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Essays on the determinants of success of crowdfunding projects

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ESSAYS ON THE DETERMINANTS OF SUCCESS OF CROWDFUNDING PROJECTS

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Essays on the Determinants of Success of Crowdfunding Projects

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ABSTRACT

Crowdfunding is a method of raising funds to support a venture, typically by raising small amounts from a large number of investors (backers or patrons). This whole process is conducted on an online platform that facilitates interactions between project creators and potential contributors. We explore in the dissertation, the determinants of the success of crowdfunding projects. The first essay, using data from Kickstarter (the leading crowdfunding platform), explores how backers to a project are interconnected with other backers through their backing of common projects thus forming an implicit backer network. We find that backers that are in central positions within the network have an impact on other backers and, through them, affect the outcomes of projects by increasing the likelihood of project success, increasing funding and decreasing the time taken to reach the funding goal. The second essay explores the unique phenomenon of patronage. Unlike the one-time contribution that backers make in Kickstarter, patrons fund the creator and their projects in a recurring manner. We use data from a leading patronage crowdfunding platform to explore what project characteristics lead to changes in patterns of patron growth and recurring contributions in crowdfunding. We find that several project characteristics not only have an impact on the change in patron and contribution functions but also in the velocity and acceleration of these functions. Both essays uncover determinants that have not been considered thus far in their respective crowdfunding context and provide recommendations for project creators and platforms to maximize the funding generated within each specific context.

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CHAPTER 1: INTRODUCTION

Crowdfunding is a method of raising funds to support a venture, typically by raising small amounts from a large number of investors. Crowdfunding has been a relatively new concept and has developed largely in tandem with web accessibility. Over the past few years, crowdfunding has gained widespread visibility and acceptance, with crowdfunding growing exponentially since 2010. In 2015, it has surpassed the venture capitalist industry and is expected to continue growing (Reddy and Tan, 2017).

Crowdfunding is conducted on online platforms that help facilitate the entire process. Platforms perform the function of a middleman that links up project creators and potential contributors, called backers. The entire process of crowdfunding typically follows a certain procedure in the past. A project creator requires funds for some venture. They go on the crowdfunding platform and create a page providing information on their project, how much funds they require, or the funding goal, and what they can offer backers. This project page will be active for a limited duration. Potential backers are able to view the page and decide if they want to contribute to the project. These backers may receive rewards in return for their contribution. With many backers contributing different amounts, if the project is able to meet its goal before the fixed duration, the creator can receive the funds and proceed with their venture.

Crowdfunding has now evolved. Instead of the typical crowdfunding, we now see a wide variety of different crowdfunding models. The equity crowdfunding model allows a backer to own shares of business or startups. A debt based crowdfunding model allows project creators to borrow money from backers and these creators will have to pay back the loan along with a set amount of interest. A patronage crowdfunding model allows backers to fund project creators in a recurring fashion instead of the one-off funding used in previous models.

Crowdfunding outcomes are mainly dependent on three key players – the platform, the creator and the backer. Each platform has a specific crowdfunding model it adheres to. The creator can leverage on their experience, the effectiveness of their appeals, their personal network and other creator specific traits to solicit funds. The backer can be influenced by their personal preferences, digital buzz, their network of friends and other backer specific traits. Determinants from these three key players should be able to predict crowdfunding outcomes. In my thesis, I investigate uncharted areas within the crowdfunding domain. I look at an unexplored determinant, the implicit backer network, and observe how it, in conjunction with other control variables, can impact backers and project outcomes. I will also examine a new crowdfunding model, the recurring crowdfunding model, that is prominently distinct from previous crowdfunding models and discover the determinants that can impact crowdfunding outcomes.

In my first essay, I explore the implicit backing network within a crowdfunding platform and the influence backers in central positions in the network have on other backers in the platform. Recent research has focused on understanding the factors contributing to project success on crowdfunding platforms. However, there is relatively little research on the platform's ability to link backers together by the projects that they have backed. I examine the importance of backer information on other backers and show that the removal of backer information from a crowdfunding platform exerts a negative effect on success rates. Using data from Kickstarter, I construct a weighted backer network based on 52,678 common projects backed by 11,134 backers. Controlling for digital media mentions and project quality, I find evidence that backers in key positions within the network have an impact on other backers and, through them, affect the outcomes of projects by providing an 80% increase in the likelihood of project success, a 158.87% increase in funding and decreasing the time taken to reach the goal by 3%. These findings are extended by exploring the differential effects of several centrality specifications in identifying influential platform users within a network.

In my second essay, I examine the patronage crowdfunding model. This crowdfunding model has three distinct differences from previous crowdfunding models: (1) funding is recurring and not a one-time contribution, (2) there is no fixed duration for the project and (3) instead of funding a project, patrons are funding a creator. The growth of patrons and contributions vary widely. I identify the determinants that an impact this growth and the dynamics associated with the rate of its growth, velocity and acceleration, at different stages of the crowdfunding process. Using data from Patreon, I obtain 3229 curves each that represents the growth of patrons and contributions. Using project type properties, different kinds of incentives, project presentation characteristics and different project categories, I find evidence that these determinants have a non-uniform impact on patron and contribution growth as well as on their dynamics. In order to control for heterogeneity, I proceed to cluster the curves and find more granular results that translates into specific recommendations for project creators and platforms utilizing the patronage model.

CHAPTER 2: CENTRAL BACKERS IN SOCIAL NETWORKS AND THEIR IMPACT ON THE OUTCOMES OF CROWDFUNDING PROJECTS

Crowdfunding platforms have gained widespread visibility and acceptance over the last decade. It has grown from a market of US$880 million in 2010 to US$34.4 billion in 2015 (Massolution 2015). By 2025, it threatens to overshadow the Venture Capitalist industry (Barnett 2015) as it is slated to grow up to US$96 billion (The World Bank 2013). Even though the growth of crowdfunding platforms has generated many innovations leading to several spectacular successes, over 64% of projects do not get funded (Kickstarter 2016). As such, there is growing interest in understanding the factors that drive crowdfunding project success.

Most recent studies focus on the structural components of crowdfunding projects, such as the type of project, funding goal, duration and number of tiers. There have also been research studying factors endemic to project creators such as their experience and previous successes (Mollick 2013; Kuppuswamy and Bayus 2017). Our paper suggests that aside from individual project and creator factors, the community of backers on crowdfunding platforms also play an integral role in affecting crowdfunding project outcomes. This community, formed by a network of backers that fund the project also double as the project's marketing team as they often help promote the project through word of mouth (Mikhaylova 2013).

Our paper contributes to the crowdfunding literature by focusing on this community. We will explore the interactions of influential backers within the community can affect crowdfunding platforms. There have been papers that have looked at an individual backer's effect on other backers such as the propensity for other backers to contribute to the project (Agrawal, Catalini and Goldfarb 2015; Burtch, Ghose and Wattal 2015; Kuppuswamy and Bayus 2017). In this research, we use existing backer networks to identify the influential backers and determine their impact on other backers and, through them, project outcomes. This network is weighted, reflecting the fact that links within real networks have differing strengths depending on the amount of interaction between backers within the network. Given that these networks are based on backers' prior backing decisions and not on explicated stated links, we combine research on probabilistic networks (Ma, Krishnan and Montgomery 2015) with statistical procedures to account for network weights (Opsahl, Agneessens and Skvoretz 2010) to estimate our backer network as a weighted network.

We also seek to address how crowdfunding platforms view and value their users. The value of each user to the platform is ambiguous, given the fluid nature of interactions within online platforms. It will benefit platforms if they knew the financial value of users within the platform so that they will be able to plan policies that ensure a net profit to the firm. In traditional customer lifetime value research, the network effects of the individual are not accounted for (Gupta and Zeithaml 2006). Our research moves to address this issue by quantifying the network influence of a particular user and their subsequent effect on project outcomes. In addition, the industry has used user activity as a way of identifying influence within the network. Our paper finds that influence through the users' position within the network instead of user activity are the main drivers of project outcomes.

Finally, much of the research in this domain is self-contained with studies using information sources within the platform. Recent research have started to explore linking media data with crowdfunding project outcomes such as using twitter data to infer how tweets can affect crowdfunding (Lu et al. 2015). We utilize a set of various digital media buzz variables such as blogs, forums, online media and social media as control variables to precisely evaluate the impact of these influential backers. A list of comparison between our contributions and our contemporaries can be found in Table 1. [Insert Table 1] We begin by conceptualizing how the behaviour of backers are interdependent in the crowdfunding community with Figure 1 showing the main model our paper seeks to test. [Insert Figure 1]

1 CROWDFUNDING

Crowdfunding refers to the practice of funding a project by drawing on small contributions from many individuals (Mollick 2014). There are three primary players in crowdfunding - the platform, the project creators and the backers. The function of the platform is to provide a digital space for users to interact within and these users fall into two main categories; project creators who approach the platform seeking funds for an idea, and backers who approach the platform seeking projects that interest them. These two groups of users are not mutually exclusive since the platform allows any user to become a project creator. Platforms will receive a proportion of the total funds collected from each successful project as revenue to support their operating costs (Kickstarter 2016). Similarly, project creators will receive funds, real-time feedback and community exposure (Branson 2015) while backers may receive a perk or reward for backing the project. Even though research has shown that there is a tendency for the community to back projects in the same geographical area (Lin and Viswanathan 2015), crowdfunding will generally allow the backer community to serve as an unofficial validation for the success of the project in a wider market. These have led to successes that would have otherwise been denied funding through traditional channels held by experts such as venture capitalist investors (Mollick and Nanda 2015). Notable examples of successes include the Pebble Watch and Oculus Rift. However, these successes are exceptions to the norm. Only 35.89% of projects seeking funding on Kickstarter, the largest crowdfunding website, were successfully funded (Kickstarter 2016). Given the low success rates, it is in the interest of project creators and crowdfunding platforms to understand the community around the platform and how it can contribute to project success.

1.1 INTERDEPENDENCE OF BACKER COMMUNITIES

In the crowdfunding space, users of a platform form an online community. Actions such as creating a project page for others to view, backing a project or viewing projects that other backers have backed are all forms of interaction within the community and require no direct communication between these users. This is consistent with prior research by Kozinets (1999) and Bagozzi and Dholakia (2002), who found that Internet users are likely to gravitate towards forming a community when connecting and interacting with other users. Evidence by Dass, Reddy and Iacobucci (2014) also suggests that individuals can become familiar with each other through online nicknames even if they do not communicate directly. Extending these findings, we expect that a community will be formed even though individual members of the community may not know or communicate with each other directly.

Recent research suggests that users within a crowdfunding community can influence each other. There have been evidence of backers relying on types of information provided by other backers, such as the existence of herding effects based of other backers' decisions (Kuppuswamy and Bayus 2017). Despite showing that backers rely on other backers for information, the information examined by prior research have mostly been aggregate actions of the entire backer body, such as the number of bids, amount backed or number of backers. Consequently, the notion that the actions of a singular backer may affect other backers has not been explored.

Although previous research has not investigated the effects of a singular backer's actions affecting other backers, there have been research that demonstrates that backers tend to pay attention to individual information from other backers. Burtch, Ghose and Wattal (2015) observed that nearly 30% of individuals in their study viewed information on other backers directly before their contribution decision on a crowdfunding project. Similarly, research in micro-loan markets have found that lenders tend to observe lending decisions made by others and factor these decisions in their decision making process (Zhang and Liu 2012).

The importance of an individual's backing action is compounded when we consider information spillover effects. Backers who observe other backers' backing actions before making their own funding decisions can in turn be used by others as a source of information when making decisions. This leads to an information cascade where actions by one individual in the can affect many others (Banerjee 1992). This is especially so in a decision-making scenario such as crowdfunding where people make decisions sequentially since the choices made earlier can be observed by others and may affect future decisions (Anderson and Holt 1997).

To verify that backers use other backers as information, we collect data on Amazon Mechanical Turk from 24 respondents who had experience backing crowdfunding projects. 50% of respondents noted that they have used other backers' contribution history to find projects to back. Respondents were also questioned on the importance of each information source that they used. They reported that the second most important source of information was "other backers that contributed to similar projects". The results of these responses support our assertion that backers utilize other backers as sources of information.

1.2 REMOVAL OF BACKER INFORMATION

In order to further verify the evidence collected from crowdfunding user responses, we look at the effects after a policy change of Kickstarter, one of the largest reward crowdfunding sites, in 2014. Before December 2014, Kickstarter had a backer tab for each project. Backers could access information on other backers of the project, which included projects that these other backers have backed in the past as well as projects that they are currently backing. No information on the amount that they backed was provided. As of December 2014, the backer tab has been removed by Kickstarter. This platform change provides a way to check if access to backer information by potential backers has any impact on project success. We find that removing backer information led to a decline in the success rates of all categories from November 2014 to December 2014, with the three largest categories of Games, Design and Technology suffering a drop of 26.71%, 33.57% and 15.38% in success rates respectively. This suggests that restricting backer information flow to other backers will lead to negative consequences such as the decrease of success rates.

The results from this policy change gives credence to our view that backers use other backers for information as the removal of the backer tab resulted in an immediate drop in success rates since backers lose an important source of information. We seek to test this observation empirically by identifying potential influential backers through their positions within the platform and mapping their effects on other backers and on project outcomes. We expect that these backers should have an unequal amount of influence in being able to reach and influence other backers by the nature of their embeddedness in the platform community.

2 INFLUENTIAL BACKERS WITHIN NETWORKS

We have established that backers do rely on other backers as sources of information. However, we have yet to substantiate the effect each of these backers have on others.

Past research have argued that when people interact with each other, certain individuals will have more influence over others and will exert an effect on other individuals' decision making processes. For instance, Engel, Kegerreis and Blackwell (1969) have shown that influential individuals such as opinion leaders have an impact on new products. Feick and Price (1987) also showed that consumers recognize that certain individuals have knowledge and expertise and are influential. More importantly, Goldenberg et al. (2009) have argued that the value of a customer to the firm includes not only the purchases made by the customer, but also the effect they have on others. Their study showed that people with large social ties known as hubs that can influence the adoption of new items on an online social network site.

Given the consensus that individuals have different levels on influence on others, we expect that influential backers should exist within our network. Research studying crowdfunding have found that this is likely to be true as users are not homogenous. Four different archetypes have been outlined in a qualitative study, two of which are of interest to us (Lin, Boh and Goh 2014). These are Active Backers who are more knowledgeable and fund high quality projects early and Trend Followers who tend to be more risk averse and may look for projects which are popular or look to other backers for clues on what to back.

The industry recognizes the potential effects of these influencers as well, with third party platforms such as BackerClub, Krowdster and Backercamp promising to connect project creators to backers that have influence. Kickstarter have encouraged project creators to leverage on the "network effects of Kickstarter" and some creators have utilized this by reaching out to potential influential backers. For instance, Ministry of Supply, a firm that has crowdfunded several projects, has stated that they target and reach out to backers that have backed multiple projects, with the rationale that if "they have backed 20 or more projects, they are likely an influential backer" (Fenzi 2013). BackerClub and Krowdster has also used activity as an indicator with BackerClub stating that the average member has "backed 106 crowdfunding projects"

(BackerClub 2017) and Krowdster targeting “Super backers” that have backed “at least 10, 20 or even 50” crowdfunding campaigns (Krowdster 2017).

Although evidence from research and industry presents the existence of influential backers, there has been a lack of consensus in methods used to identify these influential backers with research focusing more on backer characteristics to identify “active backers” while the industry uses the number of past projects backers have backed as a signal to identify influential backers. Given the lack of consensus in the metric to identify these backers, we propose a method that can be used to identify these influential backers as well as compare the influential backers identified by us against those identified by using industry consensus.

2.1 CONCEPTUALIZING CENTRAL BACKERS

In order to reliably identify influential backers in the crowdfunding context, we need to track influence through interactions between users. This influence can thus be inferred by a network that links backers together. One of the reasons for the absence of network structures in crowdfunding has been the difficulty in identifying a backer network. Most research on network influence deal with explicit connections such as tracking user influence via referrals (Trusov, Bucklin and Pauwels 2009) and friends (Trusov, Bodapati and Bucklin 2010). Due to the lack of explicit connections such as friend links, research of networks in crowdfunding have mainly focused on the number of Facebook friends the creator has instead of a backer based network (Mollick 2014; Zvilichovsky, Inbar and Barzilay 2014). Our study’s main focus is on project backers’ relations with other backers. Consequently, we do not have an explicit network to draw upon. Instead, we will use implicit links, the actual backing behaviour of backers, and a probabilistic method to construct an implicit backer network.

Since we have laid out the possibility of a network cascade effect that can result from backers using other backers as information sources, we will identify only a small group of influential backers to examine if they will be able to generate a large effect across the whole network. Our focus will thus be identifying this small group of backers. These backers will be identified through their positions within the network. Backers exist as nodes in the network, with links called edges connecting them. Social network research have identified several centrality measures that can quantify the amount of influence a node has (Kiss and Bichler 2008; Chen et al. 2011). We will look at several of these measures and use them to triangulate influential nodes within the network. We will then estimate the effects these nodes, or central backers, have on others within the network.

2.2 INFLUENCE OF CENTRAL BACKERS ON PROJECT OUTCOMES

In our conceptualization, the crowdfunding process is interdependent, with interactions between backers forming an implicit backer network that will serve as a source of influence to backers within the network. Using existing interactions to model the implicit backer network provides us a way to identify key backers that play an important role in affecting other backers. We use centrality scores as a proxy of influence and theorize that the small group of backers that are central within the network will be able to affect other backers of crowdfunding projects. For this reason, we expect that the act of a central backer contributing to a crowdfunding project will increase the number of backers contributing to the project.

H_1: A central backer contributing to a project will have a positive effect on the number of backers contributing to the project.

As mentioned before, a key indicator of crowdfunding is whether the project succeeds or fails (Mollick 2014; Kuppuswamy and Bayus 2017). However, there are several other measures that can serve as determinants of project success as well, such as how much of the project goal was funded and the amount of time the project took to meet its goal. Research by Kuppuswamy and Bayus (2017) have used the percentage of goal funded as an indicator of project success. In order to explore the effects these central backers have on project outcomes, we posit that when central backers contribute to a project, the project is more likely to succeed. Consistent with our earlier hypothesis, as backers in central positions have a larger possibility of spreading their influence through the network, the act of backing a project will increase the likelihood that other backers seeking information on whether to contribute to a crowdfunding project may be affected by this act of backing. This increase in the number of backers will, in most cases, impact several project outcome variables. Therefore, we predict the following:

H_{2a}: Crowdfunding projects are more likely to succeed when central backers contribute to the project.

H_{2b}: Crowdfunding projects will generate higher percent funding when central backers contribute to the project.

H_{2c}: Crowdfunding projects will require a shorter time to meet its funding goal when central backers contribute to the project compared to projects with no central backer contribution.

3 DATA

Our primary data source for much of the project related (project description, goal amount, amount funded etc.) and backer related information (number of backers, backer history etc.) is Kickstarter.com, the largest reward crowdfunding platform. Kickstarter categorises its projects into 15 different categories. We chose three of the largest categories on Kickstarter, Design, Games and Technology, for our study. These three categories represent more than half of Kickstarter, raising 58.3% of the total funds (Kickstarter 2016) and attracting over 56% of backers on Kickstarter (Kickspy 2015). Given their size, we expect these three segments to be appropriately representative of the backer network in Kickstarter.

As of 2016, there have been over 28,000 projects launched in the Games category, accumulating a total of over $570 million. This amount, which represents over 20% of the total funds collected by Kickstarter, makes the Games category the largest category contributing to Kickstarter's total funds raised. Even with the large amount of funds collected, the success rates of projects in the Games category remain at 34.8%. The paper will present main results from the Games category and use the Design and Technology categories as a robustness check. To account for the possibility of external information outside the crowdfunding platform affecting project outcomes, we collect data relating to digital media buzz mentions as well. Data on digital buzz were gathered through online search engines and various media platforms. Other critical data such as network characteristics were estimated through the computation of the backer network. A summary of the data and data sources is presented in Table 2. [Insert Table 2].

3.1 BACKER NETWORK CONSTRUCTION

To construct our backer network, we take a random sample of 300 Games projects from January 1 to 31 March 2014. Projects taken from this timeframe meets two conditions that are essential in our network formation; the backers chosen are recently active backers and there is a sufficient window where we can draw past backing actions from. As the basis of our network is formed from past backing actions, a larger window will facilitate a more accurate network estimation. The duration of our backing action window will thus be the entire backing history of these backers from Kickstarter's inception in April 2009 to April 2014. Some of the projects in the Games category were terminated by the project creators or Kickstarter before the end for several reasons (not much interest being shown, feasibility of the project etc.). We estimated models without these cancelled projects to eliminate any alternative explanations driven by cancelled projects that may affect our results.

Our random sample of project and full sampling of the entire population of backers within this project will be used to construct a weighted adjacency matrix. This weighted adjacency matrix is a Backer to Backer matrix (B_{ij} matrix) that has information on the links between each pair of backer in our network as well as their weights - in our case the number of common projects shared between backers. With this B_{ij} matrix, we will move on to form our backer network.

3.2 NETWORK CENTRALITY MEASURES

Our study will make use of three centrality measures to triangulate central backers within our backer network. As the structure of a social network can be described by multiple network characteristics, we will use degree to capture local network effects such as cluster formation and other measures such as closeness and betweenness to capture global network effects such as network position (Ebbes, Huang and Rangaswamy 2016).

Degree measures the number of edges the node has with other nodes and the strength of these edges. It identifies the quality of the relationship between backers (Freeman 1978). A backer that has many direct connections to other backers has a high degree score within the network. Similarly, a backer that has few connections but a lot of activity taking place between connections can also be said to possess high degree as well (Barrat et al. 2004). In the context of our network, a backer has backed a few common projects linked with many other backers as well as a backer that has backed many common projects with a few backers may both possess a high degree score. We use a 0.5 tuning parameter created by Opsahl, Agneessens and Skvoretz (2010) to treat edge weights and the number of edges with equal importance.

Closeness is a measure of how quickly a node can access other nodes within a network (Freeman 1978). In the context of crowdfunding, it calculates the sum of distances of a backer to other backers in the network. The more central a node is, the lower its total distance from all other nodes. In the context of our network, a backer that can reach others within the network by passing through a smaller number of other backers has a high closeness score and thus more influential. We invert the weights and use them as costs to represent the cost of connecting two backers (Newman 2001). We complement this by using the 0.5 tuning parameter created by Opsahl, Agneessens and Skvoretz (2010).

Betweenness quantifies a node's ability to make connections with other groups of nodes in a network, namely where the node bridges the shortest path between two other pairs of nodes (Freeman 1978). If a backer is included in many paths linking other backers to each other, that backer is more likely to be influential as they have the potential to control communication within the network. In the context of our network, if a backer is the bridge between two different groups of backers, this backer has a high betweenness score and thus is said to be more influential. We use Brandes' (2001) algorithm to calculate betweenness in weighted networks. Like previous measures, we complement this by using the 0.5 tuning parameter created by Opsahl, Agneessens and Skvoretz (2010).

4 MEASURES

Our paper explores the effects of central backers on three measures of project success:

Funding status is defined as a binary variable and captures whether the crowdfunding project was able to meet its funding goal (Zvilichovsky, Inbar and Barzilay 2013; Hu, Li and Shi 2015; Mollick 2014; Kuppuswamy and Bayus 2017). Projects that meet the goal amount by the end of the Kickstarter funding period are considered successful. Projects that fall short of the goal amount are defined as unsuccessful and the funds will not be collected from the backers.

Percent Funded measures how much funds the project was able to collect with respect to its funding goal (Kuppuswamy and Bayus 2017). We define it as the percentage of the goal amount that was raised at the end of the funding period. This measure allows us to account for the magnitude of project success. A project which was able to raise the exact goal amount receives a score of 1.0. A project with a score of 2.0 means that the funds raised is twice that of the funding goal. We calculate this metric by utilizing both the total funds raised and the funding goal amount from the Kickstarter project page.

Goal Rate is a success measure aims to define how quickly the project was able to reach the goal. The speed at which a project takes to meet its goal has not been formally explored in prior crowdfunding research. In order to partition out the effects central backers have on meeting the goal, we only consider successful projects since goal rate does not take into account projects that have failed to meet their goal. We use the number of days the project took to hit its funding goal relative to the stipulated project duration to calculate the proportion of time the project took to meet its goal. This measure ranges from 0 to 1, where a score of .8 means that the project reached its goal amount using only 80% of the funding duration of the project. This metric is calculated from the project duration data from the Kickstarter project site and the longitudinal data on contributions from Kickspy.

