdfunding Comments in

Scam Campaigns. In R. Lee (Ed.), Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (Vol. 790, pp. 137–148). Springer International Publishing. https://doi.org/10.1007/978-3-319-98367-7_11

Siering, M., Koch, J.-A., & Deokar, A. V. (2016). Detecting Fraudulent Behavior on Crowdfunding Platforms: The Role of Linguistic and Content-Based Cues in Static and Dynamic Contexts. Journal of Management Information Systems, 33(2), 421–455. https://doi.org/10.1080/07421222.2016.1205930

Stanko, M. A., & Henard, D. H. (2016). How Crowdfunding Influences Innovation. MIT Sloan Management Review, 57(3), 15.

Strip. (2025, January). What is crowdfunding? Here are four types for startups to know. https://stripe.com/resources/more/four-types-of-crowdfunding-for-startups-and-how-to-choose-one

Suligowski, R., & Ciupa, T. (2023). Five waves of the COVID-19 pandemic and green–blue spaces in urban and rural areas in Poland. *Environmental Research*, *216*, 114662. https://doi.org/10.1016/j.envres.2022.114662

Song, C., Luo, J., Hölttä-Otto, K., Seering, W., & Otto, K. (2015). Risk and Innovation Balance in Crowdfunding New Products. Proceedings of the 20th International Conference on Engineering Design (ICED 15), 8, 1–10.

StartEngine. (2023, June 5) StartEngine. Retrieved from. https://www.startengine.com/

Spence, M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355–374. https://doi.org/10.2307/1882010

Tenca, F., & Franzoni, C. (2019). Handbook of Research on Crowdfunding. In *Crowdfunding: Risk, fraud and regulation* (pp. 323–355). Edward Elgar Publishing Ltd.; Scopus. https://doi.org/10.4337/9781788117210.00020

Torabi, O., & Mirakhor, A. (2018). Controlling information asymmetry in equity crowdfunding. Journal of Economic and Social Thought, 5(1), 32-41 http://www.kspjournals.org/index.php/JEST/article/view/1610

Vismara, S. (2018). Signaling to Overcome Inefficiencies in Crowdfunding Markets. In D. Cumming & L. Hornuf (Eds.), The Economics of Crowdfunding: Startups, Portals and Investor Behavior (pp. 29–56). Springer International Publishing. https://doi.org/10.1007/978-3-319-66119-3_3

Wang, W., Wu, Y. J., & He, L. (2019). Impact of Linguistic Feature Related to Fraud on Pledge Results of the Crowdfunding Campaigns. In A. Visvizi & M. D. Lytras (Eds.), Research & Innovation Forum 2019 (pp. 459–467). Springer International Publishing. https://doi.org/10.1007/978-3-030-30809-4_42

Wati, C. R., & Winarno, A. (2018). The Performance of Crowdfunding Model as an Alternative Funding Source for Micro, Small, and Medium-Scale Businesses in Various Countries. KnE Social Sciences, 3(3), 16. https://doi.org/10.18502/kss.v3i3.1871

Wefunder. (2023, June 5) Wefunder. Retrieved from https://wefunder.com/terms

Wehnert, P., Baccarella, C. V., & Beckmann, M. (2019). In crowdfunding we trust? Investigating crowdfunding success as a signal for enhancing trust in sustainable product features. Technological Forecasting and Social Change, 141, 128-137. https://linkinghub.elsevier.com/retrieve/pii/S0040162517308831

Weir, C., Laing, D., & McKnight, P. J. (2002). Internal and external governance mechanisms: their impact on the performance of large UK public companies. Journal of Business Finance & Accounting, 29(5-6), 579-611. https://onlinelibrary.wiley.com/doi/10.1111/1468-5957.00444

Wessel, M., Gleasure, R., & KAUFFMAN, R. J. (2021). Creators and backers in rewards-based crowdfunding: Will incentive misalignment affect Kickstarter's sustainability?