Backer variables play a pivotal role in our model as our hypotheses revolve around the effects that backers central to the network can have on other backers and project outcomes. As outlined previously, we estimate the implicit backer network based on backers' previous backing decisions before identifying the 10 few influential backers within the network.

No. of Central Backers is the focal variable of our study. These denotes the number of central backers who backed the project which are obtained by identifying backers who scored high in three forms of network centrality measures – degree, closeness and betweenness. As we plan to identify the top 10 central backers, this variable will be treated as a negative binomial.

No. of Backers will denote the aggregate number of backers that have contributed to the project (Mollick 2014; Kuppuswamy and Bayus 2017). Our study's backer variable excludes backers identified as central backers and only includes all other non-central backers.

We include project characteristics to capture project heterogeneity. These characteristics are components that are found on the main page of Kickstarter projects and have been used in extant research to control for the differences in projects. We acquire data on different project characteristics and present them here as covariates in our model.

Goal Amount is the amount of funds the project is seeking. It has been shown to have a negative effect on project success, with projects that have larger goal amounts being less likely to succeed (Marom and Sade 2013; Mollick 2013, Zvilichovsky, Inbar and Barzilay 2013, Mollick 2014).

Duration is the length of time the project has to reach its funding goal. This varies with projects, with the average duration length being 30 days. Duration has been shown to have a positive effect on project success, with projects that have a longer goal amount being more likely to succeed (Mollick 2013; Zvilichovsky, Inbar and Barzilay 2013; Mollick 2014; Agrawal, Catalini and Goldfarb 2015; Kuppuswamy and Bayus 2017).

Creator Experience is the number of previous projects started by the creator. This data is taken by examining the history of the project creator and the number of projects that the creator had before the current project. Previous research has found support that a creator's past successes will affect their current project's likelihood of success (Marom and Sade 2013; Zvilichovsky, Inbar and Barzilay 2013).

Tiers represent the number of reward tiers offered by the project. Reward tiers consist of an amount associated with the tier as well as a reward. Backers whose contributions meet or exceed that amount will be eligible for the reward in that tier. The reward can range from appreciation to the product featured. Previous research has shown that tiers will affect backer support (Kuppuswamy and Bayus 2017).

Video is a binary variable that captures whether the project has a video on its project description page. This variable has been used by many crowdfunding researchers (Mollick 2013; Mollick 2014; Agrawal, Catalini and Goldfarb 2015, Kuppuswamy and Bayus 2017). The presence of video is considered as an effective information source and is expected to have an impact on the evaluation of the project by backers and on the success of the project.

The number of updates posted by the project creator for the duration of the project is also important. Previous research has shown that updates affect backer support and success rate (Kuppuswamy and Bayus 2017).

To assess the impact of different digital media buzz on backers, we collect data on the digital media buzz that was generated for the duration of the crowdfunding project campaign. We collect this data through scraping search engine results and record all mentions of the project.

There are four avenues of digital media buzz that we focus on – Forums, Online Media, Blogs and Social Media. Forums are online threads or pages that moderators maintain while other users post responses on. Online Media sites are sites that allow media such as pictures or videos to be shared. They include Podcasts, Tumblr, Instagram and Deviantart. Blogs are created by users and are often written in an informal or conversational style. Social media are posts on Twitter, Facebook or Google Plus. The data are gathered from the number of mentions in these respective avenues of digital media for the duration of the project.

A possible endogeneity that surfaces in our model is that an omitted variable, project quality, may be driving both central backers and backers to contribute to certain types of projects. In this case, any connection between central backers and backers may be due to project quality and not what our study hypothesizes. We use three different variables to account for project quality – whether the project has a video and the innovativeness and feasibility of the project. A project that has a video is often seen as an indicator of project quality and has been shown in past research (Mollick 2014). Innovativeness is the novelty of a project from a technological and market standpoint. This variable has been used on new projects to denote product quality (Kleinschmidt and Cooper 1991; Poetz and Schreier 2012). Feasibility is a measure of the likelihood of the project being a success in the market and has similarly been adapted from previous research on new products to show product quality (Poetz and Schreier 2012). Given that Innovativeness and Feasibility are subjective measures of new products, we use three different raters to rate all 300 projects on these variables. Due to the nature of crowdfunding, we use the proportional reduction in loss measure by Rust and Cooil (1994) to measure ratings for new products and find that our measures have a 75% inter-rater reliability.

Table 3 shows provides descriptive statistics of the data gathered. We further ran a collinearity test and verified that there were no multicollinearity issues. [Insert Table 3]

5 MODEL FORMULATION & ESTIMATION

We model the impact of our predictor variables on crowdfunding project success for project k as follows:

$$\begin{aligned}\mathrm{Projout_k} = {} & \beta_1\mathrm{NCB_k} + \beta_2\mathrm{NB_k} + \beta_3\mathrm{Goal_k} + \beta_4\mathrm{Dur_k} + \beta_5\mathrm{NPast_k} + \beta_6\mathrm{NTiers_k} + \beta_7\mathrm{Video_k} \\ & + \beta_8\mathrm{NUp_k} + \beta_9\mathrm{BZSoc_k} + \beta_{10}\mathrm{BZBlogs_k} + \beta_{11}\mathrm{BZForums_k} + \beta_{12}\mathrm{BZMedia_k} \\ & + \varepsilon_{\mathrm{Projout_k}}\end{aligned}$$

$$\begin{aligned}\mathrm{NCB_k} = {} & \beta_{13}\mathrm{Goal_k} + \beta_{14}\mathrm{BZSoc_k} + \beta_{15}\mathrm{BZForums_k} + \beta_{16}\mathrm{BZBlogs_k} + \beta_{17}\mathrm{BZMedia_k} \\ & + \beta_{18}\mathrm{Video_k} + \beta_{19}\mathrm{Feas_k} + \beta_{20}\mathrm{Innov_k} + \varepsilon_{\mathrm{NCB_k}}\end{aligned}$$

$$\begin{aligned}\mathrm{NB_k} = {} & \beta_{21}\mathrm{NCB_k} + \beta_{22}\mathrm{Goal_k} + \beta_{23}\mathrm{BZSoc_k} + \beta_{24}\mathrm{BZForums_k} + \beta_{25}\mathrm{BZBlogs_k} + \beta_{26}\mathrm{BZMedia_k} \\ & + \beta_{27}\mathrm{Video_k} + \beta_{28}\mathrm{Feas_k} + \beta_{29}\mathrm{Innov_k} + \varepsilon_{\mathrm{NB_k}}\end{aligned}$$

for projects k = {1,2,…}, where

$\mathrm{Projout_k}$ = Outcome of project k, (success status of the project k, percentage of the goal funded for project k or the rate that the project k takes to reach its goal). Status of the project will be analysed using a probit model as it is binary for failure and success,

$\mathrm{NCB_k}$ = Number of central backers that contributed to project k,

$\mathrm{NB_k}$ = Excluding central backers, the number of backers that contributed to project k,

Goal_k = the goal amount that project k sought to raise,

Dur_k = the funding window duration allocated for project k,

NPast_k = the number of past projects the creator of project k had on Kickstarter,

NTiers_k = the number of reward tiers project k had,

Video_k = a binary variable denoting if project k had a video or not,

NUp_k = the number of updates project k had,

$\mathrm{BZSocial}_k$ = the number of mentions project k had on social media sites,

$\mathrm{BZForums}_k$ = the number of mentions project k had on forums,

$\mathrm{BZBlogs}_k$ = the number of mentions project k had on blogs,

$\mathrm{BZMedia}_k$ = the number of mentions project k had on online media sites,

Innov_k = the innovativeness rating of project k,

Feas_k = the feasibility ratings of project k.

Variables are all mean-centred and standardized except for outcome variables and the central backer variable which is treated as a negative binomial. We estimate the three equations simultaneously using a full information maximum likelihood method.

6 NETWORK ANALYSIS RESULTS

Our constructed backer network has 11,134 backers. These backers are active users, meaning they backed more than one project in the duration of our study. We impose this constraint as backers who have backed one project have little activity within the platform and are unlikely to influence other backers, hence they are excluded when computing our network. We compile the complete backing history of these backers from April 2009 to April 2014, resulting in a total of 51,678 unique projects. Based on this backing history, we create a B_{ij} matrix of over 61 million symmetric cells with approximately 29 million connections. Of the backers who shared joint projects, there was a shared average of 1.5 common projects. [Insert Figure 2]

From our B_{ij} matrix, we derived the backer network. The three centrality measures - degree, closeness and betweenness, were estimated for each backer. We find that the majority of backers have low centrality scores with only a small proportion with high scores. Given that a random network will conform to a larger degree of homogeneity, our backer network with its high clustering, high modularity and few nodes scoring high on centrality exhibits non-random properties. This centrality distribution provides evidence that only a small proportion of backers score high on each individual centrality measure. As each centrality measure indicates a different measure of influence within the network, we will triangulate our central backers by utilizing all three measures to identify these backers. To conform to our argument that a small number of backers will be able to drive influence within the network, we identified the top 10 backers who scored high in all three centrality measures. With our influential backers identified through their centrality scores, we proceed to estimating our model.

7 EMPIRICAL MODEL RESULTS

We use a random sample of 300 projects to compute our model. We first present the effects of the presence of central backers on crowdfunding projects using descriptive data in Figures 3a, 3b and 3c. Projects were split depending on whether they had any central backers contributing to the project. On average, 85% of the 103 projects backed by central backers were successfully funded whereas only 24% of the 137 projects that were not backed by central backers were successfully funded (t=-12.11, $p<.01$). Similarly, projects with central backer contributions gained significantly higher funding than projects without central backers, achieving 465.6% funding instead of 61.54% (t=-2.95, $p<.01$). Although projects with and without central backers do not have any significant difference in goal rate, the other results are encouraging as they give credence to our hypotheses. Taking these results into consideration, we move on to an empirical analysis of our results. [Insert Figure 3]

The results of the model for Games Category are presented in Table 4. [Insert Table 4]

Based on the results in Table 4, we can see that consistent with our first hypothesis, the number of central backers have a positive impact on the number of backers contributing to a project (β=.27, $p<.01$; β=.27, $p<.01$ and β=.20, $p<.01$). Furthermore, in line with previous research, we find that the number of backers significantly affected project outcomes, with more backers leading to a higher likelihood of success (β=2.95, $p<.01$), higher percentage funded (β=5.94, $p<.01$) and shorter time to reach the goal (β=-.12, $p<.01$). This provides support for H_{2a}, H_{2b} and H_{2c} since this suggests that central backers can indirectly increase the likelihood of project success, increase the funding of a project and reduce the time taken to fund the project.

Our analysis on control variables for our model yielded results that are consistent with prior research. To control for project differences, we included several project characteristics. Table 4 showed that the project's goal amount negatively affects the project success status (β=-1.28, $p<.01$) and percent funded (β=-2.13, $p<.01$) but positively affects the time taken to reach the goal (β=.18, $p<.01$). Previous research has shown that goal amount affects the likelihood of project success, with projects that have a larger goal amount taking a longer time to achieve success (Marom and Sade 2013, Mollick 2013, Zvilichovsky et al. 2013, Mollick 2014, Kuppuswamy and Bayus 2017). We also found that for goal rate, goal amount has a positive significant relationship with central backers, with a larger goal amount corresponding to a higher number of central backers contributing to the project (β=.41, $p<.01$).

Our estimates also show that the number of updates affect both funding status (β=.75, $p<.01$) and percent funded (β=1.47, $p<.05$). This corresponds to what Mollick (2014) and Kuppuswamy and Bayus (2017) found in their research. The number of updates can signify the project creators' commitment to the project as well as provide an avenue of interaction for creators and backers, leading to a higher likelihood of funding success.

We next examine the effects of digital media buzz on backers. We find a strong effect of digital media buzz on both backers and central backers. Our results indicate that backers are significantly affected by Forums, Online Media and Social Media, with these forms digital media buzz showing significant positive effects on the number of backers that a project has. Central Backers however are slightly more complex. Although the digital medium of forums and blogs have significant positive effects on central backers, the medium of online media and social media have negative significant effects on central backers. This discrepancy can be explained by research on source credibility. Prior to this, we have suggested that central backers are "expert" backers and will tend to critically judge sources of information. Research on credibility on the web have observed that users tend to judge sources by surface credibility as well as message credibility (Wathen and Burkell 2002). Furthermore, projects that tend to have more posts in online or social media tend to be split into two groups – projects that are interesting and creative or projects that are ludicrous or have negative reputations, with the latter occupying a larger proportion of the market share. This has been corroborated by a study showing that negative news tend to be spread more on social media such as Twitter (Hansen et al. 2011). These two reasons combined will lead central backers to either ignore social and online media or to be affected negatively after objectively judging the information. These results suggest that project creators should generate interest in their project by using forums and blogs primarily to attract central backers and backers.

To sum our results up, the number of central backers has a direct (β=.41, $p<.05$) and indirect effect on status, with central backers having a positive effect on backers (β=.27, $p<.01$) and backers having a positive effect on funding status (β=2.95, $p<.01$) suggesting that projects that have central backers being able to achieve successful funding. However, the number of central backers only has an indirect effect on percent funded and goal rate, with central backers having a positive effect on backers (β=.27, $p<.01$; β=.20, $p<.01$ respectively) and backers having a positive effect on percent funded (β=5.94, $p<.01$) and goal rate (β=-.12, $p<.01$), suggesting that projects that have central backers will increase project funding by 158.9% and decrease the time taken to reach the funding goal by 3%. [Insert Figure 4] To verify our results, we ran a mediation analysis on our data. The mediation analysis mirror our results, with central backers having an indirect effect on project outcomes.

7.1 COMPARISON BETWEEN CENTRAL BACKERS & LARGE BACKERS

We have shown in our previous analysis the impact of central backers in an implicit backer network on crowdfunding project success. As mentioned, the industry tends to view backers that have backed many projects as generally influential. Similarly, research has shown that users with the highest activity rates are generally influential within the platform (Trusov, Bodapati and Bucklin 2010). In the previous analysis, 50% of our previously identified central backers can be considered as large backers since they are also within the top 10 backers that back the most projects. We thus pose this question to our research: can the market identify influential backers also based solely on the number of previous projects backed?

To separate the effects of centrality and size of backing activity, we re-estimated our model using two mutually exclusive sets of backers – Large Backers and Exclusively Central Backers. Large Backers are defined the top backers based on the number of previously backed projects but are not within the top backers scoring high on all three centrality measures. Exclusively Central Backers are the top backers based on centrality scores but are not within the top backers based on size. We re-estimated our model based on the top 10 backers of each group.

To visualize the difference between the presence of Large Backers and Exclusively Central Backers, we compare projects backed by these two groups in Figure 5. Figures 5a, 5b and 5c illustrate how the presence of Large Backers will affect project outcomes. We find that Large Backers are distinctly dissimilar from Exclusively Central Backers. Comparing the presence of Exclusively Central Backers (Figure 6) to the central backers identified in our main model (Figure 3), we see a similar pattern, with projects backed by both these types of backers outperforming projects not backed by them. However, unlike projects backed by central backers, projects backed by Large Backers display contrasting results. We observe that projects backed by Large Backers perform worse than projects that were not backed by them in all three project outcomes. The disparity between Large Backers and Exclusively Central Backers demonstrates that there is a difference between them and Large Backers are unlikely to generate the impact shown by central backers. [Insert Figure 5]

To empirically test the difference between Large Backers and Exclusively Central Backers, we repeat our estimation using these two groups. Our results show that unlike central backers, Large Backers do not significantly affect the number of backers in both our funding status and percent funded models. However, we do find that Large Backers have an indirect effect on goal rate, with a direct effect on number of backers (β=.31, *p<.01*) and a significant effect of number of backers on goal rate (β=-.15, *p<.01*). Comparatively, evidence based off Exclusively Central Backers show that these backers have an indirect effect on all three project outcomes. This implies that backers scoring high on centrality and large backers are fundamentally different, with backers high in centrality affecting the network and consequently project outcomes while Large Backers having little influence on other backers in most project outcomes. [Insert Table 5]

Aside from using large backers, we used the top backers that scored high on each individual centrality score and found that regardless of the centrality score, the results conformed with our initial finding, showing that our results are not sensitive to the centrality score used.

7.2 ROBUSTNESS CHECKS & ENDOGENEITY

As noted in our analyses, our current model incorporates the impact of the top 10 backers scoring high on all three centrality measures. For assessing the validity of using a small group of central backers, we explored the possibility that expanding the amount of identified central backers would affect our results. We replicated the analysis by identifying the top 20,50 and 100 backers that scored high in centrality. Similarly, to ensure that the finding is not category specific, we constructed backer networks for the two other largest categories, Design and Technology and estimated our model. The results of this analysis presented in Table 6 show that the key findings relating to central backers still hold even if we were to identify a larger number of central backers. Similarly, the results hold for both the Design and Technology categories as well, with the only exception being percent funded in the Design category. This shows that our results are relatively robust. [Insert Table 7]

In our previous model, we strove to address the endogeneity of project quality by using established variables that are linked to project quality to disentangle its effects from both backers and central backers. However, this is a theory driven approach. We test our model by using a statistically driven approach to deal with the endogeneity. We use the copula method put forth by Park and Gupta (2012) to couple the correlation between the central backer variable and the structural error. This method statistically handles endogeneity and requires no instrument. After including the copula control function to deal with the endogeneity, we can see that the number of central backers still retain a significant impact on the number of backers, showing that project quality is not the omitted variable driving the effect. [Insert Table 7]

8 DISCUSSION

Our results provide evidence that backers in central positions within the backer network of a crowdfunding platform have an impact on other backers and through them, on the outcomes of crowdfunding projects. Although data on users in platforms are now widely available, explicit interactions between backers may not be explicitly visible. Our research shows that network methods can be used on joint incidences of decisions made by users to map a user interaction network. These user interaction networks are shown to be able to identify key users that contribute significantly to crowdfunding outcomes.

Our research addresses constructs within the crowdfunding platform that researchers lack an accurate understanding on. Crowdfunding platforms provide a space for platform users to interact, however these interactions are not explicitly recorded. Our study offers a practical solution to the implicit network by championing the formation of a probabilistic network based on users' past actions. We show that information on these past actions are valuable through a natural experiment and recommend a set of centrality scores that can be used to identify central backers within the network. We further incorporated a comprehensive list of digital media buzz into our model as well, addressing the call for such data to be included by past research (Kuppuswamy and Bayus 2017).

On a fundamental level, firms holding more in-depth knowledge on the backer network can seek out backers that have been central to the network. Even when platforms lack an explicit network, our research has shown that firms can construct a probabilistic network based on backers past backing actions and use this to identify central backers. Once these backers are identified, firms can target them for marketing purposes such as engaging them by soliciting feedback about their product.

Running some policy simulations, we estimate that an additional central backer backing a project will have indirect effects by ensuring the success of a crowdfunding project. Similarly, it will increase the funding of a project by 158.9% and decrease the time taken to reach the funding goal directly by 3%. These statistics underscore the importance of central backers as a key metric that crowdfunding platforms should consider when implementing any changes to the platform.

What then can the crowdfunding platform do to leverage on this finding? One of the ways the platform can increase the influence of these central backers is to provide an easy way for backers to locate and observe each other. This transparency of backer information is important and can affect the platform and its user network adversely if removed. Kickstarter's decision to remove the backer tab illustrates the difficulty crowdfunding platforms face in balancing the amount of information provided to maximize the benefits it can provide while minimizing the privacy issues that will be encountered. As the detail of backer information provided increases, there will be a positive effect from the network since allowing access to information can encourage the formation of a backer network and the resulting spread of social influence within the network can generate positive crowdfunding project outcomes. Backers will be able to seek out projects that they would have otherwise not found through the network. Benefits accrued from network effects can expand depending on the amount and scope of information that is freely available. However, there is also the negative impact of information transparency stemming from privacy concerns, thus platforms need to protect contributors and allay fraud concerns (Burtch, Ghose and Wattal 2015). Current trends in privacy concerns have led to information on backers being removed or hidden from the network. From a backer's perspective, the positive effects of the backer network will be offset by the negative effects of privacy after information detail passes a certain threshold. After a certain level, information on backers becomes so invasive that any benefits accrued by the backer is effectively cancelled out. This becomes a delicate balancing act for platforms as they survive by creating value through the interaction of its users. If one group of users, such as backers, feel that their concerns are not addressed, they may choose to withdraw from the platform. This can lead to the collapse of the platform. As such, the platform will suffer losses if privacy concerns start overriding the benefits gained from the availability of information to backers. [Insert Figure 6]

Our study's findings suggest that it is in the interest of crowdfunding platforms to identify the inflection point where the positive effects of the network will be offset by the negative impact of privacy issues. This maintains a balance of encouraging the formation of a backer network while at the same time managing privacy concerns. We propose that managers can consider two methods to obtain balance between the two. One possible method relates to the quality of the information provided. Crowdfunding platforms can allay privacy concerns by identifying users not by usernames but by a serial number. Centrality scores can be shown in these profile pages and a suitable metric label such as ‘influence points’ can be created. This suggestion allows information that assists in the formation of the backer network to be present while preserving the anonymity of the individual. As such, backers can follow central backers on the platform. Similarly, crowdfunding platforms or project creators can target these central backers by encouraging them to back projects due to their positive impact on other backers.

The second possible method relates to formulating the network without information being disclosed. Platforms can create an artificial network and use simple identification criteria to identify central backers. Our paper explores an organically formed network that is developed largely without control from the platform. However, since privacy is a concern and platforms may not want to release information on backers, platforms can choose to artificially form their own backer network. Individuals can be identified by crowdfunding platforms as star backers and can be listed on the site itself. For instances, individuals that are active in each category can be identified and segmented into further subcategories. Individuals can take the role of experts in their respective subcategories and other backers can follow them. Platforms that can manage this will be able to benefit from network externalities.

8.1 LIMITATIONS & FUTURE RESEARCH

There are several limitations to our research. One of the key limitations we face is data availability. Our primary data source, Kickstarter, does not provide the exact time backers contribute to a project so we lack the means to obtain directional data for our network. The network in our study is a weighted undirected network. We can observe the connection between two backers in the network but not identify the order in which they are linked. To address this issue, we impose an additional assumption of symmetry between the nodes (Bramoulle and Fortin 2010). This assumption assumes that the links are bi-directional, forming a more conservative representation of a network. This operationalization makes our desired effect harder to detect due to the additional noise available in the network. As we are able to establish the effect of central backers even with an undirected network, a directed network should only serve to strengthen our findings. To further verify this, future research be expanded to crowdfunding sites that have temporal data and across other different categories.

8.2 CONCLUSION

With the advent of big data on networks and communities that form around online platforms, the potential to exploit network targeting strategies has become an opportunity for platforms, however it may be expensive and inefficient to target users within the network that have little influence. Our findings point to methods that can be used to locate and target platform users. We indicate that platforms should identify the optimal amount of information that should be managed to reap the rewards that network effects can bring while minimizing the detrimental effects of the loss of privacy for their users. Our results show that instead of removing information that can potentially link backers with each other, these sites should instead implement certain systems that increase the ease in which backers can link up with other backers while ensuring anonymity. This would not only allow backers to identify projects they may be interested in but also increase the likelihood of crowdfunding project success and improve the efficiency and profitability of the site itself.

CHAPTER 3: THE DYNAMICS OF RECURRING CROWDFUNDING - EXPLORING DETERMINANTS AT DIFFERENT STAGES OF THE CROWDFUNDING PROCESS

With the rapid growth of the digital economy, there is an increasing focus on how businesses and individuals can leverage on its expansion to their benefit. A key component of the growth of this digital economy is emergence of a new class of content creators. Before the 21^{th} century, companies were the main creators of content. However, with the transformation of the digital landscape, previous consumers are no longer passive receivers of content but have instead become active creators of content (Fader & Winer 2012). This led to the explosion of the digital content market, with the market exceeding an estimated US$549 billion by 2019 (Technavio 2015).

A substantial proportion of this growth is captured in sharing platforms that allow individuals to create and upload their content. Although certain platforms do allow content creators to earn revenue from their content, the process is difficult and as such monetizing their content has become one of the biggest challenges for online content creators (Ernst & Young 2010). As creators seek to find new ways to fund their content, there has been a surge towards one of the new models of raising funds online – Crowdfunding.

Our research studies the emerging context of crowdfunding creators instead of projects. Previous research in crowdfunding have focused on crowdfunding singular projects and factors that affect their funding within a fixed duration and with a targeted funding amount (Mollick 2014, Kuppuswamy & Bayus 2017). Our research focuses on the crowdfunding patronage model, a long term recurring funding model for funding creators. There is uncertainty in how project characteristics impact a long-term crowdfunding project aimed at funding creators at different stages of its crowdfunding process. We build on this stream of research by striving to provide an understanding of this new model of crowdfunding and how different project characteristics can affect the growth of the number of contributors and the amount of funding a project receives at different periods in time. Using a recurring crowdfunding site, Patreon, we explore how project characteristics affect the number of contributors, or patrons, across time as well as the contribution amount across time. We analyse not only the magnitude of patrons and contributions but also their dynamics such as velocity, the rate at which patrons and contributions change, and acceleration, the rate at which velocity changes. The influence of these project characteristics is captured across time to identify at which stage of the crowdfunding process they will have an impact on. We compare our results to existing crowdfunding research and explore how this new model reinforces or contradicts our current understanding of crowdfunding.

We further extend our research by identifying different clusters of crowdfunding projects based on the dynamics of their contribution functions (Dass and Shropshire 2012). Each of these clusters are affected by different project characteristics and they will react differently over a wide duration. With this information, content creators will be able to identify the patterns of patron and funding growth at a more specific level. With this a deeper understanding on the project characteristics that drive patrons and contributions across different stages, creators can optimally utilize different project characteristics at different time periods to maximize the value of their project. Policymakers of recurring crowdfunding platforms can further tailor their platform architecture to accentuate different information indicators that are deemed important by funding contributors so as to attract contributors and increase the revenue generated by the platform. In doing so, we seek to address the concerns the crowdfunding industry have on the recurring funding process. Our research will also be of interest to academics as long-term funding has been a phenomenon that has not been explored in the context of crowdfunding even though it has been expanding in the industry (Chaykowski 2018).

1 FUNDING CONTENT IN THE DIGITAL ERA

Digital content- content distributed through electronic channels, is gaining increasing importance in the current digital economy. In recent years, users of the web have moved past purely communication with others to the creation and consumption of digital content. Digital content has become so prominent that it has established itself as a cornerstone of the digital society (Rowley 2008). The evolving nature of the web has further allowed many users to easily transition into content creators (Cormode and Krishnamurthy 2008). Put together, this trend shows that as the effort required in content creation and distribution decreases due to continued improvement in technology, a greater amount of content and services will thus become readily available and as such, will gain increased importance in the digital landscape (World Economic Forum 2016). Evidence of this is in the exponential growth of the digital content market with the global digital video content market alone being slated to grow to $121.47 billion by 2020 (Technavio 2016).

Much of the growth in digital content comes from a large plethora of user-generated content online. One of the biggest user-generated platform, Youtube, has more than 400 hours of content uploaded every minute, which serves as a testament to the increasing importance of user-generated content (Tran 2017). To cater to the increase in digital content and the value that it provides, a large number of platforms now provide a location to host these different forms of content. Many of these platforms run on a model where they rely on users creating the content to sustain themselves from advertising revenue. In order to maximize profits, platforms allow users to have free access to rely on network effects to draw in a large base of users (Parker and Van

Alstyne 2005). This coupled with the ease of uploading content on the platform has encouraged more users to become content creators within the platform as the nature of online platforms allow users within the platform can easily shift between a content consumer to a content producer (Parker et al. 2016). An example of this is Youtube, the largest video sharing website with a business model that rely on their users creating content (Burgess and Green 2009). Other examples of platforms that serve as intermediaries for hosting user-generated content include deviantArt for artwork, Wordpress for novels and Soundcloud for music and podcasts. Through these platforms, users are able to share their content with the rest of the web.

However, in recent years, as platforms continue to grow, there has been a push within the platforms themselves to develop a sustainable business model to maintain the level of user-generated content. In order to provide incentives for content creators to continue producing content, many of these business models allow content creators to obtain a cut of the profits. For instance, Youtube switched its business model in 2012 to incorporate advertisements to allow both Youtube and large content creators to generate income through brand advertisers (Lawler 2012). This has been expanded in 2014 to distinguish between successful content and other content with the Google Preferred model that allows advertisers to pay a higher rate to advertise on the content of successful Youtube creators (Google 2016). The revenue sharing model has also been adopted in other platforms such as deviantArt's ad service that generates revenue for the platform and content producers through the placement of advertisements by brands on the pages on content producers (deviantArt 2018) and its print shop which allows content creators to sell their art for a 20% profit of the selling cost (deviantArt 2018).

These monetization methods have generated a new wave of content creators who them to continue creating content for their consumers for free while generating earnings from platforms.

However, even with these revenue sharing initiatives adopted by platforms, many of these low to mid-level content creators are struggling to generate profits (Blake 2017, Harbinger 2017). This is especially pronounced on platforms that requires the content creator to be an established partner before they are allowed to monetize their content. Examples of these platforms include Youtube (Youtube 2018) and SoundCloud, a platform for sharing music (SoundCloud 2018).

With the rise of the consumer-creator profession as an industry mainstay, more content creators are participating and making content creation into careers. As such, financial compensation has become particularly important with calls within the industry to find ways to compensate content creators to ensure that content creation remains sustainable (Bhargava and Klat 2017, Ryan 2018).

2 GROWTH OF THE RECURRING CONTRIBUTION MODEL

The industry as a collective have responded with two separate models to increase the revenue generated by content creators – the subscription model and the patronage model. Both of these models are recurring models, with the subscription model driven largely through the platforms that host the content of creators and the Patronage model driven by funding from consumers of the content.

2.1 PLATFORM-DRIVEN SUBSCRIPTION MODEL

The Subscription Model charges consumers of the subscription service on a monthly basis. Consumers that subscribe for a digital content gains access to content or additional services. This model has been seen outside of our particular context and is similar to the subscription services for utilities such as phone bills (Danaher 2002) and for informational goods such as access to news and online databases (Fishburn and Odlyzko 1999, Jain and Kannan

2002). The subscription model is platform dependent as it is initiated by the platform that hosts the creators' content. Content creators are passive adherents within the model as they have little influence on the terms of the subscription service. This model allows content creators to generate a consistent stream of revenue from subscribers of their channels every month. An example of this is the Twitch Partner Program on the Twitch platform. Twitch is live video streaming platform with over 15 million daily active users that allows content creators to stream videos (Twitch 2017). Although users are able to gain access to the content on Twitch, users can choose to pay to subscribe to channels and gain access to a subscriber only chat and several paraphernalia that can be used within the chat (Twitch 2018). The revenue generated from subscriptions will be split equally between the content creator and the platform, with each creator gaining a revenue stream equivalent to the number of people who subscribe to their content (Twitch 2017).

2.2 CROWDFUNDING AND THE PATRONAGE MODEL

In comparison, the patronage model gives the creator more control over the terms of the entire recurring funding process. The patronage Model depends on recurring crowdfunding. Crowdfunding, which is when many individuals contribute small amounts of funding in order to fund a project or a cause, allows content consumers to fund creators they support. This model is not driven by the platforms that host the creators' content but by third party crowdfunding sites. Individuals involved in crowdfunding decide on the amount that they wish to contribute.

There are several key differences in the established crowdfunding model and the patronage model. In an established crowdfunding model, the purpose of crowdfunding is to fund a project. Projects have a funding goal - a targeted amount of funds that they aim to collect within a fixed duration. A project is deemed successful only if the project manages to meet its funding goal within the time period. After its funding duration, if the project was successfully funded, the amount pledged will be given to the creators who are then obliged to complete their project and deliver the rewards promised to contributors. We illustrate this with the Oculus Rift example (Kickstarter 2012). The Oculus Rift project was launched on 1st August 2012 and sought $250,000 to fund a Virtual Reality headset. The funding duration ended on 1st September 2012, with the project receiving $2,437,429 from 9,522 backers.

In comparison, the patronage model funds creators instead of individual projects. Contributors that fund a creator are effectively funding future content produced by the creator, becoming virtual patrons of the content creator. The structure of a Patronage model does not include a fixed duration, patrons can continuously fund a creator and can, at any time, stop funding at their own discretion. There is no measure of explicit success or failure in a Patronage model as there is no funding goal to reach. Funds will be deducted at set intervals from patrons. We illustrate this with the creator, Chapo Trap House (Chapo Trap House 2018). Chapo Trap House is a free weekly podcast on political humor created in March 2016. They adopted a patronage model in May 2016 to fund the costs of creating the podcast. As of March 2018, Chapo Trap House has 21,921 patrons providing $97,815 per month.

Although, both the platform-driven subscription model and the patronage model are able to generate recurring revenue streams for content creators, there is an increasing shift towards the patronage model as this model is not platform specific and has more flexibility in implementation by content creators compared to the subscription model. Crowdfunding platforms have such as Patreon and Flattr have sprung up to allow content creators from different platforms to receive financial support from their content consumers. This model has become increasingly mainstream that even Kickstarter, a platform synonymous to crowdfunding, has started their version of a patronage platform recently in December 2017 (Chen 2017).

Although there has been research and industry consensus on the determinants of crowdfunding, there has been no research at this current point on recurring crowdfunding. Given the differences between crowdfunding for projects and crowdfunding for creators, we expect that drivers of crowdfunding success in the former may not hold true in the context of crowdfunding for creators.

3 PATTERNS OF GROWTH IN THE RECURRING CROWDFUNDING PROCESS

Previously, we have distinguished between crowdfunding for projects and crowdfunding for creators. The contrast between their purpose will drive differences in how contributors react. As crowdfunding a project has a fixed duration and goal, contributors that are funding the project will generally increase over time and will remain contributors until the project ends. As funds are generally not deducted if the project is unsuccessful, there is no loss for contributors if the project fails to meet its goal within the funding duration and thus they will remain as contributors until the end of the project. This results in an increasing funding crowdfunding pattern with contributors being more likely to contribute during the first and last weeks of the crowdfunding project with the last week serving as a motivator for potential contributors to fund the project either to receive the rewards associated with the project or to ensure that the project meets its goal before ending (Kuppuswamy and Bayus 2018).

However, crowdfunding patterns for crowdfunding creators are distinctly more heterogenous. The recurring nature of crowdfunding, along with a lack of a fixed goal and a fixed duration results in differences in the reaction of patrons. As there is no fixed duration, patrons can choose to support creates at any time, similarly they can pull their funding at their own discretion as well. This results in patterns that can increase or decrease across time. The lack of a goal or a duration results in patrons receiving no motivators when they are required to contribute and as a result contribution patterns are less stable comparing to crowdfunding projects. We illustrate this with patterns of actual crowdfunding for projects and creators. [Insert Figure 7]

3.1 MEASURES OF CROWDFUNDING PATTERNS

Due to the large amount of heterogeneity between patterns of crowdfunding for creators, coupled with the unique nature of the recurring crowdfunding process, we are interested in identifying the factors that affect crowdfunding patterns across the recurring crowdfunding process.

To achieve this, we first identify crowdfunding patterns that are of interest to creators and platforms. Crowdfunding research have often studied two key metrics of crowdfunding, the number of contributors of a crowdfunding project and the funding received by the crowdfunding project (Mollick 2014, Kuppuswamy and Bayus 2017). These two indicators, in conjunction with the funding goal, provide information on how successful the crowdfunding project is. In exploring the patterns of recurring crowdfunding, we use the same metrics as relevant outcomes of the recurring crowdfunding process. As such, our research objective will explore the patterns of change in the number of patrons and the patterns of change in the amount of contributions when crowdfunding a creator.

Within these two metrics, there are two other methods of quantifying patterns of change. What we have discussed thus far relate to the change in magnitude of patrons or contributions.

For example, we are able to tell that from day 1 to day 10 of crowdfunding for a particular creator, the number of patrons increases from 1 to 100. However, we are not able to identify the dynamics behind how this change comes about. It is possible that the number of patrons undergoes a large change at the start, with a larger number of patrons funding the creator in the initial period. It is also equally possible that the number of patrons undergo a large change at the end, with a larger number of patrons funding the creator in the later period. The difference in possibilities will lead to different actions from the creator, with one creator treating the initial period of paramount importance in attracting patrons and the other creator choosing to focus their efforts on the later period. This information that is not supplied by the previous patron and contribution patterns but is provided by estimating the velocity of the patterns. Velocity of growth in patrons and contributions determines the change in the number of patrons and contributions across the time passed. With velocity, we are able to easily distinguish when a large change occurs. In our earlier example, the velocity of contribution patterns will be able to show that a large change occurs at the early periods in the first scenario with an increase in velocity at the earlier stages while the second scenario shows that the large change occurs at the later periods with an increase in velocity at later periods. Thus, velocity patterns will allow creators and platforms understand how patrons and contributions change over time.

Another measure that captures a different aspect of how patterns evolve across time is acceleration. The rate at which the velocity of the patrons and contributions change is captured by acceleration. The growth of patrons can change at a constant rate, a slower rate or a faster rate. At a granular level, it informs the creator which period has the largest impact on velocity and directs creators to focus their efforts in those periods. For instance, in a scenario where there is increasing velocity at the early stages of the crowdfunding process, knowing whether the velocity is increasing at an increasing rate, a stable rate or a decreasing rate will generate different responses from the creator. If velocity is increasing at an increasing rate, the creator will know that the factors that are responsible for the velocity increase gains momentum as time passes and as such is important throughout the entire velocity increase cycle. If velocity is increasing at a decreasing rate, the creator should acknowledge that the factors responsible for the velocity increase has the greatest traction at the start and can creators can divest attention and effort away from these factors after the initial velocity change has occurred. As changes in acceleration will change how creators understand how patrons and contributions change over time, it is an important dynamic that should be explored.

We thus focus on two different metrics, the number of patrons and the funding amount received across all time periods in the recurring crowdfunding process, and three different dynamic representations of these two metrics. This comprises of the actual magnitude of the number of patrons and the funding amount received across time, the velocity of the change in the number of patrons and funding amount received across time and the acceleration of the change in the number of patrons and the funding amount received across time. These 6 patterns will serve as the dependent variables for our study.

3.2 FACTORS THAT IMPACT CROWDFUNDING PATTERNS

As the aim of our research is to identify factors that can impact the patterns of crowdfunding across the entire funding duration, we propose several variables that may influence patterns of growth. As this is a relatively new context, we use information freely available on the project page of the recurring crowdfunding projects. These variables are grouped into four broad categories in our research – Project Type, Nature of Incentives, Project Presentation Characteristics and Project Category.

Project Type

Project Type outlines the properties of the crowdfunding project. These variables include the type of crowdfunding imposed by the project creator and the explicitness of content. In our study's recurring crowdfunding context, the project creator is free to specify whether they are collecting funding on a per item basis (item focused projects) or over a set duration (duration focused projects). For projects that are item focused, funds will be deducted from patrons whenever the creator produces an item. Depending on the project type, items can range from videos (Pentatonix 2018) to comics (Revoy 2018) to even art pieces (Mullins 2018). For projects that are duration focused, funds will be deducted after every month akin to a subscription service (Chapo Trap House 2018). The choice of crowdfunding type governs how patrons interact financially with the creator and may have an impact on the growth of crowdfunding patterns.

The explicitness of the content captures the type of content that the creator produces. Content is considered explicit if it deals with sensitive material, offensive material or pornographic material. In mainstream crowdfunding platforms, such as Kickstarter and Indiegogo, policies are in place to remove these types of projects (Indiegogo 2018, Kickstarter 2018). In comparison, the patronage model funds creators and does not discriminate between the content funding. As such, the flexibility of the recurring crowdfunding platforms has allowed many fringe creators with niche target segments access to crowdfunding. The explicit nature of content may motivate interested patrons to fund creators at certain stages of the crowdfunding process, due to the sensationalist nature of such content, or the difference the content makes in motivating patrons to continue funding the project is of interest to us.

Nature of Incentives

There has been evidence that rewards in crowdfunding do drive contributor support, with increasing number of rewards in crowdfunding projects linked to an increase in the number of contributors (Kuppuswamy and Bayus 2017). Although the context of our research is different, we believe that incentives will have an impact on crowdfunding patterns for patronage models. We observe four different forms of incentives – the number of perks, the number of free content, the number of exclusive content and the percentage of exclusive content created.

Project creators adopt a patronage model in order to fund their content creation process. The content they create can continue to be accessed for free. However, in adopting this model, creators can offer patrons incentives to fund them. This may take the form of perks based off the amount they contribute to the project. Some perks are intangible benefits such as having their names featured in the end credits of videos or early access to content (Pentatonix 2018, Revoy 2018). Some perks however are tangible, such as a promised artwork every period (Chan 2018). Although the perks offered on Patreon may not be as substantive as those on other crowdfunding sites such as Kickstarter, they may still have an effect on contribution amounts similar to the effects documented in previous research (Kuppuswamy & Bayus 2017).

Another incentive that may motivate patrons to continue funding the creator is the number of free content provided by the creator. As the creator continues to produce content, they can choose to release the content for free on the platform their content originates from as well as sharing the content on the crowdfunding site. The magnitude of free content may motivate patrons to fund the creator as a reciprocal effort to reward the creator for producing more content for the community and serves as an incentive for increasing number of patrons and contributions. The free content provides information that may influence potential patrons in their decision on whether to contribute to the crowdfunding project.

The number of exclusive content produced by the content creator also serve as an incentive that can motivate patrons to fund the creator. Aside from free content, the content creator is able to share exclusive content on the crowdfunding site as well. The exclusive content can only be viewed by pre-existing patrons and can range from early access to free content to additional content that is exclusive only to patrons who fund them such as behind the scenes content or content specially prepared for patrons.

A further factor that may serve as an incentive for patrons to fund the creator is the percentage of exclusive content created. A larger proportion of exclusive content compared to free content produced will indicate that the creator has a higher predisposition to offer benefits to their patrons rather than sharing more content with the public. This focus offers a deeper insight to the priorities of the creator that mere magnitude of free and exclusive content is unable to provide. A creator that has a higher focus on exclusive content may impact crowdfunding patterns in a different way compared to a creator with a focus on free content. We address how these incentives impact crowdfunding patterns at different stages of the crowdfunding process in our analysis.

Project Presentation Characteristics

In the project page, the platform requires the project creator to provide a brief introduction to potential backers on their work. The project presentation characteristics found within this page may have an impact on crowdfunding patterns. Previous research on crowdfunding has shown that the presence of a video in the project description have a positive impact on crowdfunding (Mollick 2014). This can be attributed to the fact that a video is a source of information for the potential backer. As such, a potential backer would have more details on the project thus increasing their confidence that the project has been thoroughly thought out. The video also allows creators to personally appeal to potential backers which may increase the likelihood of potential backers contributing. We explore the impact a video has across the entire recurring crowdfunding process.

Previous research on crowdfunding has also shown that the number of words in the project description has been shown to have a positive effect in crowdfunding (Marom and Sade 2013). The effect arises from the information provided in a longer project description. Similarly, we expect that a longer project description will impact on our recurring crowdfunding project compared to a short one. We include the number of words in our model to identify at which stage will the length of the project description have an impact over the course of the recurring crowdfunding process.

The second observable factor within the presentation of the project is the presence of formatting in the project description. Project descriptions that are not formatted tend to comprise of large paragraphs with no headings or sub-headings. Visually, these project descriptions are messy, and the words are harder to parse. This lead to lower processing fluency, which has been shown to have a negative effect on motivation (Song and Schwarz 2008). We expect that a properly formatted project description, with headings and sub-headings, with important parts highlighted will affect crowdfunding patterns compared to a project description with no formatting.

The project presentation also informs potential patrons of any milestone goals the creator has. Milestone goals are promises made by the creator to their content consumers. If the creator reaches a certain level of funding, passing the goal amount listed by the milestone, the creator is obligated to fulfil the promises in the goal. An example of milestone goals are promises to start give away contests after a certain contribution level or to start doing different forms of content (Chan 2018). These milestone goals may serve as targets for patrons to strive to reach so that the community will be able to receive the promised benefit in the milestone itself. This will in turn will have an impact on patterns of growth for patrons and contributions.

Another project presentation characteristic that may have an impact on crowdfunding patterns is the presence of a sample. As we have discussed earlier, a recurring crowdfunding model seeks to fund the creator and their future creations and not a specific project. As such, the creator will have a portfolio of previous creations which can serve as samples to allow potential patrons a preview of the types of future content they can expect. Potential backers can evaluate the form of content, the quality of the content and other noticeable measures that can serve as the basis of their judgement before making their contribution decision.

The final information on the project presentation that may impact patterns of growth in patrons and contributions is the number of platforms listed on the page itself. Creators can include links within the project description page that allow potential patrons to access the content hosting platform that houses their content and other platforms that they use to interact with consumers of the content. Listed platforms can include content hosting platforms such as Youtube and deviantArt, media platforms such as Twitter and even personal platforms such as blogs and personal webpages. The number of platforms allow patrons access to the project creator as well as serve as a testament to their content quality as potential patrons can access the hosting platform to view previous content by the creator. These components of the project presentation may have differing impacts on different stages the recurring crowdfunding process and are easily observable from the project page itself, hence we include them in our model.

Project Category

The last group of variables that we study are project category variables. The content produced by creators fall under a wide range of categories. They can be separated in eight distinct categories. They include Writing, Video, Games, Podcasts, Music, Comics, Photo and Animation. We list the following types of content that can be classified under each category. Content that primarily focus on writing, such as reviews, blog posts, fictional stories can be classified under Writing. Content produced under the Video category include videos made by Youtube creators and live-stream videos by Twitch streamers. Gaming content mainly encompasses creators that create video or table-top games. Content under the podcast category deals with episodic series of audio broadcasts. Music content includes original music and music covers. The category of comics includes comics and drawings such as sketches and comic series. Photography content takes the form of photographic art or content on photo sharing sites such as Instagram. Animation is primarily focused on animated gifs, picture or shorts. We include these to measure whether the nature of the content can drive growth in patrons and contribution across the entire recurring crowdfunding process.

4 RESEARCH OBJECTIVE

Our research objective is to identify the independent variables that can impact the patterns of growth across different periods of the crowdfunding process. We will use variables relating to Project Type, Nature of Incentives, Project Presentation Characteristics and Project Categories and establish how these variables will impact the number of patrons and the funding amount received and their respective velocity and acceleration changes across time. Below is a figure of our model. [Insert Figure 8]

The flow of our research will be as follows: We will first collect the data required by gathering the patron and contribution data from recurring crowdfunding projects. Then we will access their project pages to code our independent variables from information provided in the project description. We then set up our data by configuring the data to obtain curves that show the change in the number of patrons and contributions as well as their respective velocity and acceleration curves. We then prepare our data for analysis by smoothing the curves for use before finally performing functional data analyses with our curves as dependent variables and with our previously gathered independent variables.

5 DATA AND VARIABLE DESCRIPTION

The data used in the study is data collected from Patreon, the largest recurring funding crowdfunding platform. Content creators can create a page on Patreon allowing consumers of their content to support them financially by becoming patrons and contributing funds. Creators have full control of whether they decide to collect funds for each content produced or after a certain period has passed such as on a per month basis. Funds will be automatically deducted from patrons with approximately 90% of the funds collecting going to the creator and approximately 10% serving as Patreon’s and other third party’s administrative fees (Patreon 2017). Consumers can choose to support the creator with a contribution of any given amount. However, even if they do not choose to contribute, they are still able to enjoy content provided by the content creator for free (Owens 2017). There are currently over 3.7 million pledges for recurring contributions on Patreon, with a total estimated monthly payout of over $11 million (Graphtreon 2018), with content creators such as Chapo Trap House earning over $96,000 per month from over 21,000 patrons (Chapo Trap House 2018).

We collected data on 3229 projects that were launched between June 2014 and May 2015. Data relating to each Patreon project, its description and other unique project characteristics are coded by entering the Patreon page and coding the information available. As we are interested in analysing the patterns of growth for patrons and contributions, we collect longitudinal data on the patrons and the funding the project receives over a period of 300 days. Our data has 288,830 maximum patrons in a day, with duration focused projects earning $1,367,818 per month and item focused projects earning $351,526 per item in total.