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97–121. https://doi.org/10.1509/jm.15.0413

Winter, J. C. F. de, Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman Correlation Coefficients Across Distributions and Sample Sizes: A Tutorial Using Simulations and Empirical Data. Psychological Methods, 21(3), 273–290. https://doi.org/10.1037/met0000079

Wood, L. (2021, February 11). *World Crowdfunding Market Growth, Trends, and Forecasts 2021-2026: Reward-based Crowdfunding is Expected to Grow Significantly—ResearchAndMarkets.com*. https://www.businesswire.com/news/home/20210211005592/en/World-Crowdfunding-Market-Growth-Trends-and-Forecasts-2021-2026-Reward-based-Crowdfunding-is-Expected-to-Grow-Significantly---ResearchAndMarkets.com

Xu, J., Chen, D., & Chau, M. (2016). Identifying features for detecting fraudulent loan requests on P2P platforms. 2016 IEEE Conference on Intelligence and Security Informatics (ISI), 79–84.

Ye, T., Zheng, J., Jin, J., Qiu, J., Ai, W., & Mei, Q. (2024). Using Artificial Intelligence to Unlock Crowdfunding Success for Small Businesses (No. arXiv:2407.09480). https://doi.org/10.48550/arXiv.2407.09480

Yin, Z., Huang, G., Zhao, R., Wang, S., Shang, W.-L., Han, C., & Yang, M. (2024). Information disclosure and funding success of green crowdfunding campaigns: A study on GoFundMe. *Financial Innovation*, *10*(1), 147. https://doi.org/10.1186/s40854-024-00666-8

Younkin, P., & Kashkooli, K. (2016). What problems does crowdfunding solve? California Management Review, 58(2), 20-43. http://journals.sagepub.com/doi/10.1525/cmr.2016.58.2.2

Zenone, M., & Snyder, J. (2018). Fraud in Medical Crowdfunding: A Typology of Publicized Cases and Policy Recommendations: Fraud in Medical Crowdfunding. Policy & Internet. https://doi.org/10.1002/poi3.188

Appendixes

Appendix A: The questionnaire

Q1: Please select the list of mechanisms applied by your platform along with the respective years of implementation.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Background check													
Financial information													
Monitoring account activities													
Social media													
Cookies													
Google Analytics													
Third-party-Identity verification													

Q2: Are there any other mechanisms not included in the previous table?

☐- Yes

☐- No

If the answer is yes, the responder will go to question 3; otherwise, they will go to question 4.

Q3: Please specify the mechanism's name and the year it was implemented.

☐- Mechanism name

☐- The year of implementation

☐- Is there any other mechanism?

☐-Yes

☐- No

If the answer is yes, the responder will repeat the same steps in question Q3; otherwise, they will go to question 4.

Q4 During the period of 2009 – 2023, did any campaigns get suspended or cancelled?

☐- Campaign name

☐- Number of funders

☐- The goal of the campaign (in USD)

☐- Amount of funds collected (in USD)

☐- Campaign duration (in days)

☐- Suspended year

☐- Cancelled year

☐- Is there any other suspended or cancelled campaign?

☐- Yes

☐- No

If the answer is yes, the responder will repeat the same steps in Q4; otherwise, they will go to question 5.

☐

☐

Appendix B: Definition of platform governance mechanisms (PGMs) and control variables

Attribute	Definition
The log-likelihood	The model's fit to the data is measured by how well it fits; the closer this value is to zero, the better the model fits the data.
The Pseudo R-squared	A measure of model fit, where higher values indicate a better fit
The LL-Null	The log-likelihood value of the null model (a model with only the intercept)
The number of funders	Refer to the number of funders who participated in each campaign.
Pledged amount	Refer to the amount of money raised by each campaign, regardless of the campaign's success or failure.
Duration	Refer to the time each campaign takes
Fraud cases	Refer to the number of fraud cases that the platform has suspended.
Background check	Refer to the information that the platforms require to register, such as name, address, and phone number.
Financial information	Refer to a credit check that includes the bank account, tax information and credit card number.
Social media	Refer to the link for the Facebook profile information that the platform may access from users' accounts, such as email address, name, profile picture, and list of friends, if the users have allowed the platform to access this information.
Cookies	Refer to a string of information that a website stores on a visitor's computer, such as Flash cookies and pixels. Platforms use cookies to identify and track visitors and their usage.
Google Analytics	A tool to collect information when a user visits the platform and applications, or use it
Monitoring account activities	Refer to specific information, including device information, which includes the IP address, operating system information, web browser and/or device type and language, as well as the information about the interaction with the platform, such as the pages or other content that have been viewed.