5.1 DEPENDENT MEASURES

We have compiled patron and contribution data from a third-party platform, Graphtreon. At we are interested in the patterns of change in our dependent measures, we collect longitudinal data on our variables of interest over a period of 300 days. These 300 days represent the first 300 days of a Patreon project's lifespan. As we are able to observe the entire change of patron and contributions over the entire time period, we form curves that represent how the number of patrons and contributions change over time.

Patron Curves. This curve represents the change in the number of patrons across the first 300 days of a project's lifespan. Patreon projects have an indicator that captures the number of patrons currently funding the project at any given time. Data on this indicator is taken daily and the subsequent curve formed by the aggregation of the data across 300 days serve as our patron curve for each individual project.

Velocity of Patron Curves. The velocity of patron curves captures the rate at which the patron curve changes. We obtain the velocity of patron curves by taking the first order differential of patron curves for each individual project (Ramsay et al. 2009). The resulting curve allow us to observe the changes in the velocity of the patron curves across time.

Acceleration of Patron Curves. The acceleration of patron curves captures the rate at which velocity changes. We obtain the acceleration of patron curves by taking the second order differential of patron curves for each individual project (Ramsay et al. 2009). The resulting curve allow us to observe the changes in the acceleration of the patron curves across time.

Contribution Curves. This curve represents the change in the amount of contribution across the first 300 days of a project's lifespan. Patreon projects have an indicator that captures the amount of contributions the project has at any given time. Data on this indicator is taken daily and the subsequent curve formed by the aggregation of the data across 300 days serve as our contribution curve for each individual project.

Velocity of Contribution Curves. The velocity of contribution curves captures the rate at which the contribution curve changes. We obtain the velocity of contribution curves by taking the first order differential of contribution curves for each individual project (Ramsay et al. 2009). The resulting curve allow us to observe the changes in the velocity of the contribution curves across time.

Acceleration of Contribution Curves. The acceleration of contribution curves captures the rate at which velocity changes. We obtain the acceleration of contribution curves by taking the second order differential of contribution curves for each individual project (Ramsay et al. 2009). The resulting curve allow us to observe the changes in the acceleration of the contribution curves across time.

5.2 INDEPENDENT VARIABLES

To explore the factors that may have a potential effect on patterns of recurring crowdfunding and its dynamics, we collect data on several independent variables that we expect would have an impact.

Project Type

Crowdfunding type. This binary variable indicates if the crowdfunding project is an item focused project (funds are collected per item) or a duration focused crowdfunding model (funds are collected per month). This is indicated within the crowdfunding page, with duration focused projects as 0 and item focused projects as 1.

Explicit Content. This variable indicates whether the crowdfunding project contains explicit material such as sensitive material or material related to violence or pornography. The content produced by the creator is coded to reflect whether the content is explicit or not, with non-explicit content as 0 and explicit content as 1.

Nature of Incentives

No. of Perks. The number of perks offered to patrons by the project creator. This variable is available within the crowdfunding page.

No. of Free Content. The number of free content available at the moment of data collection. This information is taken from the number of content posts tagged as public in the crowdfunding page.

No. of Exclusive Content. The number of exclusive content at the moment of data collection. This information is taken from the number of content posts tagged as patron only in the crowdfunding page.

Percentage of Exclusive Content Created. The proportion of exclusive content out of all content produced by the creator. This variable is the number of exclusive content the creator has produced relative to all the content the creator has produced. It indicates the predisposition of the content creator in offering more benefits to their patrons compared to the general content consumer.

Project Presentation Characteristics

Video. Video captures whether the crowdfunding project page has a video and is taken from the project description page, with projects that have no video as 0 and projects with video as 1.

No. of Words. The number of words used in the project description.

Format. This variable capture whether formatting is present in the project description of the Patreon project. Projects that have proper sub-headings for different segments of the project description, using bold or italics to highlight certain important portions or color to organize information in the project description or considered formatted projects, with non-formatted projects as 0 and formatted projects as 1.

No. of Goals. The number of milestone goals a Patreon project has. This is available in the main page of the crowdfunding project.

Sample. Sample denotes whether a specimen of the content is provided in the crowdfunding project page, with projects that have no sample as 0 and projects with a sample provided as 1. This is coded from the project description page.

No. of Platforms. The number of other platforms listed in the description page of a Patreon project. This is taken by coding the links to the number of other platforms that appears throughout the entire project description page.

Project Category

Writing Category. The content created by the creator primarily belongs to the writing category.

Video Category. The content created by the creator primarily belongs to the video category.

Games Category. The content created by the creator primarily belongs to the game design and creation category.

Podcast Category. The content created by the creator primarily belongs to the podcast or audio broadcast category.

Music Category. The content created by the creator primarily belongs to the music category.

Comics Category. The content created by the creator primarily belongs to the comics or drawing category.

Photography Category. The content created by the creator primarily belongs to the photographic art category.

Animation Category. The content created by the creator primarily belongs to the animation category.

The descriptive statistics for our independent variables can be found in the table below. Notably, the number of duration focused projects is three times larger than the number of item focused projects, with creators showing a preference in collecting their funds on a monthly basis. [Insert Table 8]

6 MODEL FORMULATION AND ESTIMATION

Our interest in the growth and changes of crowdfunding patterns requires us to use methods that are able to model funding dynamics and determine the relationship of relevant variables on the funding process. We use the tools provided by functional data analysis to address these issues.

Functional Data Analysis is a statistical method used to analyse curves. It has three key areas that make it appropriate to use for our current research.

First, we are interested in exploring the dynamics behind our current data, which is highly heterogenous and distinctly non-linear. Other econometric methods focus on data points and may not be able to capture the dynamics behind the curves. Functional Data Analysis uses the curves as the core of its analysis and provides empirical results based off the dynamics of the curve (Reddy and Dass 2006). Using this method, we are able to consider the curves of our crowdfunding patterns as dependent variables.

Second, functional data analysis can capture nuances in relationships between the variables and the curves across time. Certain variables may only have an impact on the functions at different times. Functional data analysis is able to account for these time-varying relationships unequivocally (Dass and Shropshire 2012).

Third, results from functional data analysis have been shown to be able to predict future trajectories of growth for new curves based off analysis of existing curves. This is especially so in dynamic environments (Dass and Shropshire 2012). Data from new products penetration has shown that functional data analysis is able to perform accurate predictions with only principal component scores of existing similar products (Sood et al. 2009). As one of our main concerns in this research is to allow new entrants in Patreon to predict how their project will do as well as to highlight important project characteristics that will affect their project contribution patterns, we find that this method will be able to address our concerns in a satisfactory manner.

6.1 DATA CONFIGURATION

To perform our analyses, we first need to set up our data to ensure that we will be able to run our subsequent analyses. We have obtained daily data on the number of patrons that are contributing to projects as well as the contribution amounts of projects for first 300 days of the project's lifespan ($Y_{i,t=1} \ldots Y_{i,\, t=300}$). We have a total of 3229 curves for both dependent variables ($Y_{1,t} \ldots Y_{3229,t}$). To consider all curves jointly in our analysis, we configure the data into a matrix with the form:

$$\underline{y}(t) = \begin{bmatrix} y_{1,\, t=1} & y_{1,\, t=2} & \cdots & y_{1,\, t=300} \\ y_{2,\, t=1} & \cdots & \cdots & y_{2,\, t=300} \\ \vdots & \cdots & \cdots & \vdots \\ y_{3229,\, t=1} & \cdots & \cdots & y_{3229,\, t=300} \end{bmatrix}$$

We form 2 matrix that encompasses the patron and contribution curves of the 3229 projects in our data set. As we are also interested in the velocity and acceleration of patron and contribution curves we take the first order differential and second order differential of these 3229 curves and further form the matrix for velocity, $\underline{y}'(t)$, and acceleration, $\underline{y}''(t)$.

We form a similar matrix set that groups the independent variables together:

$$X^T = \begin{bmatrix} X_{1,t=1} & X_{2,t=1} & \dots & \cdots & \cdots & X_{20,t=1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{1,t=300} & \dots & \dots & \dots & \dots & X_{20,t=300} \end{bmatrix}$$

with *X* comprising of all 20 independent variables listed earlier. Once the variables are prepared, we proceed to reduce the noise within the curves in preparation for our analysis.

6.2 SMOOTHING THE CURVES

Curves formed from raw data tend to be noisy, with many spikes throughout the entirety of the curve. We are interested in the patterns of the curves and as such require a way to remove this random noise in order to distinguish the patterns of the curves. To achieve this, we use a method called smoothing (Ramsey and Silverman 2005).

We scale our temporal data between 0 and 1, with 0 being the day the Patreon project launched and 1 being the 300th day of our dataset. This is done to align all curves since our data ranges from June 2014 to May 2015 with projects varying in start date. This would also increase the ease of smoothing the curves as we now split the curves into 100 equal portions known as knots (Reddy and Dass 2006). The curve within each portion is then smoothed by fitting a basis spline, a piecewise polynomial that will generate a polynomial functional form as per convention. This form is more flexible as it does not impose any restrictions and can account for different functional forms (Ramsey and Silverman 2005). In order to prevent overfitting of the curves, we specify a smoothing parameter with a roughness penalty. This roughness penalty avoids overfitting of the data by trading off curve roughness at the expense of lack of data fit (Ramsay et al. 2009).

We impose a roughness penalty function (PEN) with the aim of identifying a function that minimizes the penalized residual sum of squares (PENSS) (Reddy and Dass 2006):

$$PEN_m = \int [D^m f(t)]^2 \, dt$$

$$PENSS_{\lambda,m}^{(j)} = \sum^{n} \left(y_i^{(j)} - f^{(j)}(t_i) \right)^2 + \lambda PEN_m^{(j)}$$

where $D^m f$ is the *m*th derivative of function *f*, λ represents the smoothing parameter, $y_i^{(j)}$ represents the observed data for each Patreon project and $f^{(j)}(t_i)$ denotes the functional value obtained from the smoothed spline.

We implement this to smooth the curves for both the number of patrons across time, the amount of contributions across time as well as the smoothed curves for the velocity and acceleration of patron and contribution curves.

6.3 FUNCTIONAL REGRESSION

Our main goal of this paper is to explore how different project characteristics will impact our dependent variables – patron and contributions curves along with their respective velocity and acceleration. Using the previously prepared data, we are able to run a regression to identify how our independent variables impact patterns of crowdfunding at different stages of the crowdfunding process. We use functional regression where:

$$\underline{y}(t) = X^T \underline{\beta}(t) + \underline{\varepsilon}(t)$$

with $\underline{\beta}(t)$ reflecting the varying effects of independent variables at varying stages of our crowdfunding process (Wang et al. 2008).

The model we use for determining how project characteristics will impact recurring contributions is separated into a model for item focused projects and duration focused projects. Item focused projects will provide us data on the contribution per item while duration focused projects provide a different form of data - their contributions per month. Given that these parameters are distinctly dissimilar, we need to separate them out before estimating the effect of project characteristics on recurring contributions. As such, we consider both types of projects separately in our estimation of patterns of change in contribution amount.

7 RESULTS

Figure 9 shows the results of smoothing the patron functions and their respective velocity and acceleration functions. The smoothed curves will be used for our subsequent analysis. We compute the average smoothed curves to illustrate how the patterns change. We interpret the decrease in velocity and deceleration to be when the curve moves towards the 0 and an increase in velocity and acceleration to be when the curve moves away from 0. We can see that projects tend to increase in patrons over time, with a decreasing velocity that increases slightly in the mid stages of crowdfunding process and a deceleration that stops briefly at the mid stages of the crowdfunding process before a period of increasing acceleration that stabilizes at the later stages of the crowdfunding process. [Insert Figure 9]

As contributions from item focused projects and duration focused projects are not comparable, we smooth them within their crowdfunding type. Comparing the average patterns of both curves, we see a contrast between how patterns of contributions for both crowdfunding types evolve across time. We notice that contributions for item focused projects decreases sharply towards the later stages of the crowdfunding process. Although the pattern of decrease is also observed for contributions of duration focused projects, the pattern is not that sharp. Contributions for item focused projects have a decreasing velocity that stabilizes in the mid stages of the crowdfunding process before increasing in velocity for the rest of the process. This is reflected in their acceleration, which shows deceleration up to the mid stages of the crowdfunding process before entering a state of increasing acceleration. For duration focused projects, we observe a sharp decrease in velocity in the early stages of the crowdfunding process before increasing slightly at the mid stages followed by an increasing velocity at the later stages. The acceleration of the duration focused project decelerates in the early stages before stabilizing. After stabilization, the contributions go through a period of increasing acceleration before decelerating again. The contrast between the patterns of these two crowdfunding types are distinct and thus should be considered separately in later analysis on contributions. [Insert Figure 10 & 11]

We inspect the correlation of our variables before continuing with our analysis. Our model does not suffer from multicollinearity issues [Insert Table 9]

We run a regression on our proposed model and obtain the coefficients of the independent variables across the entire crowdfunding process. These coefficients take the form of a curve with an example shown in Figure 12. To interpret the curve, we note that curves with the confidence bands above or below the 0 would mean that the variable has a significant impact on our dependent variable for that particular time period. [Insert Figure 12]

7.1 IMPACT OF FACTORS ON PATTERNS OF PATRON GROWTH

We show the results of our analysis for the pattern of the patrons in Table 10. Incentives seem to factor is as important variables in affecting the number of patrons, with number of perks, number of free content, number of exclusive content and percentage of exclusive content all having positive significant effects on the entire patron curve. However, these incentive variables have differing impacts on the velocity and acceleration curves of patrons. Although all these variables have an impact on the velocity of the change in the number of patrons, the effect of the number of exclusive content lasts the longest, affecting the velocity from the initial crowdfunding stages all the way to the end of the mid stages of crowdfunding. The number of perks has the shortest impact on velocity, lasting up to the first 120 days, with the number of free content and the percentage of exclusive content lasting longer. We note that aside from percentage of exclusive content, the other incentive variables all have a negative impact on acceleration, with number of perks and free content impact extending from the initial stages to the mid stages of the crowdfunding process while the number of exclusive content only having an impact from the period between the 150th to the 195th day. With this we can conclude that incentives in general will have a positive impact on patron growth as well as the rate of patron growth. As such, creators should offer more perks, more free content and more exclusive content in order to attract patrons. In particular, creators need to ensure that the amount of exclusive content they offer is more than the amount of free content as patrons are sensitive to this throughout the entire crowdfunding process. [Insert Table 10]

Characteristics of Project Presentation also have an impact on the growth of the number of patrons. One notable variable that impact the patron curves is the number of words, which has a positive impact on patrons throughout the entire crowdfunding process, a positive impact on velocity in the mid stages of crowdfunding, and an impact on acceleration at the late stages of crowdfunding. We do see a negative impact of number of milestone goals on patrons from the initial stages of crowdfunding up to the 165th day, this along with a negative impact on acceleration at the later stages of the crowdfunding process shows that creators should not have too many milestone goals as it will decrease the number of patrons at the early stages of crowdfunding.

We also identify categories that are able to attract patrons throughout the entire crowdfunding process. Content from the Video, Games and Podcast categories have a positive impact on the number of patrons across the entire crowdfunding process. This is especially notable for Video and Podcast content as they have a positive impact on velocity as well.

7.2 IMPACT OF FACTORS ON PATTERNS OF CONTRIBUTION GROWTH FOR ITEM FOCUSED PROJECTS

Unlike the results that we have obtained for patron growth, contribution growth for item focused projects are dissimilar. The most important distinction is the fact that free content and the percentage of exclusive content do not have a significant impact on contribution growth. An increase in the number of perks has a positive impact on contributions throughout the crowdfunding process. The number of perks also has a positive impact in the initial stages and a negative impact in the later stages, with a negative impact on acceleration from the mid to late stages. Furthermore, the number of exclusive content has a positive impact on contributions across the entire crowdfunding process, with a positive impact on velocity in the initial to mid stages of crowdfunding and a positive impact on acceleration in the initial stages but a negative impact on acceleration at the mid to late stages of crowdfunding. Put together, this suggests that more perks and exclusive content will increase contributions, however, the rate of increase starts to slow down at the later stages of crowdfunding. [Insert Table 11]

Other notable variables that impact contributions are the number of words and that the content produced is from the video category. We observe a positive impact of the number of words throughout the entire crowdfunding process, signalling that the more words in the project description, the more contributions will grow, especially in the early stages and later stages of crowdfunding since they also have a positive impact on acceleration in the first 30 days and the last 45 days. We also observe a positive impact of video content after the first 30 days and this impact will last for the rest of the crowdfunding process. Velocity is also affected by video content, with a positive impact during the mid stages of crowdfunding.

7.3 IMPACT OF FACTORS ON PATTERNS OF CONTRIBUTION GROWTH FOR DURATION FOCUSED PROJECTS

Contribution growth for duration focused projects are mainly driven by incentives and specific categories. [Insert Table 12]

Similar to factors that impact patrons, factors that impact contributions for duration focused projects comprise of all forms of incentives. The effect of all these incentives last through the entire crowdfunding process. However, these incentives have different impact on the velocity of contributions, with the number of perks having a positive impact on velocity at the early and late stages of crowdfunding, the percentage of exclusive content having an impact in the first 75 days, the amount of free content having an impact on the first 120 days and the number of exclusive content having an impact in the mid stages of the crowdfunding process. The number of free content also has a negative impact on acceleration over the first half of the crowdfunding process with perks having a negative impact on acceleration between the 60th to 150th day and a positive impact on acceleration from the 225th day onwards. Put together, this suggests that although all these forms of incentives increase contributions, content creators should focus generating free content up to the first 120th day. After that, content creators should focus less on free content as its impact on the velocity at which contribution grow is non-significant after that period. Creators should continue to focus on exclusive content and perks as these will have a positive impact the velocity at the mid stages for the former and the velocity and acceleration at the late stages of crowdfunding for the latter.

We note that content produced in the categories of videos, games and podcasts have a positive impact on contribution growth, with podcasts having a positive impact on the velocity of contribution growth in the mid stages of the crowdfunding process as well.

The results obtained from the impact of different factors on the growth of patron and contributions suggest that different factors will have disparate effects at different stages of the crowdfunding process. Knowing the impact these variables have on patterns of crowdfunding is important in aiding us understand the crowdfunding process. Certain variables such as free content may have an impact on patron growth and contributions for duration focused projects, will not influence contributions for item focused projects. Similarly, knowing that variables have an impact in different stages such as the significant impact on free content on velocity in the early stages of contributions for duration focused projects will give content creators a guideline on which factors to emphasize at different stages of the crowdfunding process in order to maximize revenue.

8 FUNCTIONAL CLUSTERING

In our previous analysis, we considered curves at an aggregate level, with all curves being considered for our regression. With this, we question whether certain patterns that could be observed by smaller groups of homogenous curves are meaningful for creators and platforms to consider. The heterogeneity of the large number of curves will obscure patterns between more homogenous groups of curves and to uncover these potentially meaningful patterns, we conduct a principal component analysis and clustering of our aggregate curves.

Instead of considering a set of discrete values, our principal component analysis considers a set of curves to identify the significant primary modes of variation available in the patterns (Ramsey et al. 2009). Our principal component scores are calculated as such:

$$S_{ip} = \int e_p(s)\, z_i(s) ds$$

where S_{ip} is the score for each of the p principal components, with $e_p(s)$ representing a set of p principal component curves with $z_i(s)$ representing the set of smoothed curves (Dass and Shropshire 2012).

We can further classify curves based on their structure by grouping similar curves together through clustering the curves (James and Sugar 2003). We use the k-means clustering to minimize the within-cluster sum of squares:

$$\arg min \sum_{i=1}^{k} \sum_{z(s)_j \in H_i} \left\| z_j(s) - \mu_i \right\|^2$$

where we cluster a set of n response curves $z_n(s)$ by partitioning them into $k$sets of $H = \{h_1, \ldots, h_k\}$ (Dass and Shropshire 2012).

The results of our principal components analysis and clustering are shown below. [Insert Figure 13]

We are able to identify the three functional components within the different patterns of each curve. Further, using the elbows of the scree plots, we are able to identify the appropriate number of clusters for the curves of the number of patrons, contributions for item focused projects and contributions for duration focused projects. Based off their aggregated project categories and the type of content and creators, we have developed an initial cluster description for each of these clusters. [Insert Table 13]

We have identified four clusters after minimizing for within-cluster heterogeneity for patterns in patron growth, five clusters for patterns of contributions for item focused projects and four clusters for patterns of contributions for duration focused projects.

Clusters vary in size and there are some smaller clusters that can be described based off their content. Projects that have been identified as having similar patterns and comprising of large popular creators and are seen as extremely well performing projects are termed Established Projects. Another group of projects have been identified based on their content to be hedonic projects as they focus on projects that consumers can derive enjoyment from such as videos of creators sailing the world.

For larger clusters, we tend to identify them based off the content categories of projects within the cluster. Projects with a heavy emphasis on sound, such as groups comprising of a majority of video, podcast or music content are termed as audio heavy projects. Projects grouped together that have a strong emphasis on what consumers view, with content generally in the video and comics category are termed visual heavy projects. Content that have a heavy emphasis on the video category, we term as video heavy projects and the bulk of the projects will be grouped under generic projects.

8.1 IMPACT OF FACTORS ON PATTERNS OF PATRON GROWTH FOR DIFFERENT CLUSTERS

We compare the average curves of different patron clusters. We can observe that clusters have different patterns of patron growth, velocity and acceleration. This is especially true of Cluster A3 as acceleration of patron growth decelerates once more at the later stages after decelerating once at the early stages of the crowdfunding process while cluster A2 and A3 have no deceleration at later stages. The distinct differences in the patterns of curves lead us to conclude that splitting them into small homogenous clusters will give us more accurate results when we try to examine the factors that may impact patterns of contributions. [Insert Figure 14]

After clustering the groups, we go through the same process in order to obtain results for our analysis of factors that affect patron patterns. As there are too few projects in Cluster A1, we were not able to obtain coefficients for the factors within the cluster due to the small sample size. We proceed to report the results of the follow three clusters.

In Cluster A1, we observe several interesting differences from the aggregated results we presented earlier. For instance, explicit content has a negative impact on the number of patrons throughout the entire crowdfunding process. This would suggest that creators should avoid creating content that is not safe for all ages. Furthermore, the number of free content has a negative impact on patrons in the first 30 days while the number of exclusive content has a positive impact on patrons in the last 45 days. This result suggest that creators should not produce free content at the start of the project and need to have a sizable amount of exclusive content by the late stages of the project in order to generate more patron growth. The positive impact of formatting on patron growth at the first 30 days and its related negative impact on velocity in the first 45 days suggest that the project description page needs to be properly formatted in order to attract patrons and this effect slowly decreases until the 45^{th} day. We also note that the number of platforms have a negative impact on patrons from the mid stages of the crowdfunding process all the way to the end but this is attenuated by negative velocity and positive acceleration at the end. This suggests that including too many links to other platforms will decrease patrons, but this problem is lessened towards the end of the crowdfunding period as the rate of decrease slows down at an increasing pace. [Insert Table 14]

In Cluster A3, the most meaningful factor is the number of free content. We find that the number of free content has a positive impact on the first 135 days in the crowdfunding project's lifespan. This implies that in order to stimulate patron growth, creators for visual heavy projects should focus on creating more free content at the start of the project. [Insert Table 15]

In Cluster A4, we find that incentives and different project presentation characteristics have an impact on patron growth. A summary of the results would indicate that creators should focus on having more perks, more free content, more exclusive content, a higher percentage of exclusive content compared to free content, more words in the project description and a sample within the project description through the entire crowdfunding process. This is especially the case for perks as it is the only variable that has a positive effect on late stage velocity as well as a positive effect on acceleration for the first 270 days. Creators can also leverage on the fact that explicit content has an impact after the initial stages and this positive impact lasts all the way to the end of the crowdfunding period. Creators should avoid listing too many platforms in their project page as it has a negative impact across the entire crowdfunding period. Results from this generic cluster are markedly different from results provided by the aggregate group of patron curves earlier and as such may allow for more specific recommendations and more accurate results after accounting for heterogeneity in curves. [Insert Table 16]

8.2 IMPACT OF FACTORS ON PATTERNS OF CONTRIBUTION GROWTH FOR ITEM FOCUSED PROJECTS IN DIFFERENT CLUSTERS

Similar to what we expect, we see that the clusters have different patterns. For instance, previously when considering these curves as an aggregated group, the pattern of change for contributions, its velocity and its acceleration is most similar to our current Cluster B2. However, comparing Cluster B2 to our largest cluster, B4, we observe that the patterns of growth for contributions are different. Projects in B4 can be seen as less successful projects as they start off with a small peak before decreasing with a slight increase close to the later stages of the crowdfunding process before finally decreasing again. B2 however has a general increasing trend, with a peak at the later stages before slightly decreasing close to the end of our time period. [Insert Figure 15]

For the groups of projects subdivided into different clusters, we find that Clusters B1 and B3 have small samples and as such are unable to estimate the coefficients of our independent variables. On the other hand, Cluster B5 has no significant variables, which might mean that there are other variables that we have not accounted for that may be driving the patterns of contribution growth in Cluster B5.

In Cluster B2, although a few factors demonstrate significant impact on velocity and acceleration, as their impact on contributions is not significant, we do not interpret them. The factors that have a significant impact on contributions are the type of content produced by the creator, more specifically whether the content comes from the comics and animation category. We find a positive impact on contributions for the first 120 days. [Insert Table 17]

In Cluster B4, we see that factors that drive patrons to contribute are mainly perks, exclusive content, the number of words in the description and the number of platforms. These variables all have positive effects on the contribution across the entire crowdfunding period with number of platforms having an additional positive initial impact on velocity in the first 45 days. Furthermore, we note that for the first 105 days, it is important to ensure that the percentage of exclusive content is higher than free content as it will have a positive impact up to the 105th day. We find that having a sample of content in the project description will have an impact from the 15th day onwards up to the final part of the crowdfunding process. We can conclude that generic projects that ask for contributions on a per item basis should focus on exclusive content as free content is not important, should have samples and a long project description as well as links to numerous platforms in order to maximize revenue. [Insert Table 18]

8.3 IMPACT OF FACTORS ON PATTERNS OF CONTRIBUTION GROWTH FOR DURATION FOCUSED PROJECTS IN DIFFERENT CLUSTERS

There are distinct differences in the clusters when we compare the average curves generated by each cluster. Notably, although Clusters C1 and C2 may be similar, with increasing contributions throughout most of the crowdfunding process and a decrease in contributions at the later stages. Cluster C3 display growth that is dissimilar, with contributions peaking at the early stages of the crowdfunding process, decreasing in the mid stages of the crowdfunding process before increasing to a higher peak and decreasing again at the later stages. This pattern was not obvious when we considered contribution curves as an aggregated group but appears distinctly after we have broken them down into smaller, homogenous groups. [Insert Figure 16]

We present the results for Cluster C2 and C3. As Cluster C4 is small, we are unable to recover coefficients for our factors of interest. Similarly, we find that C1 has no factor that has an impact on contributions and although a few factors demonstrate significant impact on velocity and acceleration, as their impact on contributions is not significant, we do not interpret them.

We find that for Cluster C2, most variables only have an impact after the initial stage of the crowdfunding process. Content explicitness only has a negative impact on contributions after day 90 and lasts till day 270. Similarly, the presence of a sample only has a negative impact after day 135 till the end of the crowdfunding process. The number of words and milestone goals have a positive impact on contributions after day 60 and 120 respectively. [Insert Table 19]

For Cluster C3, the generic cluster, we find that the nature of incentives matters the most to contributions, with number of perks, number of free content, number of exclusive content and percentage of exclusive content driving positive contribution growth throughout the entire period. We further note that the number of words and the fact that the content is explicit will also have a positive impact on contributions. We note that three particular factors - whether the content is explicit, number of exclusive content and percentage of exclusive content, have positive impacts on velocity as well. Creators collecting funds on a periodic basis can thus focus on these factors in attracting more funds. [Insert Table 20]

9 DISCUSSION

Our results provide evidence that patterns of recurring crowdfunding differ and factors that influence this difference in patterns have non-uniform effects throughout the entire crowdfunding process. We have further incorporated the heterogeneity of the curves into our model by striving to cluster them into groups with small within cluster heterogeneity. The results from these clusters, especially the generic clusters, provide us with more accurate information on what factors affect patron growth, contribution growth and their respective velocities and acceleration.

On a fundamental level, given that this is a relatively new crowdfunding model, we are able to provide specific recommendations to crowdfunding practitioners and the crowdfunding industry on what affects recurring contributions. Once the crowdfunding industry has gained a rudimentary understanding of this new patronage model, they will be able to better leverage this model to maximize the support they can gain from their patrons.

Our main recommendations are constructed using the generic project results for each of our dependent variables – patron growth, contribution growth for item focused projects and contribution growth for duration focused projects.

For patron growth, we recommend that creators have sufficient incentives in place to motivate potential patrons into supporting them. A good guideline would be to have a wide variety of perks and continuously produce a mixture of free and exclusive content while making sure that the value patrons receive from contributing is always higher by producing a larger proportion of exclusive content. The project description should be long and have a sample of the content that is being produced. However, projects should not have too many links to other platforms through the whole crowdfunding process or too many milestone goals in the initial period as potential patrons may view creators as overreaching and thus not join as a patron.

For growth in contributions of projects collecting funds at a per item level, we recommend ensuring a wide variety of perks while producing more exclusive content. As free content has no impact and patrons are sensitive to the ratio of exclusive to free content, it is plausible that a creator would want to choose to move entirely into creating only exclusive content. The project description should be long with a sample of the content created placed in the project page after the initial stages of adopting the patronage model. Creators should also ensure that patrons are able to reach them by having as many touch points as possible in the form of platform links in the project page.

For growth in contributions of projects collecting funds at a per month level, we recommend ensuring a wide variety of perks, with more free content and exclusive content while making sure that the percentage of exclusive content relative to free content is always high. Having a long project description is also recommended along with creating explicit content.

Crowdfunding platforms that are conducting recurring crowdfunding can make use of the information provided by our research by emphasizing, through the platform architecture, on factors that motivate a potential patron to back. For example, as exclusive content has a positive impact on patron growth and contribution growth, the crowdfunding site can intentionally separate exclusive content into a new tab and have visuals that draw attention to the tab whenever a user visits the project page. Similarly, for factors that have a negative impact, the platform can deemphasize the factor to increase patrons or contributions to the project page. Managing their website interface and directing users' attention either to or away from these factors would in turn increase their revenues as well.

Finally, from the average contribution curves, we have shown that the patronage model as a whole is able to generate substantial revenues for creators. This success will allow third party hosting platforms to maintain their creators as they can now ensure their creators have a sustainable source of income outside their current platform. Hosting platforms can thus advocate recurring crowdfunding as a viable addition to their revenue sharing plans and thus prevent their creators from disengaging from the platform due to a lack of a stable income.

9.1 LIMITATIONS AND FUTURE RESEARCH

We acknowledge that our research has several limitations in terms of the data. As this is the first paper that deals with recurring funding, we have used freely data available from the Patreon's project page as possible variables that may drive change. Certain variables such as the number of words in a project description may not be able to provide a deeper understanding of the sentiments or quality of the project description apart from its length. Furthermore, as mentioned previously, the nature of recurring crowdfunding is to fund creators. These creators would already have a presence on a different platform before they decide to adopt a patronage model. Our research does not account for the variables that are in their content hosting platform such as the quality of previous content, the number of existing fan base or the popularity of the content hosting platform as the platforms vary too much and some content hosting platforms lack metrics that allow them to be cross-compared with other platforms (i.e. comparing Youtube with a personal webpage on stories). Future research can address these by using natural language processing methods to code the sentiment of the project description as well as collecting variables outside of the crowdfunding site.

Our research may also suffer from limited length of the funding process. We currently use the project's first 300 days and explore how our variables may impact the curve and its dynamics across this time period. However, some variables may only affect patterns at a later stage of the crowdfunding process, such as after the first year into the crowdfunding. Although our choice was motivated by platform changes as Patreon has decided to allow creators to hide contribution information in 2017, future research can explore the possibility of collaborating directly with the crowdfunding platform or to use other crowdfunding sites to address this issue.

9.2 CONCLUSION

As research on the recurring crowdfunding process is in its nascent stage, with a lack of research on the phenomenon, our research has providing a theoretical framework to the recurring crowdfunding process and identifying the determinants that impact the patterns of growth for patron and contributions as well as dynamics such as velocity and acceleration on the rates of growth. We have further separated projects by grouping them into relatively homogenous groups and have identified the factors that can affect patron and contribution growth in each of these groups. In uncovering these significant factors, we provide practitioners in the field recommendations on which factor they should focus on at different stages of the crowdfunding process in order to maximize crowdfunding revenue. We hope that in using dynamic data, future research studying recurring contributions can continue study contribution growth while including the temporal dimension as it provides us with more granular information that can generate more specific recommendations at different stages of the entire process.

CHAPTER 4: THESIS CONCLUSION

The papers in this thesis addresses issues within the crowdfunding domain. Both papers explore constructs that have not been previously explored in the field. The implications derived from these studies serve as important contributions to this domain.

In the first paper, the focus was on the typical crowdfunding model, with a single contribution by each backer for the entire duration of the crowdfunding process. The first paper explores influence between backers and recovers an implicit backer network using previous backing behaviour of backers on the platform. The paper is able to identify influential backers and show that backers in central position within the network has an impact on other backers and through them, crowdfunding outcomes such as success, funding amount and rate at which the project reaches its funding goal.

For the second paper, the focus is on a model that has not been explored by previous researchers of the crowdfunding domain – the recurring funding model. As there is no time limit to this model, the patterns of growth of patrons and contributions are not restricted by a fixed duration. This results in a wider variety of possible determinants with a larger range of potential effects across different stages of the crowdfunding process. We are able to identify determinants that impact patterns of patron and contribution growth across the different stages of the crowdfunding process.

There is more work to be done in order to allow us to be fully satisfied with our results. For the first paper, in order to address concerns with interpretation of the weighted network, we have collected data on demohour, a Chinese crowdfunding site. Demohour provides information on the exact time a backer contributes to a crowdfunding project along with the contribution amount. This will allow us to form a directional weighted network to ensure that our results are robust even if time and funding data included. For the second paper, we are deliberating on the possibility of merging data found on Patreon with metrics found on the creators' hosting platform. As cross comparability between platforms is a challenge, one possibility could be conducting multiple functional regressions across each sizable platform separately.

We also provide several suggestions in the direction the field can progress. As we have established that crowdfunding is a phenomenon that is evolving and expanding, more research needs to be conducted to understand the field. There have been new forms of crowdfunding that have evolved from the initial types of crowdfunding. We have explored in this research the changes between crowdfunding a project and its alternative of crowdfunding a creator, with Kickstarter creating a new platform to tap into that market. Similarly, equity crowdfunding has evolved with the inclusion of blockchain, which is a record for digital assets. Potential investors can now crowdfund a project that offers digital coins in exchange for an investment of Fiat currency (such as US Dollars) or cryptocurrency (such as Bitcoin), with Indiegogo creating a new platform to enter this new market (Indiegogo, 2018). With these models constantly evolving and with such a large financial impact on the online marketplace, research on crowdfunding needs to keep pace with these new models so that users of crowdfunding from the creators to backers and even the platforms themselves can ensure the most efficient and effective way to to stimulate progress and growth in crowdfunding.

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APPENDIX

Figure 1 Conceptual Model of Crowdfunding Success

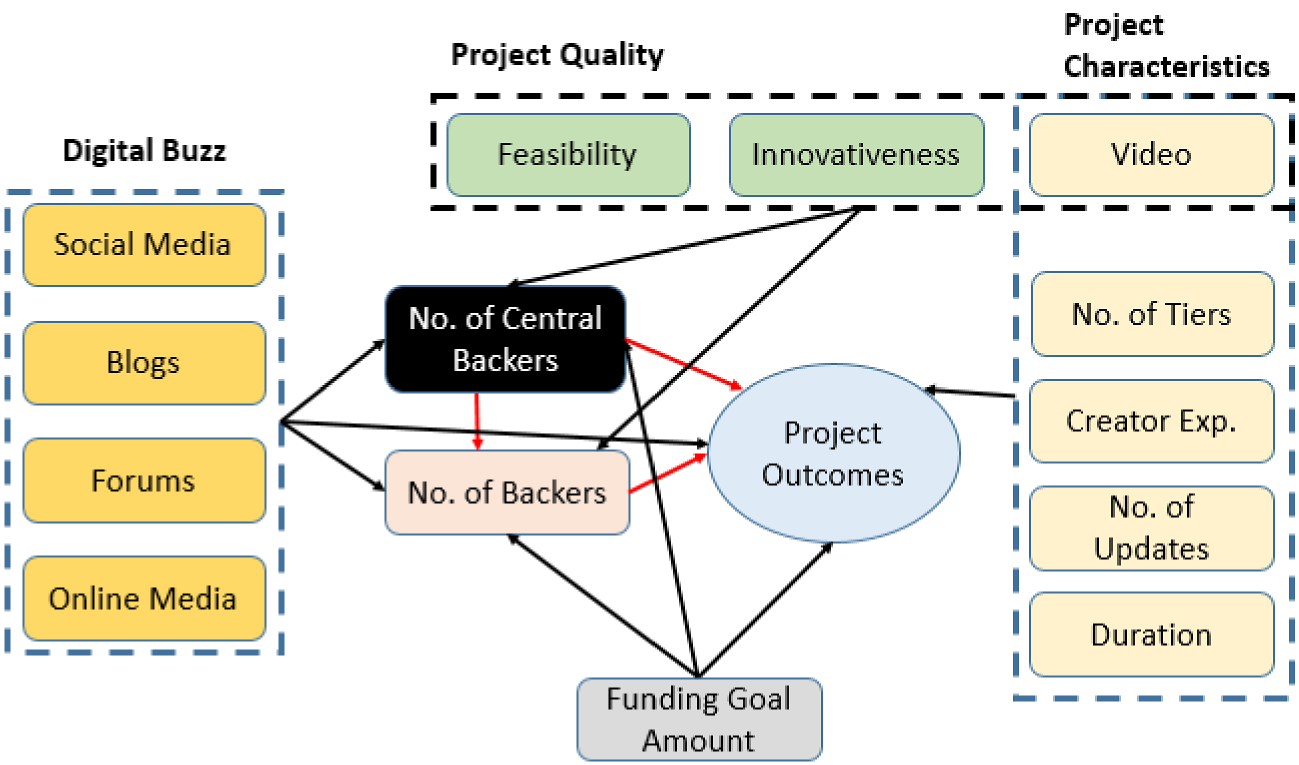
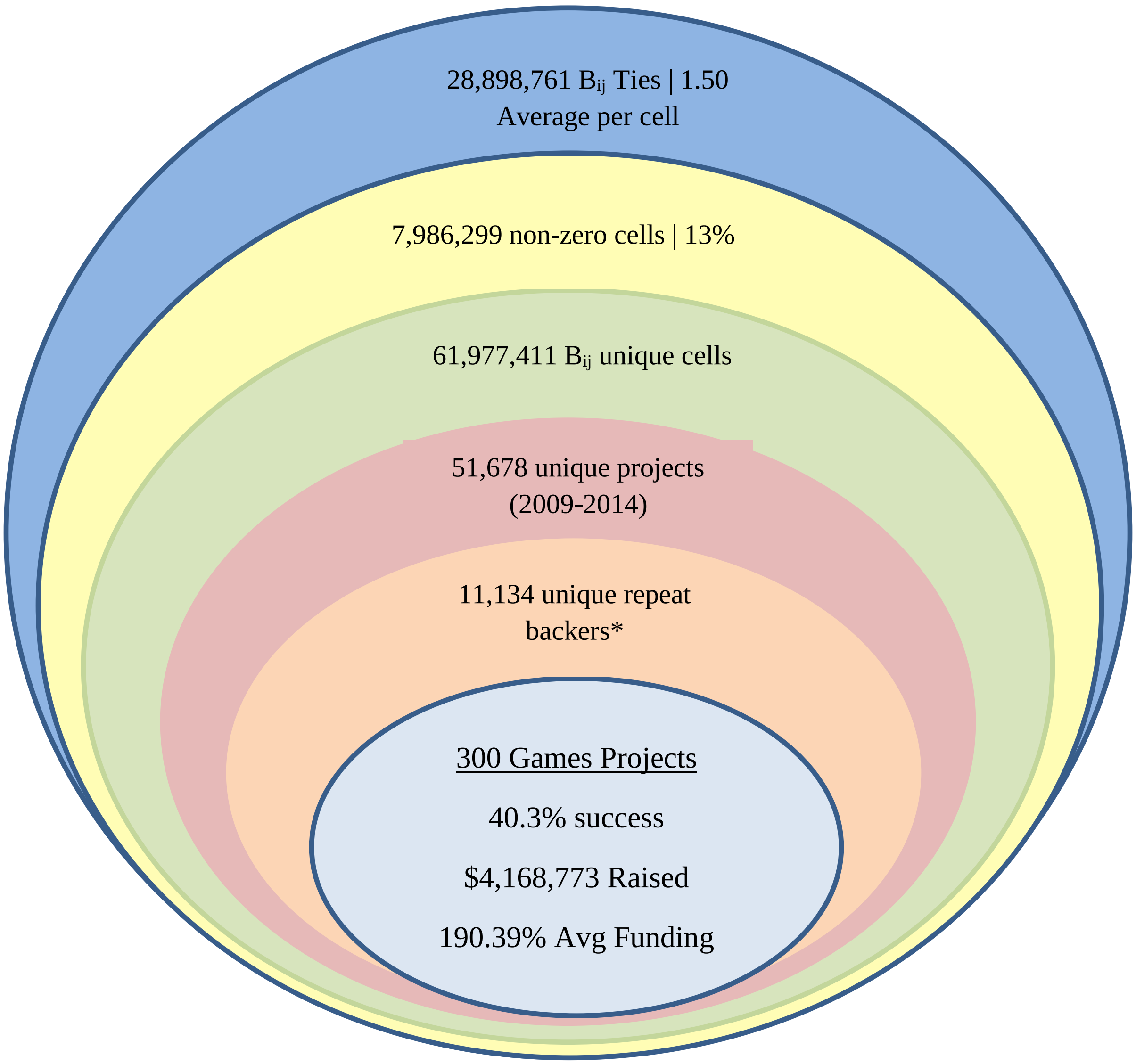


Figure 2 Data for Network Estimation



*Unique backers who backed more than one project

Figure 3 Presence of Central Backers on Project Outcomes

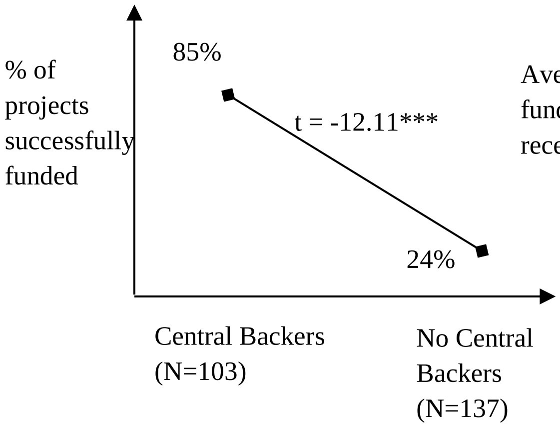


Fig 3a Presence of Central Backers on Funding Status

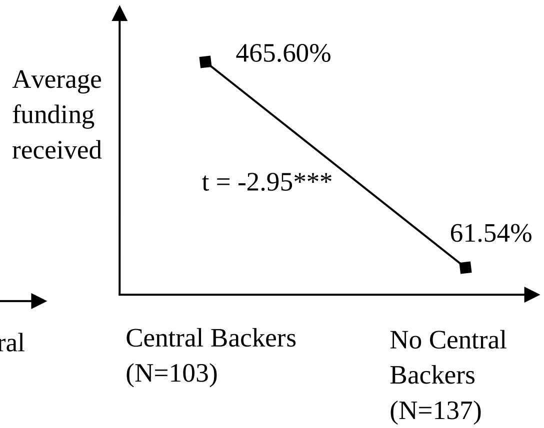


Fig 3b Presence of Central Backers on Percent Funded

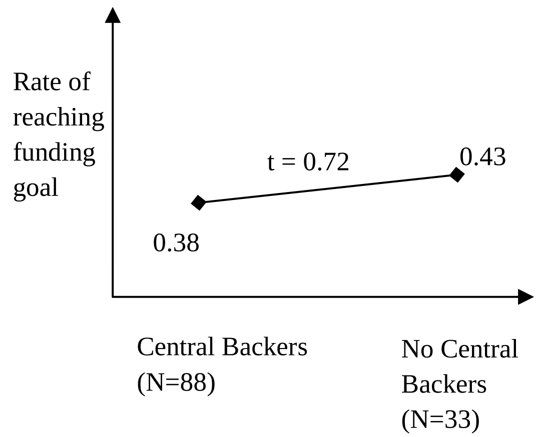
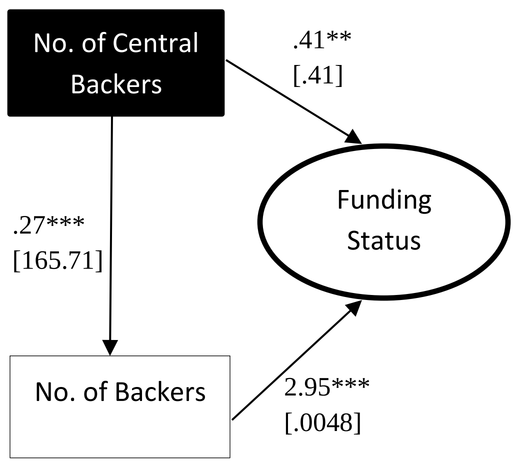
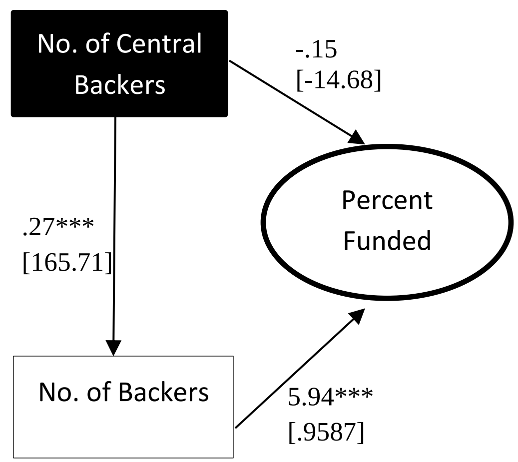


Fig 3c Presence of Central Backers on Goal Rate

Figure 4 Indirect Effects of Central Backers





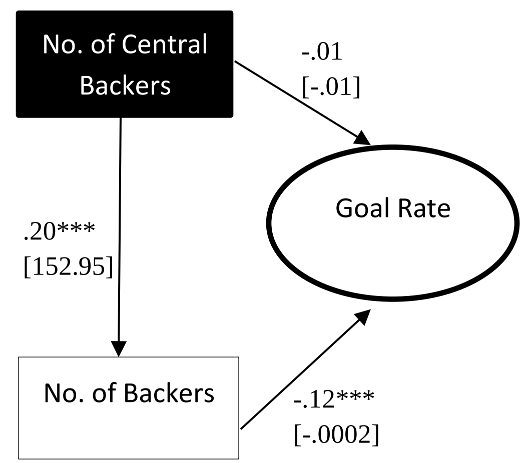


Fig 4a Direct & Indirect Effects of Backers and Central Backers on Funding Status

Effect	Estimates	% of Effect
Direct Effect of Central Backers on Funding Status	.41	33.9%
Direct Effect of Central Backers on Backers	165.71	
Direct Effect of Backers on Funding Status	.0048	
Total Indirect Effect of Central Backers on Funding Status	.80	66.1%

Fig 4b Direct & Indirect Effects of Backers and Central Backers on Percent Funded

Effect	Estimates	% of Effect
Direct Effect of Central Backers on Funding Status	-	-
Direct Effect of Central Backers on Backers	165.71	
Direct Effect of Backers on Funding Status	.9587	
Total Indirect Effect of Central Backers on Funding Status	158.87	100%

Fig 4c Direct & Indirect Effects of Backers and Central Backers on Goal Rate

Effect	Estimates	% of Effect
Direct Effect of Central Backers on Funding Status	-	-
Direct Effect of Central Backers on Backers	152.95	
Direct Effect of Backers on Funding Status	-.0002	
Total Indirect Effect of Central Backers on Funding Status	-.0306	100%