Attribute	Definition
Third-party verification	Platforms rely on third-party service providers that help offer, improve, promote, and protect.

Appendix C: The original list of dataset columns.

1. Kickstarter platform

   id, name, blurb, goal, pledged, state, slug, disable_communication, country, currency, currency_symbol, currency_trailing_code, deadline, state_changed_at, created_at, launched_at, staff_pick, is_starrable, backers_count, static_usd_rate, usd_pledged, creator, location, category, profile, spotlight, urls, source_url, friends, is_starred, is_backing, permissions, country_displayable_name, current_currency, currency_trailing_code, usd_type, usd_pledged_real, usd_goal_real.

2. Indiegogo platform

   id, title, tagline, collected_amount, goal, percent_funded, currency, category, category_name, subcategory, subcategory_name, location, country, status, start_date, end_date, duration, backers_count, funding_type, platform_fee, service_fee, total_fees, net_funding, campaign_url, image_url, video_url, creator_name, creator_id, creator_type, team_members, updates_count, comments_count, perks_count, perks, risk_level, featured, trending, popularity_score, engagement_score, success_probability.

3. Equity platforms

   id, company_name, legal_name, website, blog, angellist_url, linkedin_url, twitter_url, facebook_url, description, tagline, country, state, city, founded_at, first_funding_at, last_funding_at, total_funding_usd, funding_rounds, investors_count, market, industry, sector, stage, valuation, revenue, employees, has_patents, has_users, has_paying_customers, has_partnerships, has_social_impact, has_female_founders, has_male_founders, has_technical_founders, has_repeat_founders, has_exits, has_board, has_advisors, has_pitch, has_video, has_updates, has_comments, has_rewards, has_goal,

goal, pledged, backers_count, success, launched_at, deadline, duration, currency, fx_rate, usd_pledged, usd_goal, category, subcategory, platform, campaign_type, campaign_status, round, round_type, round_size, round_valuation, market_size, addressable_market, obtainable_market, market_at_round_target_market_type, traction, growth_rate, burn_rate, runway, profitability, gross_margin, net_margin, churn_rate, retention_rate, conversion_rate, customer_acquisition_cost, lifetime_value, ltv_cac_ratio, monthly_active_users, daily_active_users, downloads, sessions, engagement_rate, bounce_rate, click_through_rate, impressions, followers, likes, shares, comments_count, ratings, reviews, average_rating, nps, satisfaction_score, complaints, refunds, disputes, fraud_flag, risk_score, verification_status, compliance_status, legal_status, tax_status, registration_status, certification_status, license_status, audit_status, approval_status, rejection_reason, cancellation_reason, update_count, communication_count, response_time, support_tickets, resolution_time, escalation_count, feedback_score, sentiment_score, text_length, readability_score, keyword_count, uniqueness_score, plagiarism_score, spam_score, quality_score, trust_score, popularity_score, visibility_score, ranking, position, score, index, weight, importance, priority, flag, indicator, dummy, binary, numeric_code, category_code, group_code, segment, cluster, label, target, outcome, final_status.

Appendix D: The final list of dataset columns.

1. Kickstarter platform

   The number of funders, pledged amount, duration, background checks, financial information, social media, cookies, Google Analytics, third-party identity verification, fraud cases, success, COVID-19, and Kickstarter.

2. Indiegogo platform

   Pledged amount, duration, background checks, financial information, social media, cookies, Google Analytics, third-party identity verification, success, COVID-19, and Kickstarter.

3. Equity platforms

   The number of funders, pledged amount, duration, background checks, financial information, social media, cookies, Google Analytics, third-party identity verification, success, COVID-19, and equity.