Figure 5 Presence of Different Backers on Project Outcomes

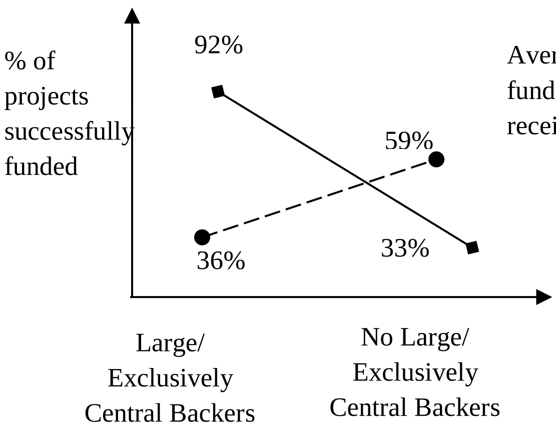


Fig 5a Presence of Different Backers on Funding Status

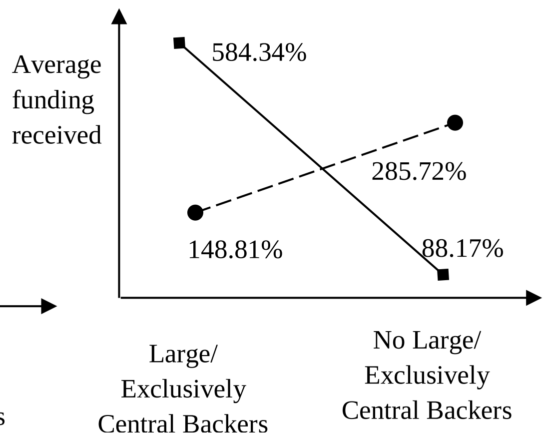


Fig 5b Presence of Different Backers on Percent Funded

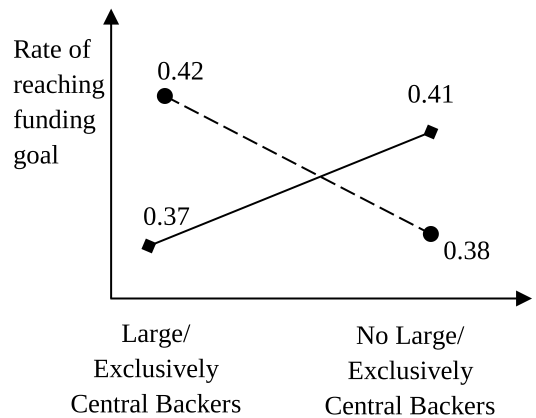


Fig 5c Presence of Different Backers on Goal Rate

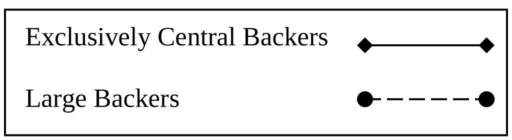


Figure 6 Balancing Privacy Concerns and Profits

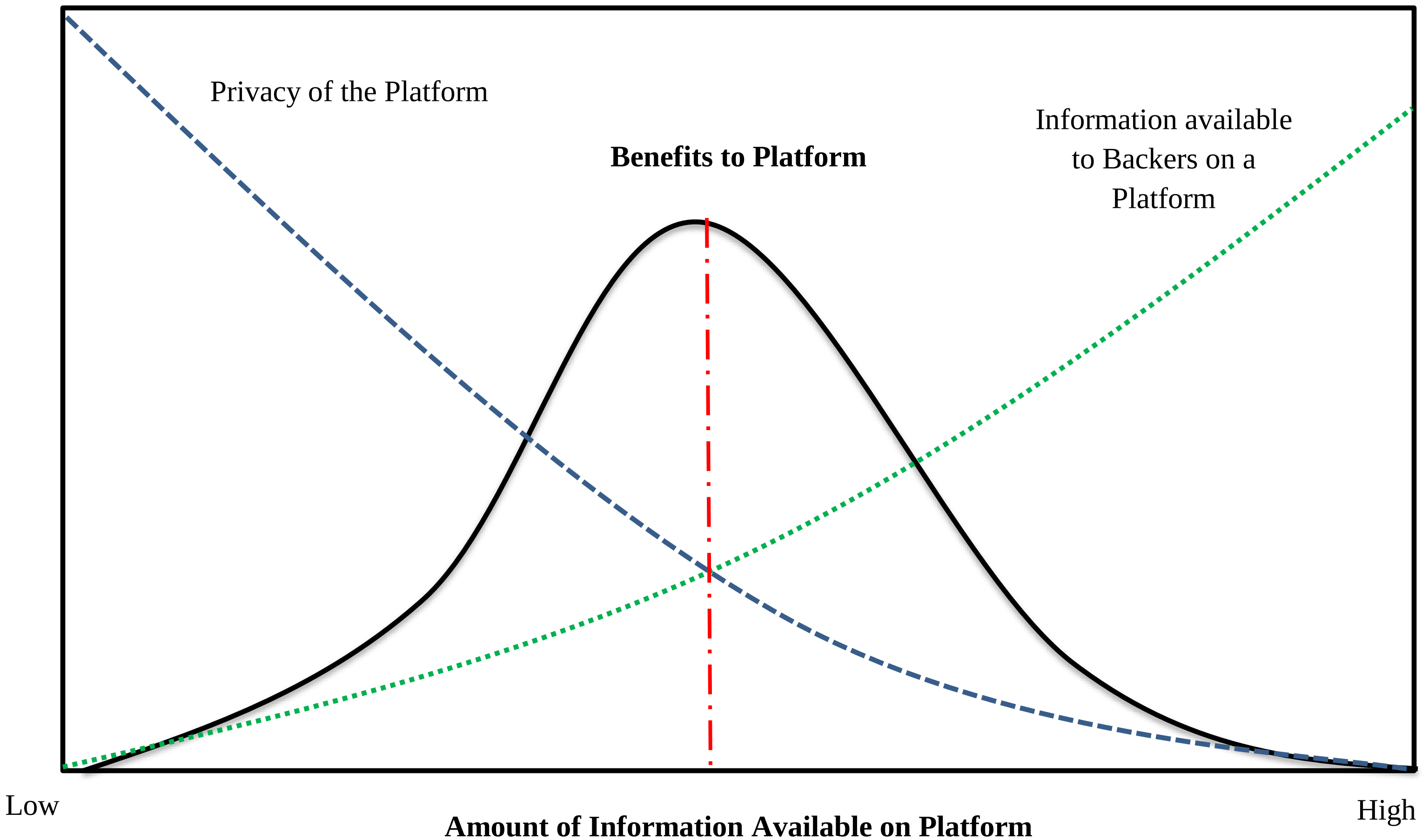


Figure 7 Patterns of Crowdfunding projects and Crowdfunding Creators

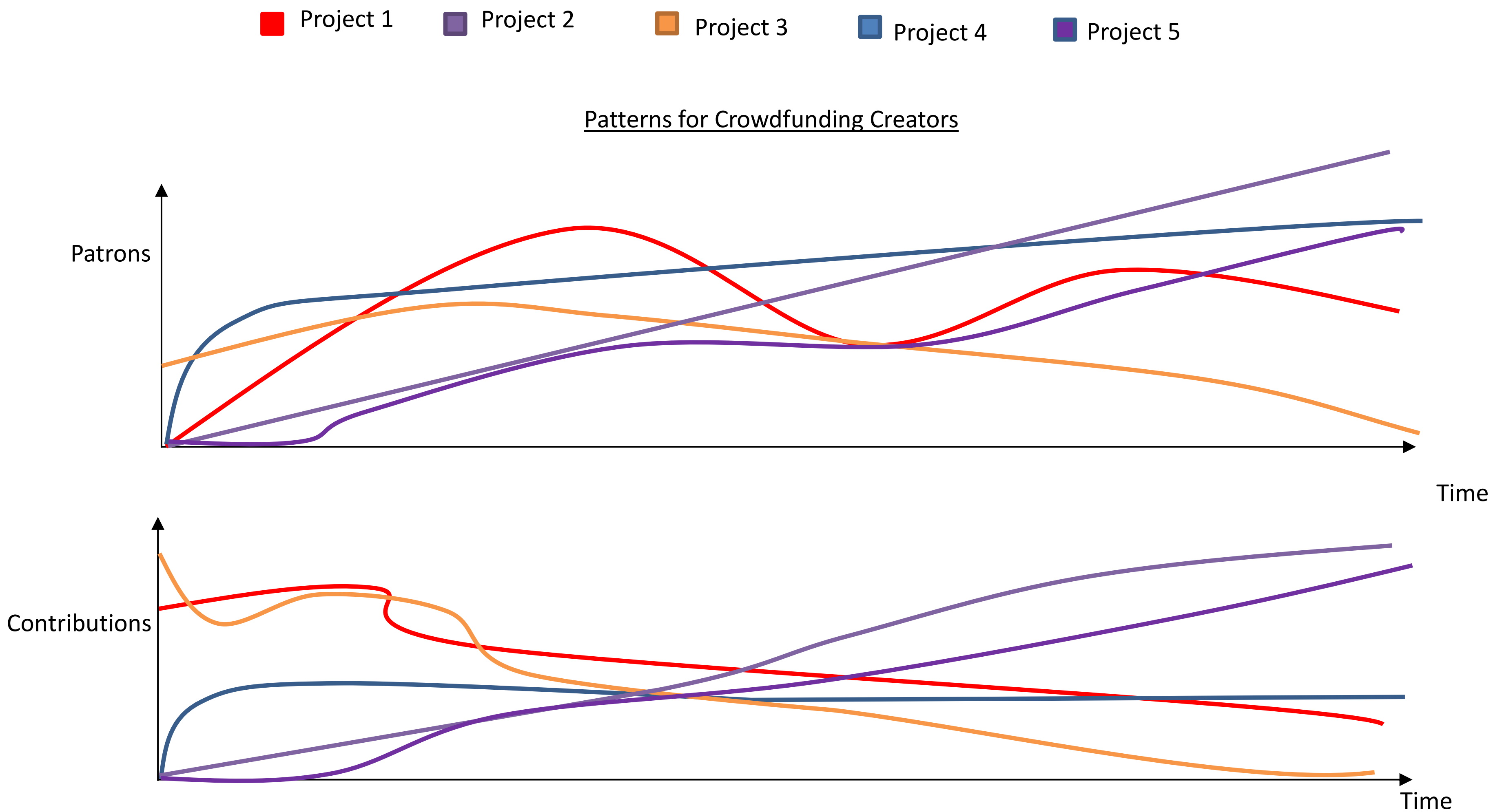


Figure 8 Our Proposed Model

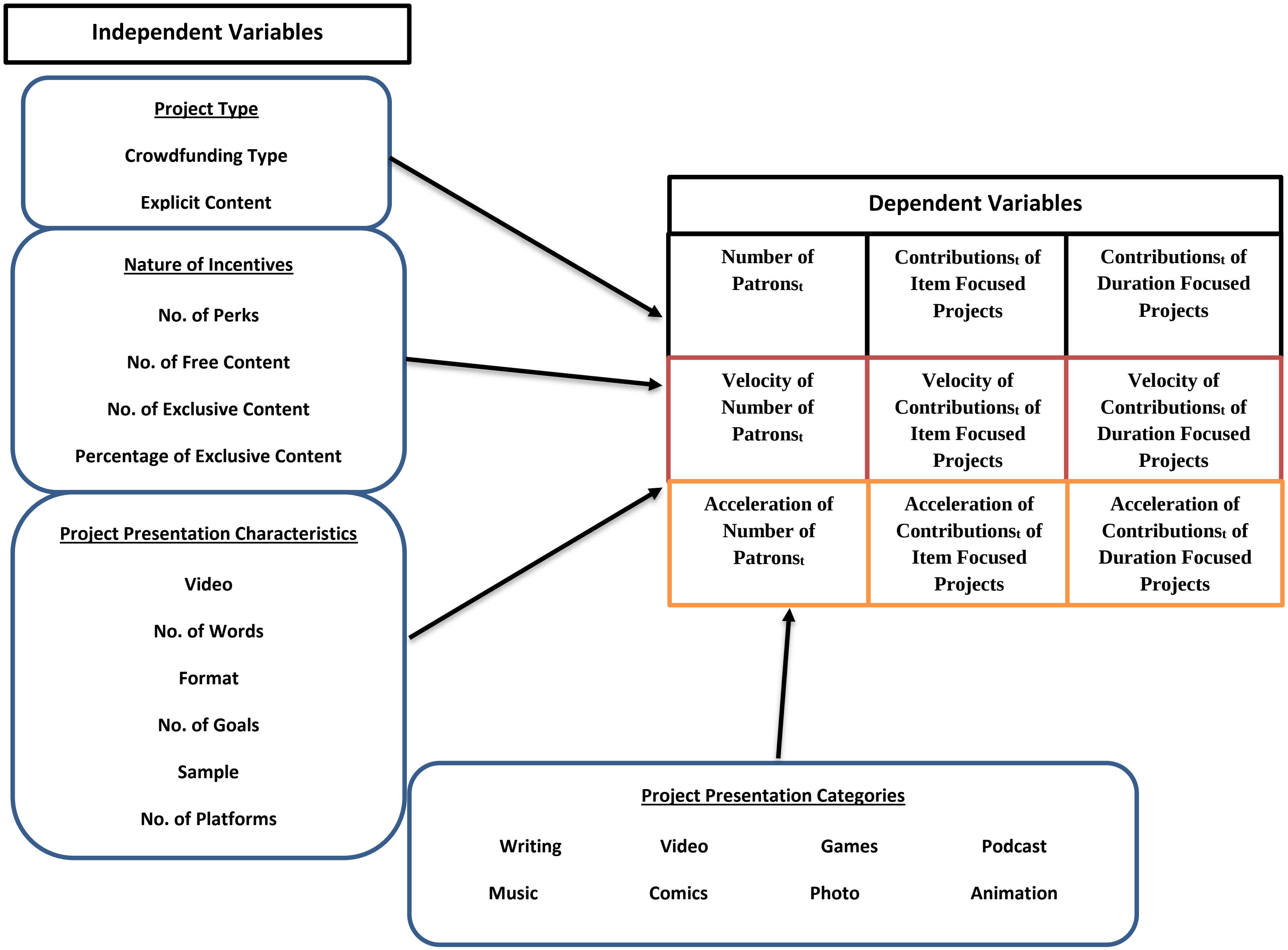


Figure 9 Smoothing Functions of Patreon Projects

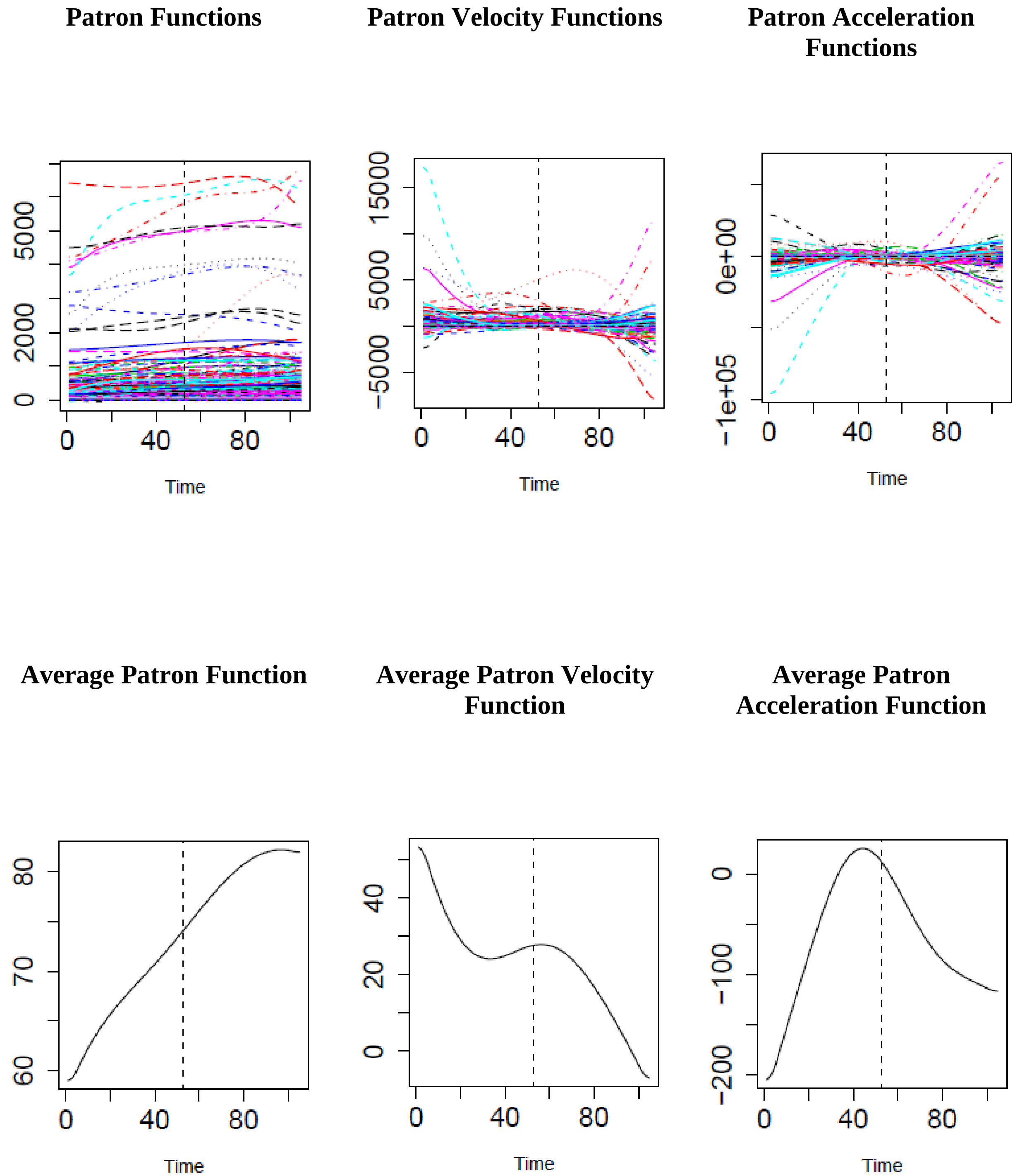


Figure 10 Smoothing Contribution Functions of Item Focused Projects

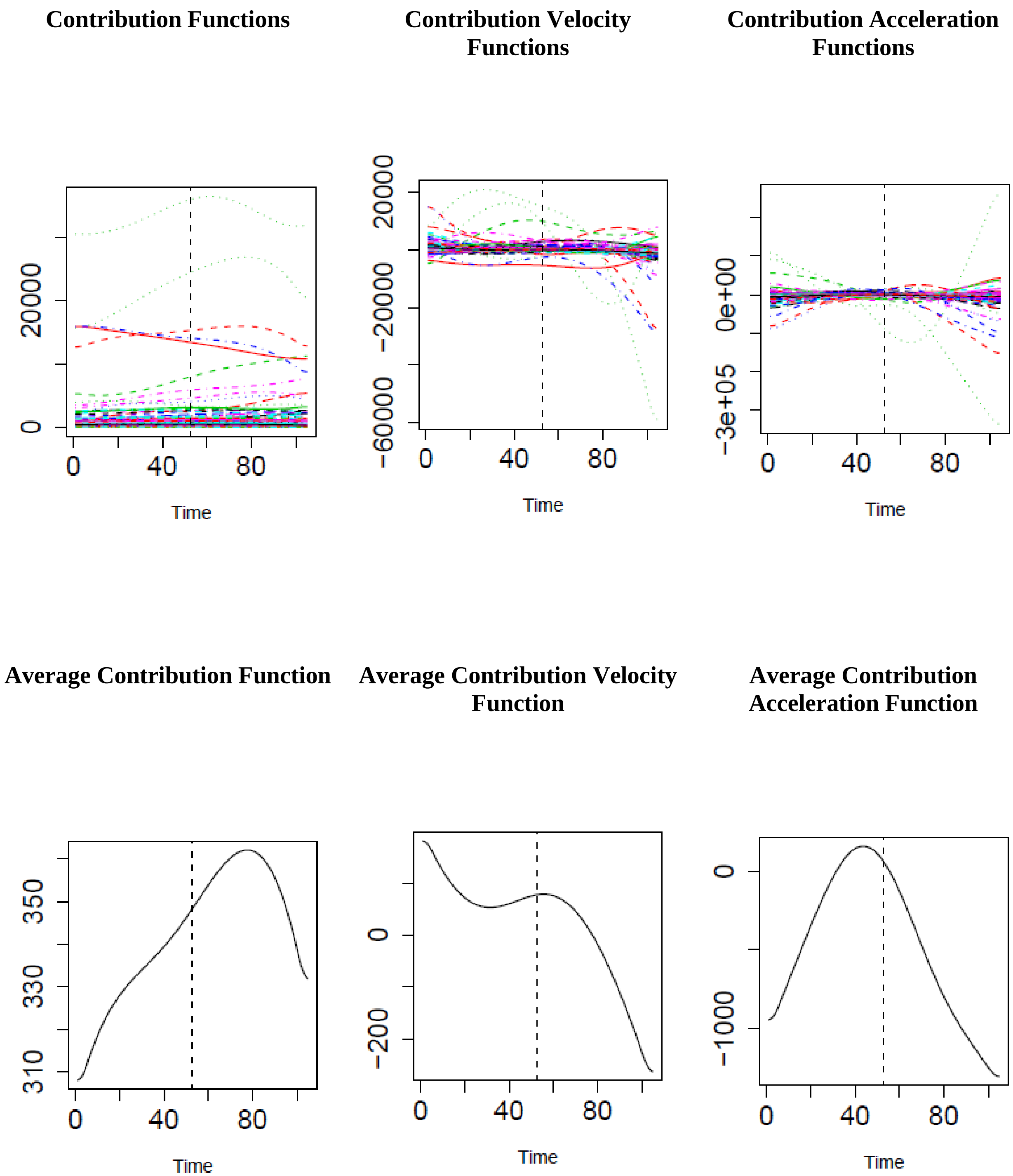


Figure 11 Smoothing Contribution Functions of Duration Focused Projects

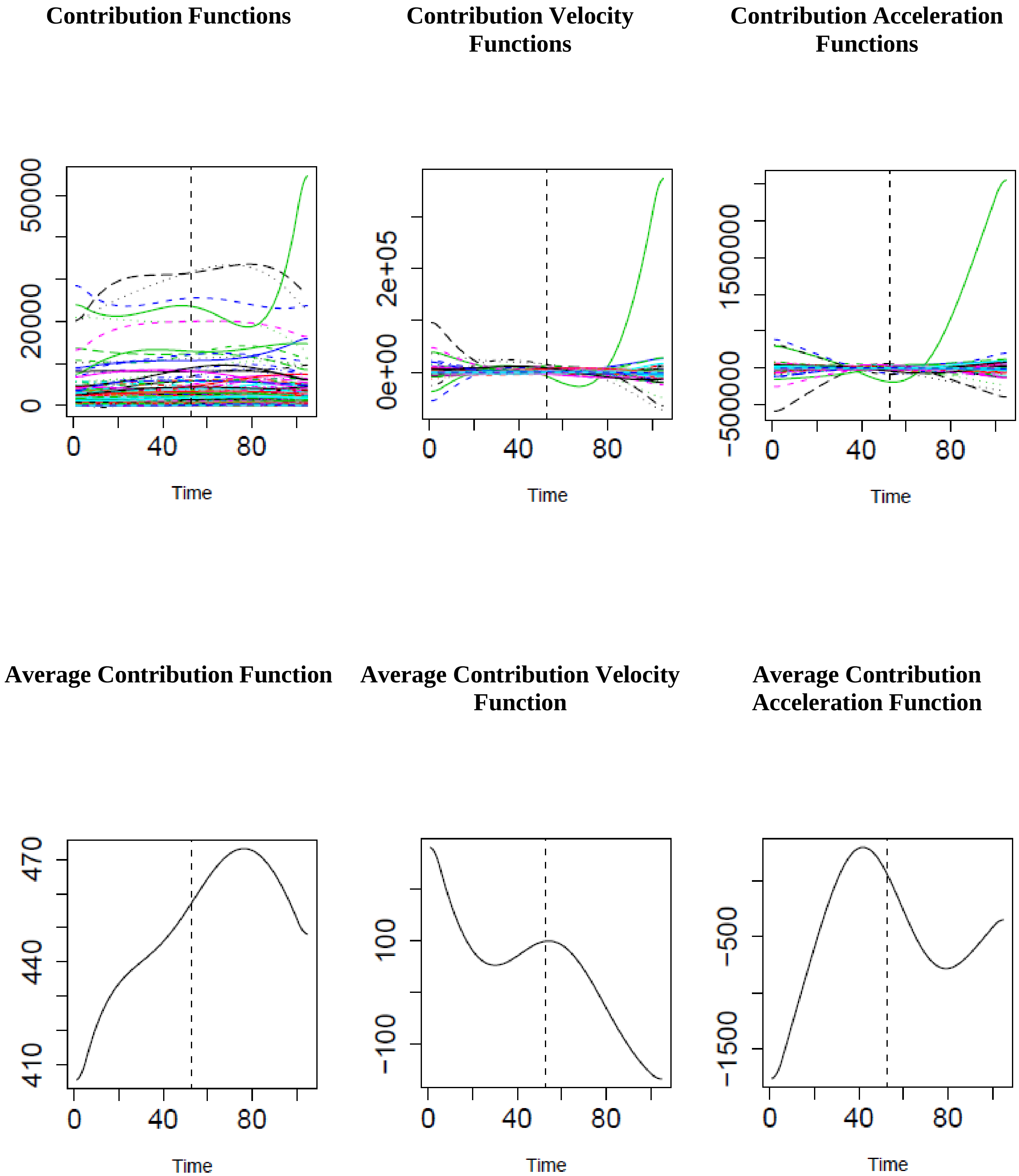


Figure 12 Sample Variables with Significant Impact on the dynamics of Recurring Contributions on Duration focused Projects

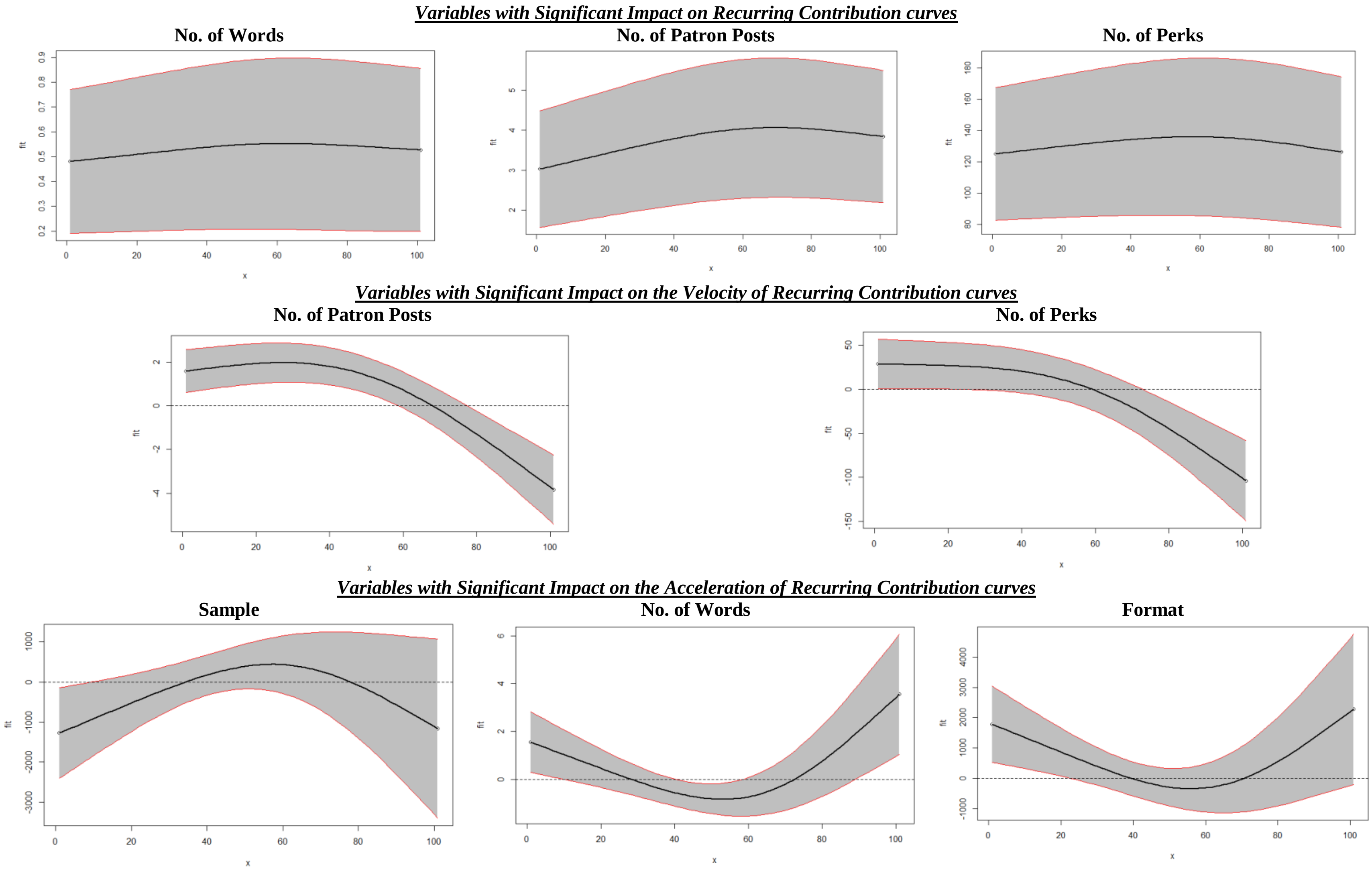
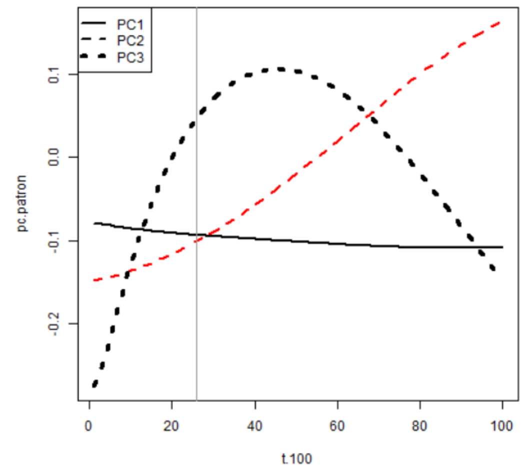
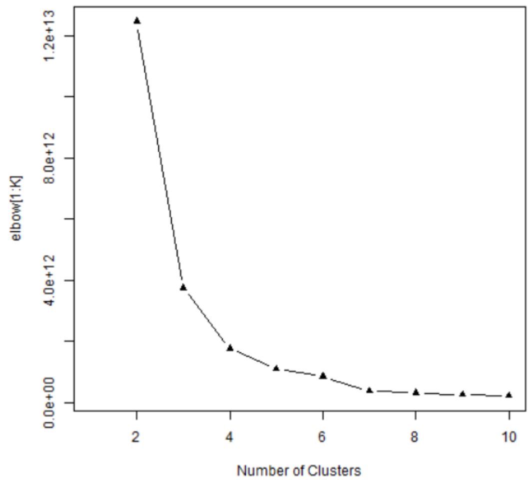


Figure 13 Functional Principal Component Analysis and Identifying Number of Clusters

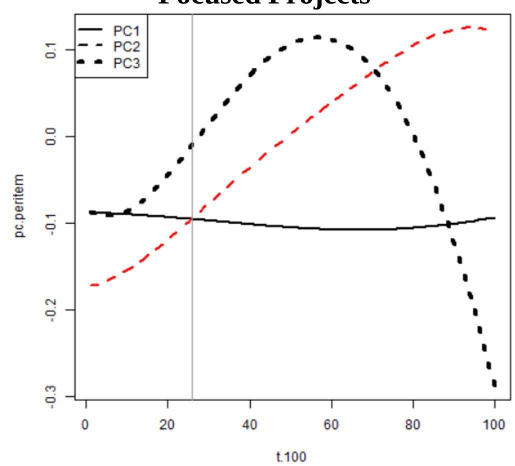
fPCs of Patron Functions



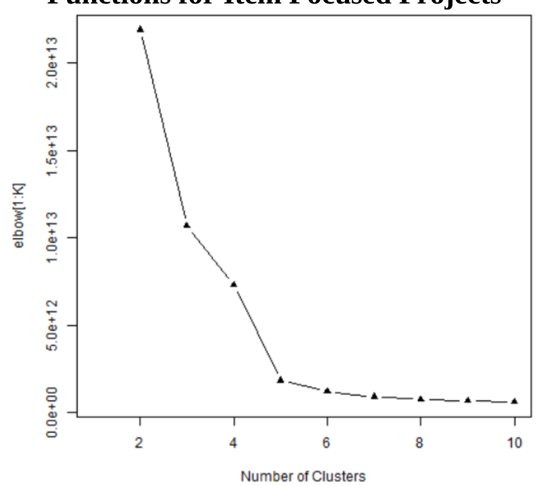
Number of Clusters for Patron Functions



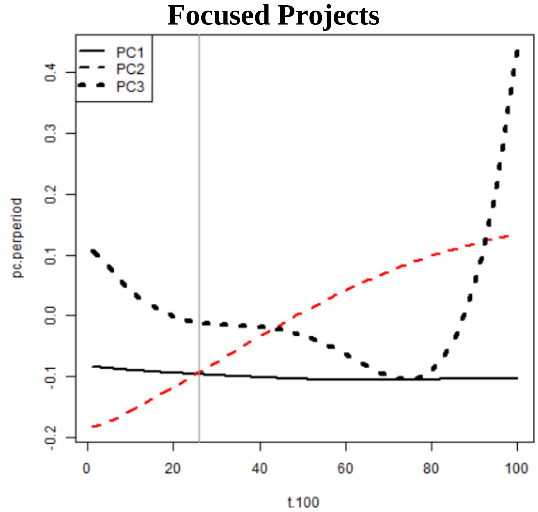
fPCs of Contribution Functions for Item Focused Projects



Number of Clusters for Contribution Functions for Item Focused Projects



fPCs of Contribution Functions for Duration Focused Projects



Number of Clusters for Contribution Functions for Duration Focused Projects

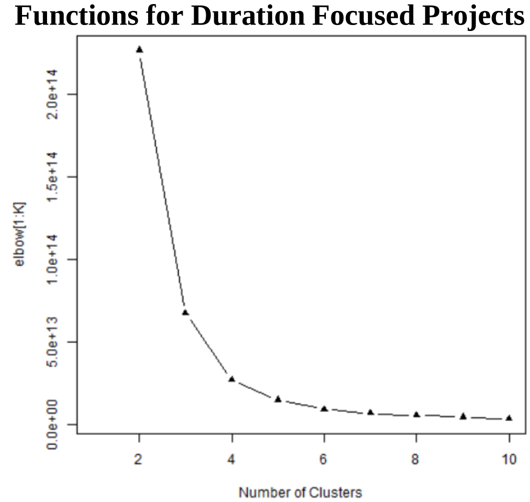


Figure 14 Average Patron Function for Clusters

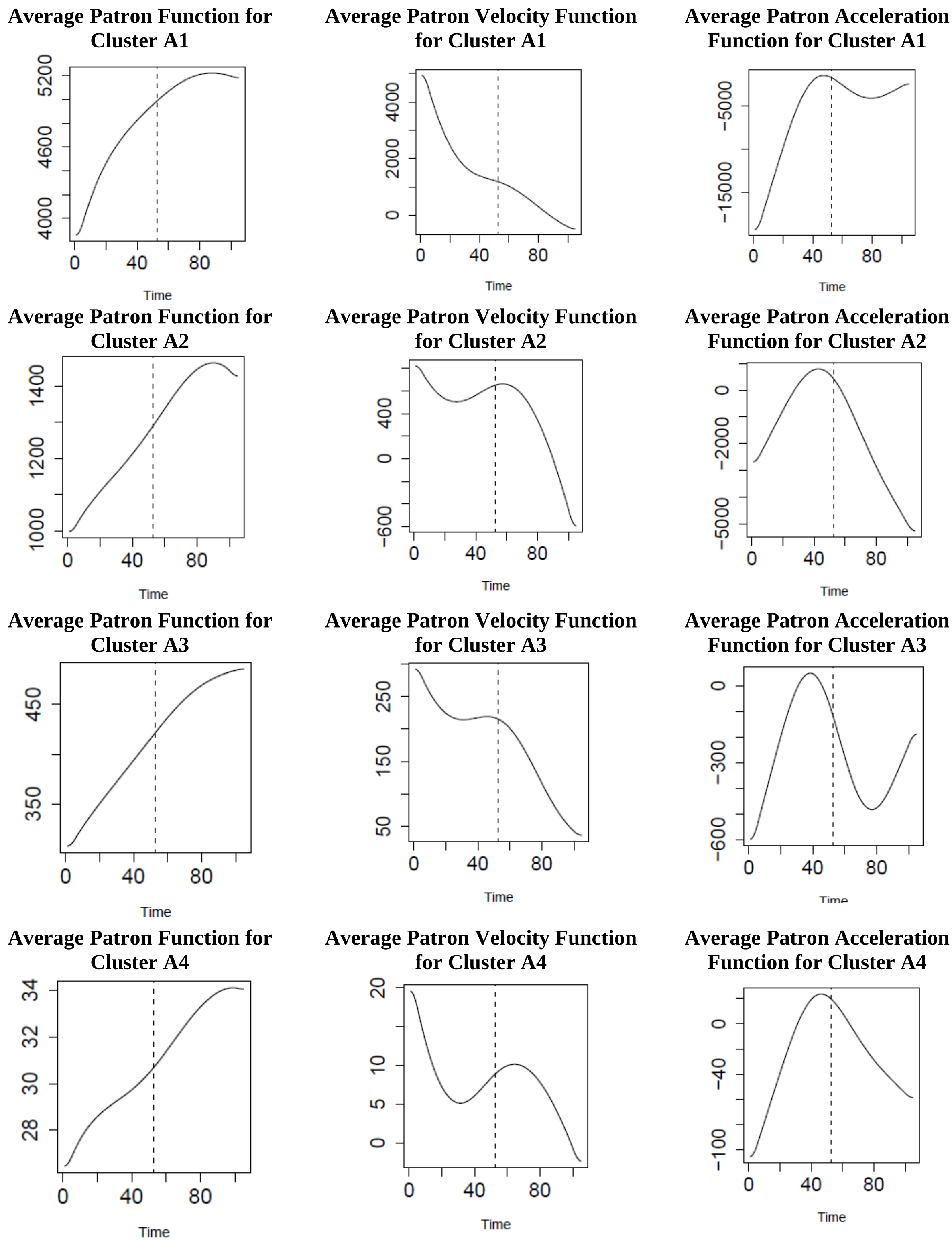


Figure 15 Average Contribution Function for Item based Project Clusters

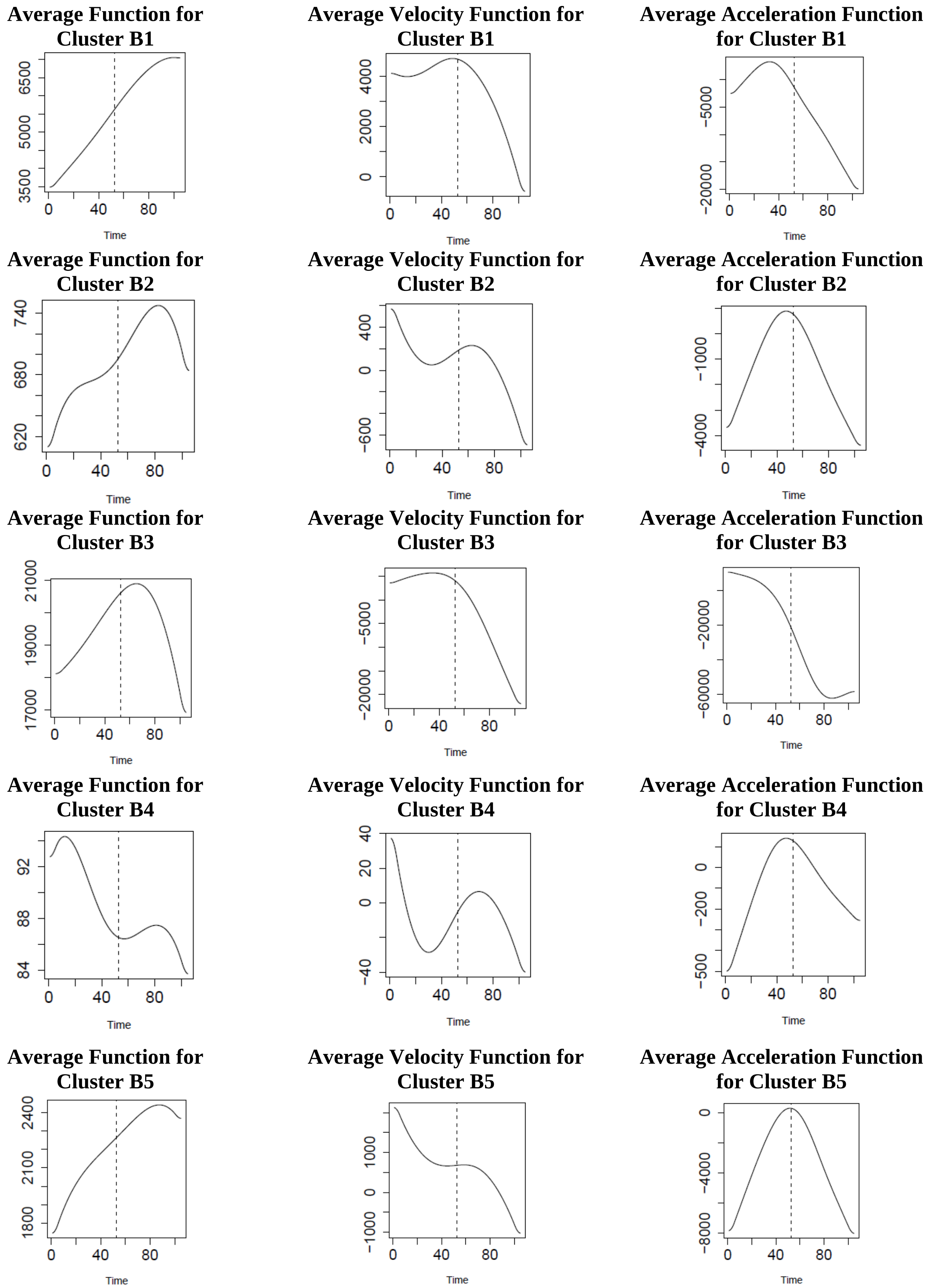


Figure 16 Average Contribution Function for Duration based Project Clusters

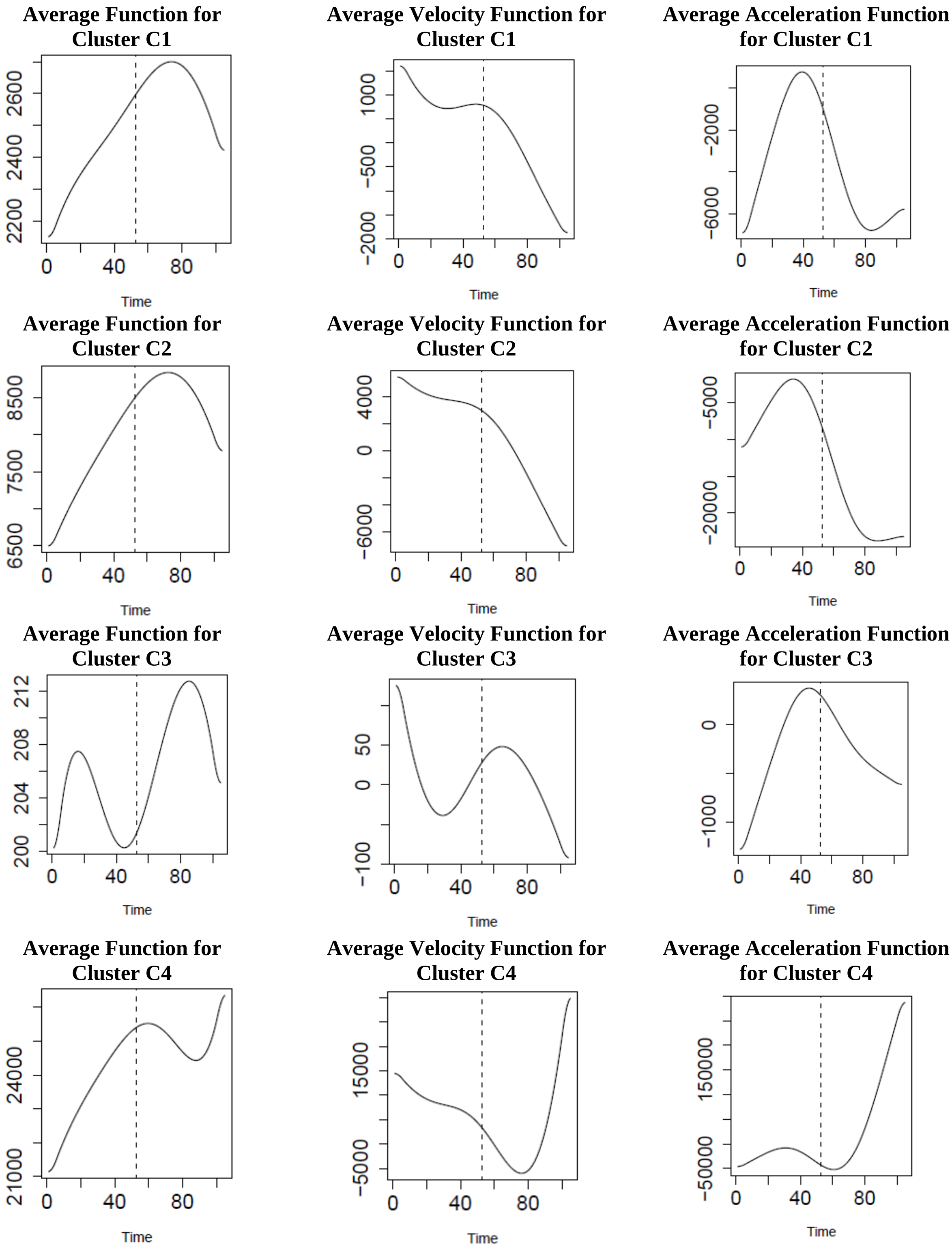


Table 1 Our Contributions

Published Papers	Platform Changes	Individual Backer Effects on other Backers	Weighted Backer Networks	Online Buzz	Identifying Influential Backers
Mollick (2014)	X	X	X	X	X
Lu et al (2015)	X	X	X	✓	X
Agrawal, Catalini and Goldfarb (2015)	X	✓	X	X	X
Burtch, Ghose and Wattal (2015)	✓	✓	X	X	X
Ordanini et al (2015)	X	✓	X	X	X
Kuppuswamy and Bayus (2017)	X	✓	X	X	X
This Current Research	✓	✓	✓	✓	✓

Table 2 Data Sources and Data Items

Classification	Measures	Meaning	Source
Project Outcomes	Status	Project Success or Failure	Kickstarter Page
	% Funded	Percentage of the Project Goal Funded	Kickstarter Page
	Goal Rate	Time taken for project to reach its goal	Kickspy
Backer Variables	Central Backers	No. of backers contributing to the project that are high on centrality measures	Web Crawler
	Backers	No. of backers contributing to the project that are not identified as central backers	Kickstarter Page
Project Characteristics	Duration	Total duration of the project	Kickstarter Page
	Creator Experience	No. of other projects created by the project creator	Kickstarter Page
	Tiers	No. of project reward tiers	Kickstarter Page
	Video	Presence of a video on the project page	Kickstarter Page
	Updates	No. of updates by the creator for the duration of the project	Kickstarter Page
	Goal Amount	The amount the project is seeking to raise	Kickstarter Page
Project Quality	Innovativeness	The novelty of a project from a technological and market standpoint	Ratings of the Project Page
	Feasibility	The likelihood of a project being a success in the market	Ratings of the Project Page
Digital Buzz Variables	News & Review Sites	No. of news & review sites reports for the duration of the project	Web Search of News/Review sites
	Forums	No. of forum threads created for the duration of the project	Web Search of Forum Threads
	Online Media	No. of media site posts created for the duration of the project	Web Search of media sites
	Blogs	No. of blog mentions posted for the duration of the project	Web Search on Blogs

Table 3 Descriptive Statistics

			Correlation Matrix																
Variable	**M**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1.Duration (log)	3.41	.33	1.00																
2.Goal amount (log)	8.86	1.66	.22	1.00															
3. Forums	2.21	2.92	-.03	.14	1.00														
4. Media	.54	1.35	.06	.24	.47	1.00													
5. Blogs	.85	2.08	-.02	.19	.48	.47	1.00												
6. Social	75.64	429.01	-.01	.11	.50	.54	.51	1.00											
7. No. of Central Backers	1.33	2.24	-.10	.09	.39	.09	.26	.05	1.00										
8. No. of Backers	324.40	619.09	-.07	.21	.59	.54	.48	.45	.61	1.00									
9. Tiers	10.43	6.62	.19	.38	.21	.25	.29	.18	.06	.25	1.00								
10. Video	.83	.37	.03	.20	.15	.15	-.03	.07	.16	.13	.23	1.00							
11. Updates	8.18	10.12	.09	.14	.35	.23	.29	.05	.40	.36	.40	.10	1.00						
12. Innovativeness	3.46	2.09	.06	.34	.21	.25	.25	.19	.29	.32	.33	.31	.26	1.00					
13. Feasibility	5.49	2.31	-.07	-.30	.08	-.05	-.02	-.09	.19	.08	-.06	-.01	.05	-.18	1.00				
14. Creator Experience	1.72	5.97	-.17	-.11	.06	-.05	-.01	-.03	.33	.07	-.15	.01	.01	.03	.13	1.00			
15. Status	.50	.50	-.10	-.22	.39	.23	.31	.14	.51	.43	.20	.004	.46	.16	.18	.17	1.00		
16. Percent Funded	234.95	933.64	-.09	-.16	.12	.01	.04	.02	.33	.40	.02	-.02	.23	.13	.09	.07	.24	1.00	
17. Goal Rate	.20	.32	.06	.01	.19	.20	.19	.08	.21	.14	.18	.07	.27	.19	.01	-.03	.62	-.04	1.00

Notes: Multicollinearity is not an issue with all variables having a VIF < 5.

Table 4 Results for the Games Category

	Status			% Funded			Goal Rate		
	Status	**No. of Backers**	**No. of Central Backers**	**% Funded**	**No. of Backers**	**No. of Central Backers**	**Goal Rate**	**No. of Backers**	**No. of Central Backers**
Outcome Variables									
No. of Backers	2.95(.77)***			5.94(.88)***			-.12(.04)***		
No. of Central Backers	.41(.18)**	.27(.02)***		-.15(.43)	.27(.02)***		-.01(.02)	.20(.03)***	
Project Characteristics									
Duration (log)	-.005(.12)			-.07(.53)			.03(.03)		
Creator Experience	-.002(.14)			-.001(.56)			-.05(.03)		
Tiers	.35(.21)			-.04(.63)			-.02(.03)		
Updates	.75(.28)***			1.47(.63)**			-.04(.03)		
Goal Amount (log)	-1.28(.22)***	.06(.4)	-.01(.11)	-2.13(.57)***	.06(.04)	-.01(.11)	.18(.04)***	.11(.07)	.41(.11)***
Project Quality Indicators									
Innovativeness		.02(.04)	.51(.11)***		.02(.04)	.51(.11)***	-.03(.04)	.05(.07)	.34(.09)***
Feasibility		.04(.04)	.65(.13)***		.04(.04)	.65(.13)***	-.01(.04)	.07(.06)	.49(.10)***
Video	-.02(.14)	-.05(.04)	.16(.12)	-.17(.55)	-.05(.04)	.16(.12)	.03(.03)	-.06(.06)	.21(.11)*
Digital Media Buzz Variables									
Forums	-.18(.23)	.14(.05)***	.35(.06)***	-.97(.70)	.14(.05)***	.35(.06)***	-.03(.04)	.15(.08)**	.21(.07)***
Online Media	-.13(.21)	.31(.05)***	-.21(.11)*	-1.73(.71)**	.31(.05)***	-.21(.11)*	.02(.04)	.34(.08)***	-.38(.12)***
Blogs	.53(.32)	.02(.05)	.27(.08)***	-.92(.68)	.02(.05)	.27(.08)***	-.01(.04)	-.02(.07)	.15(.09)*
Social Media	-.02(.60)	.18(.05)***	-.16(.08)**	-.40(.71)	.18(.05)***	-.16(.08)**	.02(.04)	.17(.08)**	-.08(.11)
Log Likelihood	-566.85			-2442.39			-341.83		

*** p<0.01 **p<0.05 *p<0.1

Table 5 Alternative Backer Specifications & their Characteristics

	Status		% Funded		Goal Rate	
	Status	**Backers**	**% Funded**	**Backers**	**Goal Rate**	**Backers**
Using Large Backers (N=10)						
No. of Backers	5.62(1.13)***		5.79(.71)***		-.15(.04)***	
No. of Large Backers	-1.39(.33)***	.04(.07)	-.50(.79)	.04(.07)	.03(.05)	.31(.12)***
Log-Likelihood	-507.51		-2393.15		-232.93	
Using Exclusively Central Backers (N=10)						
No. of Backers	2.88(.76)***		6.03(.88)***		-.11(.04)***	
No. of central backers	.53(.21)**	.28(.03)***	-.22(.44)	.28(.03)***	-.02(.02)	.21(.03)***
Log-Likelihood	-513.89		-2389.68		-315.57	
Using Degree to Identify Central Backers						
No. of Backers	2.95(.77)***		5.94(.88)***		-.12(.04)***	
No. of central backers	.41(.17)**	.27(.02)***	-.15(.43)	.27(.02)***	-.01(.02)	.20(.03)***
Log-Likelihood	-566.86		-2442.39		-341.83	
Using Closeness to Identify Central Backers						
No. of Backers	3.01(.65)***		5.82(.84)***		-.13(.04)***	
No. of central backers	.46(.18)***	.24(.02)***	-.05(.40)	.24(.02)***	-.01(.02)	.17(.03)***
Log-Likelihood	-582.14		-2458.81		-349.55	
Using Betweenness to Identify Central Backers						
No. of Backers	2.99(.79)***		5.66(.81)***		-.13(.04)***	
No. of central backers	.27(.16)*	.29(.03)***	.12(.52)	.29(.03)***	-.01(.02)***	.21(.05)***
Log-Likelihood	-588.19		-2461.62		-335.44	

Table 6 Robustness Checks

	Status		% Funded		Goal Rate	
	Status	**Backers**	**% Funded**	**Backers**	**Goal Rate**	**Backers**
Using a larger pool of central backers (N=20)						
No. of Backers	2.70(.77)***		6.00(.91)***		-.11(.04)**	
No. of Central Backers	.38(.14)***	.17(.01)***	-.11(.26)	.17(.01)***	-.01(.01)	.13(.02)***
Log-Likelihood	*-616.59*		*-2493.80*		*-380.30*	
Using a larger pool of central backers (N=50)						
No. of Backers	2.79(.79)***		7.28(1.05)***		-.10(.05)*	
No. of Central Backers	.17(.08)**	.12(.01)***	-.33(.17)*	.12(.01)***	-.01(.01)	.10(.01)***
Log-Likelihood	*-670.12*		*-2542.81*		*-408.38*	
Using a larger pool of central backers (N=100)						
No. of Backers	3.10(.82)***		7.19(1.12)***		-.09(.06)*	
No. of Central Backers	.05(.05)	.09(.01)***	-.22(.13)	.09(.01)***	-.01(.01)	.08(.01)***
Log-Likelihood	*-773.08*		*-2644.09*		*-449.53*	
Results from the Design Category						
No. of Backers	3.63(.78)***		.92(.57)		-.11(.03)***	
No. of Central Backers	-.14(.16)	.40(.05)***	-.09(.50)	.40(.05)***	-.03(.03)	.39(.06)***
Log-Likelihood	*-686.11*		*-1500.67*		*-351.37*	
Results from the Technology Category						
No. of Backers	3.48(.71)***		1.66(.22)***		-.08(.04)*	
No. of Central Backers	-.20(.14)	.21(.04)***	-.25(.17)	.21(.04)***	-.08(.02)***	.15(.06)**
Log-Likelihood	*-702.63*		*-1281.58*		*-285.82*	

*** p<0.01 **p<0.05 *p<0.1

Table 7 Dealing with Endogeneity through Copula

	Original Equation	**Copula Model**
No. of Central Backers	307.46(28.79)***	347.36(73.88)***
Duration (log)		
Creator Experience		
Tiers		
Updates		
Goal Amount (log)	38.55(27.05)	27.67(21.01)
Innovativeness	11.75(28.39)	
Feasibility	23.22(26.26)	
Video	-29.14(26.06)	
Forums	88.42(32.10)***	88.12(30.86)***
Online Media	193.41(31.08)***	191.31(50.58)***
Blogs	10.63(31.35)	32.76(29.08)
Social Media	111.73(32.22)***	99.21(173.29)
Copula CF		-47.31(31.25)
Adj R-squared	0.64	0.65

Table 8 Descriptive Statistics for Independent Variables

Descriptive Statistics				
Variables	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Project Type				
Crowdfunding Type	.26	.44	0	1
Explicit Content	.25	.43	0	1
Nature of Incentives				
No. of Perks	4.07	2.60	0	34
No. of Free Content	98.38	191.11	0	2318
No. of Exclusive Content	100.96	195.42	0	3747
% of Exclusive Content	.48	.35	0	1
Project Presentation Characteristics				
Video	.37	.48	0	1
No. of Words	271.29	278.16	0	8612
Format	.18	.39	0	1
No. of Goals	2.78	2.57	0	21
Sample	.71	.45	0	1
No. of Platforms	2.33	1.41	0	12
Project Category				
Cat Writing	.08	.27	0	1
Cat Video	.25	.43	0	1
Cat Games	.08	.26	0	1
Cat Podcast	.08	.27	0	1
Cat Music	.07	.25	0	1
Cat Comics	.19	.39	0	1
Cat Photo	.01	.11	0	1
Cat Animation	.03	.18	0	1

Table 9 Correlation of Independent Variables

	Correlation Matrix																			
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1. Crowdfunding Type	1.00																			
2.Video	.08	1.00																		
3.Sample	-.03	.40	1.00																	
4.No. of Words	-.01	.05	.15	1.00																
5.Format	-.04	-.01	.10	.20	1.00															
6.No. of Free Content	-.09	.19	.10	.04	.03	1.00														
7.No. of Exclusive Content	-.16	-.04	.07	.05	.12	.10	1.00													
8.% of Exclusive Content	.13	.23	.04	-.02	-.06	.39	-.34	1.00												
9.No. of Goals	-.06	.03	.12	.14	.11	.04	.11	-.06	1.00											
10.No. of Platforms	-.08	.19	.28	.08	-.02	.12	-.001	.10	.09	1.00										
11.No. of Perks	-.07	.12	.14	.13	.06	.05	.15	-.04	.34	.10	1.00									
12.Explicit Content	-.10	-.23	-.03	-.04	.04	-.10	.19	-.26	.03	-.10	.01	1.00								
13. Cat Writing	.04	-.11	-.09	.06	-.04	-.05	-.08	.01	-.03	-.07	-.02	-04	1.00							
14. Cat Videos	-.02	.40	.08	-.01	-.08	.28	-.12	.27	-.02	.11	.00	-.24	-.17	1.00						
15. Cat Games	-.02	-.06	.02	.15	.05	-.06	-.06	-.02	.02	-.07	-.06	.05	-.08	-.17	1.00					
16. Cat Podcasts	.08	-.01	-.09	-.05	-.06	-.04	-.06	.05	.05	.03	.01	-.11	-.08	-.17	-.08	1.00				
17. Cat Music	.19	.21	.06	.01	-.01	-.05	-.06	.08	-.03	.07	.10	-.14	-.08	-.16	-.08	-.08	1.00			
18. Cat Comics	-.10	-.24	.04	-.04	.07	-.07	.22	-.24	.04	-.06	.01	.13	-.14	-.28	-.14	-.14	-.13	1.00		
19. Cat Photography	-.02	.01	.02	.03	.03	-.01	.03	-.03	.04	-.01	.08	.03	-.03	-.06	-.03	-03	-.03	-.05	1.00	
20: Cat Animation	.04	.04	.04	-.03	.02	-.03	.01	-.03	.02	-.04	-.01	.10	-.05	-.11	-.05	-.05	-.05	-.09	-.02	1.00

Notes: Multicollinearity is not an issue with all variables having a VIF < 5.

Table 10 Summary of Results for the Impact of Project Characteristics on the Number of Patrons

Variables	Patron Functions (y)			Patron Functions' Velocity (v)			Patron Functions' Acceleration (a)		
	Effect	**Valence of Impact**	**Significant Period**	**Effect**	**Valence of Impact**	**Significant Period**	**Effect**	**Valence of Impact**	**Significant Period**
Project Type									
Crowdfunding Type									
Explicit Content									
Nature of Incentives									
No. of Perks	✓	+	0-300	✓	+	0-120	✓	-	0-150
No. of Free Content	✓	+	0-300	✓	+	0-150	✓	-	0-185
No. of Exclusive Content	✓	+	0-300	✓	+	0-240	✓	-	150-195
% of Exclusive Content	✓	+	0-300	✓	+	0-210			
Project Presentation Characteristics									
Video									
No. of Words	✓	+	0-300	✓	+	80-190	✓	+	270-300
Format									
No. of Goals	✓	-	0-165				✓	-	255-300
Sample									
No. of Platforms									
Project Category									
Cat Writing									
Cat Videos	✓	+	0-300	✓	+	75-210			
Cat Games	✓	+	0-300						
Cat Podcasts	✓	+	0-300	✓	+	30-300			
Cat Music									
Cat Comics									
Cat Photo									
Cat Animation									

Table 11 Summary of Results for the Impact of Project Characteristics on the Recurring Contributions for Item Focused Projects

Variables	Contribution Functions (y)			Contribution Functions' Velocity (v)			Contribution Functions' Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Explicit Content									
Nature of Incentives									
No. of Perks	✓	+	0-300	✓	+ | -	0-60 | 195-300	✓	-	150-300
No. of Free Content									
No. of Exclusive Content	✓	+	0-300	✓	+	0-240	✓	+ | -	0-45 | 120-300
% of Exclusive Content									
Project Presentation Characteristics									
Video									
No. of Words	✓	+	0-300				✓	+ | - |+	0-30 | 120-165 | 255-300
Format							✓	+	0-75
No. of Goals									
Sample							✓	-	0-30
No. of Platforms									
Project Category									
Cat Writing									
Cat Videos	✓	+	30-300	✓	+	90-135			
Cat Games									
Cat Podcasts									
Cat Music									
Cat Comics									
Cat Photo									
Cat Animation									

Table 12 **Summary of Results for the Impact of Project Characteristics on the Recurring Contributions for Period Focused Projects**

Variables	Contribution Functions (y)			Contribution Functions' Velocity (v)			Contribution Functions' Acceleration (a)		
	Effect	**Valence of Impact**	**Significant Period**	**Effect**	**Valence of Impact**	**Significant Period**	**Effect**	**Valence of Impact**	**Significant Period**
Project Type									
Explicit Content				✓	+	0-45	✓	-	0-75
Nature of Incentives									
No. of Perks	✓	+	0-300	✓	+	0-60 & 285-300	✓	- | +	60-150 | 225-300
No. of Free Content	✓	+	0-300	✓	+	0-120	✓	-	0-150
No. of Exclusive Content	✓	+	0-300	✓	+	75-180			
% of Exclusive Content	✓	+	0-300	✓	+	0-75			
Project Presentation Characteristics									
Video									
No. of Words									
Format									
No. of Goals				✓	+	120-195	✓	+ | -	105-150 | 240-300
Sample									
No. of Platforms									
Project Category									
Cat Writing									
Cat Videos	✓	+	0-300						
Cat Games	✓	+	0-300						
Cat Podcasts	✓	+	0-300	✓	+	75-180			
Cat Music									
Cat Comics									
Cat Photo									
Cat Animation				✓	+	120-150			

Table 13 Overview of Identified Clusters

Function	Clusters	Cluster Size	Content Category	Avg. Range of Functions	Cluster Description
Patron Function	A1	9	88.9% Video	3000 – 5200	Established Projects
	A2	28	32% Video, 18% Podcast, 14% Games, 14% Comics	1000-1500	Audio heavy Projects
	A3	154	30% Video, 21% Comics, 16% Games, 12% Podcast	250-500	Visual heavy Projects
	A4	3038	25% Video, 20% Art, 19% Comics	0-34	Generic Projects
Item Focused Recurring Funding	B1	4	50% Video, 25% Games, 25% Art	3500-6700	Hedonic Projects
	B2	89	34% Video, 27% Music	600-740	Audio heavy Projects
	B3	5	40% Video, 40% Music, 20% Art	17,000-21,000	Established Projects
	B4	725	22% Video, 15% Art, 14% Music, 13% Comics, 11% Writing	84-94	Generic Projects
	B5	19	42% Video, 11% Music, 11% Podcast, 11% Writing	1700-2500	Video heavy Projects
Duration Focused Recurring Funding	C1	119	32% Video, 16% Game, 16% Comics, 13% Podcast	2000-2800	Progression based Projects
	C2	21	29% Video, 24% Game, 19% Podcast	6500-9000	Content Requisite Projects
	C3	2241	25% Video, 22% Art, 22% Comics	200-212	Generic Projects
	C4	6	83% Video, 17% Art	21,000-26,000	Established Projects

*Distribution of Project Category – 25% Video, 20% Art, 19% Comics, 8% Writing, 8% Games, 8% Podcast, 7% Music, 3% Animation, 1% Photography 2% Misc

Table 14 Summary of Results for the Impact of Project Characteristics on Cluster A2

Variables	Patron Functions (y)			Patron Functions’ Velocity (v)			Patron Functions’ Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Crowdfunding Type									
Explicit Content	✓	-	0-300						
Nature of Incentives									
No. of Perks				✓	-	240-300			
No. of Free Content	✓	-	0-30	✓	+	255-300			
No. of Exclusive Content	✓	+	255-300	✓	-	60-300			
% of Exclusive Content				✓	-	270-300			
Project Presentation Characteristics									
Video									
No. of Words									
Format	✓	+	0-30	✓	-	0-45			
No. of Goals	✓	+	135-300						
Sample				✓	-	0-15			
No. of Platforms	✓	-	165-300	✓	-	75-300	✓	- | +	45-135 | 240-300
Project Category									
Cat Writing									
Cat Videos				✓	-	0-60			
Cat Games	✓	+	0-15	✓	-	0-210	✓	+	255-300
Cat Podcasts				✓	-	0-60			
Cat Music				✓	-	0-60			
Cat Comics				✓	-	0-60			
Cat Photo	✓	+	0-90	✓	-	0-135			
Cat Animation									

Table 15 Summary of Results for the Impact of Project Characteristics on Cluster A3

Variables	Patron Functions (y)			Patron Functions' Velocity (v)			Patron Functions' Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Crowdfunding Type Explicit Content				✓	+	255-300	✓	+	225-300
Nature of Incentives									
No. of Perks No. of Free Content No. of Exclusive Content % of Exclusive Content	✓	+	0-135	✓	-	180-225			
Project Presentation Characteristics									
Video No. of Words Format No. of Goals Sample No. of Platforms				✓	+	285-300			
Project Category									
Cat Writing Cat Videos Cat Games Cat Podcasts Cat Music Cat Comics Cat Photo Cat Animation	✓	+	0-240						

Table 16 Summary of Results for the Impact of Project Characteristics on Cluster A4

Variables	Patron Functions (y)			Patron Functions' Velocity (v)			Patron Functions' Acceleration (a)		
	Effect	**Valence of Impact**	**Significant Period**	**Effect**	**Valence of Impact**	**Significant Period**	**Effect**	**Valence of Impact**	**Significant Period**
Project Type									
Crowdfunding Type									
Explicit Content	✓	+	60-300	✓	+	0-225	✓	-	0-45
Nature of Incentives									
No. of Perks	✓	+	0-300	✓	+	255-300	✓	+	0-270
No. of Free Content	✓	+	0-300	✓	+	0-45			
No. of Exclusive Content	✓	+	0-300	✓	+	0-265	✓	-	225-300
% of Exclusive Content	✓	+	0-300	✓	+	0-30	✓	-	0-45
Project Presentation Characteristics									
Video									
No. of Words	✓	+	0-300	✓	+	0-195			
Format									
No. of Goals	✓	-	0-75	✓	+	90-225			
Sample	✓	+	0-300						
No. of Platforms	✓	-	0-300						
Project Category									
Cat Writing	✓	+	0-300						
Cat Videos	✓	+	0-300	✓	+	105-300			
Cat Games	✓	+	0-300	✓	+	0-120			
Cat Podcasts	✓	+	0-300	✓	+	0-195			
Cat Music	✓	+	0-300	✓	+	0-15	✓	-	0-15 | 285-300
Cat Comics	✓	+	0-300						
Cat Photo									
Cat Animation	✓	+	0-300						

Table 17 Summary of Results for the Impact of Project Characteristics on Cluster B2

Variables	Contribution Functions (y)			Contribution Functions' Velocity (v)			Contribution Functions' Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Explicit Content									
Nature of Incentives									
No. of Perks									
No. of Free Content									
No. of Exclusive Content									
% of Exclusive Content									
Project Presentation Characteristics									
Video									
No. of Words									
Format									
No. of Goals				✓	+	0-45 | 270-300	✓	-	0-105
Sample									
No. of Platforms									
Project Category									
Cat Writing				✓	+	285-300			
Cat Videos				✓	+	285-300			
Cat Games				✓	-	120-195			
Cat Podcasts									
Cat Music							✓	+	240-300
Cat Comics	✓	+	0-120						
Cat Photo									
Cat Animation	✓	+	0-120	✓	-	120-195			

Table 18 Summary of Results for the Impact of Project Characteristics on Cluster B4

Variables	Contribution Functions (y)			Contribution Functions' Velocity (v)			Contribution Functions' Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Explicit Content							✓	-	0-30
Nature of Incentives									
No. of Perks	✓	+	0-300	✓	-	150-210			
No. of Free Content									
No. of Exclusive Content	✓	+	0-300						
% of Exclusive Content	✓	+	0-105						
Project Presentation Characteristics									
Video									
No. of Words	✓	+	0-300						
Format									
No. of Goals				✓	+	120-210	✓	+	0-75
Sample	✓	+	15-300						
No. of Platforms	✓	+	0-300	✓	+	0-45			
Project Category									
Cat Writing									
Cat Videos	✓	+	0-30 | 240-300	✓	+	270-300			
Cat Games									
Cat Podcasts				✓	+	240-300	✓	-	0-30
Cat Music							✓	-	0-30
Cat Comics							✓	-	0-45
Cat Photo									
Cat Animation	✓	+	0-300						

Table 19 Summary of Results for the Impact of Project Characteristics on Cluster C2

Variables	Contribution Functions (y)			Contribution Functions' Velocity (v)			Contribution Functions' Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Explicit Content	✓	-	90-270						
Nature of Incentives									
No. of Perks									
No. of Free Content									
No. of Exclusive Content									
% of Exclusive Content									
Project Presentation Characteristics									
Video				✓	+	285-300			
No. of Words	✓	+	60-300						
Format									
No. of Goals	✓	+	120-300						
Sample	✓	-	135-300						
No. of Platforms									
Project Category									
Cat Writing	✓	-	120-300						
Cat Videos									
Cat Games									
Cat Podcasts	✓	-	135-270						
Cat Music									
Cat Comics	✓	-	150-300						
Cat Photo									
Cat Animation									

Table 20 Summary of Results for the Impact of Project Characteristics on Cluster C3

Variables	Contribution Functions (y)			Contribution Functions' Velocity (v)			Contribution Functions' Acceleration (a)		
	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period	Effect	Valence of Impact	Significant Period
Project Type									
Explicit Content	✓	+	0-300	✓	+	0-30	✓	-	0-45 | 285-300
Nature of Incentives									
No. of Perks	✓	+	0-300						
No. of Free Content	✓	+	0-300						
No. of Exclusive Content	✓	+	0-300	✓	+	0-225	✓	-	210-300
% of Exclusive Content	✓	+	0-300	✓	+	0-15 | 270-300	✓	-	0-75
Project Presentation Characteristics									
Video									
No. of Words	✓	+	0-300						
Format									
No. of Goals									
Sample									
No. of Platforms							✓	+	0-45
Project Category									
Cat Writing									
Cat Videos	✓	+	0-300						
Cat Games	✓	+	0-300						
Cat Podcasts	✓	+	0-300						
Cat Music	✓	+	0-300				✓	-	290-300
Cat Comics	✓	+	120-300						
Cat Photo				✓	+	90-270			
Cat Animation	✓	+	0-300						