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Essays on Crowdfunding: Exploring the Funding and Post-funding Phases and Outcomes

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Essays on Crowdfunding: Exploring the Funding and Post-funding Phases and Outcomes

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Business Administration
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ABSTRACT

In the recent years, crowdfunding (a phenomenon where individuals collectively contribute money to back different goals and projects through the internet) has been gaining a lot of attention especially for its socio-economic impact. This dissertation explores this phenomenon in three distinct but related essays. The first essay explores the nature and dynamics of backers’ contributions and uses the insights generated to develop a forecasting model that can predict crowdfunding campaign outcomes. The second essay investigates how creators’ crowdfunding campaign design decisions impact their funding and post-funding outcomes. Interestingly, the essay highlights that certain crowdfunding campaign design decisions have differential effects on both funding and post-funding phases and this has implications for creators, backers, and crowdfunding platform owners. Finally, the third essay investigates whether creators’ post-funding relations-building efforts with backers matter and how such relations-building efforts might impact the performance of their subsequent crowdfunding campaign. In general, this dissertation not only increases our understanding of the crowdfunding phenomenon across the funding and post-funding phases, it also provides insights and tools that can help stakeholders maximize the benefits accruable to them when they engage in crowdfunding.
CHAPTER 1: INTRODUCTION AND BACKGROUND

In the recent times, the internet has not only served as an enabler for a phenomenon whereby individuals from around the world come together to contribute financial resources to fund causes, ideas, projects, products, or businesses; but it has also spurred its diffusion and growth propelling it into a mainstay for financing. Though not an entirely new phenomenon, in the sense of individuals coming together to contribute or pool financial resources, the internet has enabled the phenomenon termed “crowdfunding” to flourish. In a recent Fortune magazine article (Noyes 2014), crowdfunding has been referred to as the democratization of fundraising.

With the sustained growth and diversification\(^1\) of crowdfunding, its socio-economic potential is becoming more and more evident. From helping individuals raise money to cover medical and funeral expenses to providing early stage capital to innovators which help bring creative ideas to live, crowdfunding continues to prove value. Outstanding examples of crowdfunding include Eric Migicovsky’s e-Paper Watch which raised about $10.3 million on a $100,000 goal from about 70 thousand individuals on its first campaign on Kickstarter, and subsequently went on to raise over $20.3 million on a $500,000 goal from about 80 thousand individuals for its Pebble Smartwatch on a second run. In addition, Oculus Rift, a virtual-reality gaming hardware company funded through the crowdfunding mechanism was subsequently acquired by Facebook for about $2 billion. Industry reports on crowdfunding show that in 2014, the crowdfunding market grew by 167 percent (Massolution 2015a) and is not only expected to reach $90 to $96 billion by

---

\(^1\) As of 2015, there are over 1250 crowdfunding platforms specializing in different types of crowdfunding and targeted at specific types of funders and fundraisers.
Owing to its explosive growth and game-changing capabilities, crowdfunding has also been gaining a lot of attention among practitioners, academics and policy makers (Burtch et al. 2013; Gabison 2015; Massolution 2013; Mollick 2014). As it transitions into the mainstay of new venture and capital financing, there is a need to explore the phenomenon and to shed more light on it. From exploring its workings and dynamics and providing decision support tools that can help stakeholders maximize the benefits accruable from using crowdfunding platforms, to understanding and defining the roles of stakeholders, to quantifying some of its economic impact to society. Insights from these can help build better platforms to support the phenomenon, help come up with policies which can be used to better regulate crowdfunding markets created, and also inform crowdfunding market participants (fundraisers and funders).

In this work, we begin to tackle some of the issues highlighted above. In the first essay (Chapter 2), we try to understand the differences in contribution patterns in successful and unsuccessful crowdfunding campaigns based on the dynamic properties. We then use insights generated from our understanding of the properties of campaigns to propose and develop a forecasting model that can support crowdfunding market participants in their decision making process. We find that there are significant differences in the patterns of contributions between successful and unsuccessful crowdfunding campaigns. For instance, we observe that successful crowdfunding campaigns tend to start with a bang, and have most of the contributions come in at the early phase of the fundraising cycle. This suggests that for campaign creators, they may have to do some offline marketing or advertising of their campaigns to close associates and relatives before launching if they intend to meet their funding goal.

In the second essay (Chapter 3), we investigate how strategic crowdfunding campaign design decisions affect both funding and post-funding outcomes. In this case we focus on the differential impacts of these decisions on both fundraising and product delivery. While creators may be focused on getting their venture fully funded during the fundraising phase by strategically designing crowdfunding campaigns with 2025, but also should have outgrown the global venture capital market to a tune of 1.8 times by the same time (Noyes 2014).
higher chances of funding success, we show that some these strategic fundraising campaign design
decisions can negatively impact outcomes in the post-funding phase. In the third essay (Chapter 4), we
investigate how creators (project owners) relations-building efforts from prior crowdfunding campaigns
affect the performance of their subsequent crowdfunding campaign. It has been reported that crowdfunding
campaigns experience significant failure rates (Kuppuswamy and Bayus 2017). Moreover, (Skinevski}y et
al. 2017) suggests that creators may need to build social capital on crowdfunding platforms which they can
subsequently tap into in future crowdfunding campaigns. However, they do not outline the mechanisms
through which creators build social capital. We identify relations-building efforts as a mechanisms through
which social capital can be built, and which in turn can lead to success in subsequent crowdfunding
campaigns.

Although the three essays in this dissertation explore the crowdfunding phenomena and how it
relates to all stakeholders, it mostly takes the perspective of the creator (project owner or crowdfunder).
CHAPTER 2: FORECASTING FUNDING OUTCOMES IN CROWDFUNDING

Abstract

The crowdfunding mechanism has proven to be a practical alternative for raising funds especially with the widespread use of the Internet. One limitation of current crowdfunding platforms is that it is hard for creators and backers to anticipate the success of crowdfunding campaigns. In this paper, we tackle this limitation. We take a two-pronged approach to building our forecasting model. First, we explore the nature and heterogeneity of contribution dynamics in crowdfunding campaigns and compare them across two natural groups (successful and unsuccessful campaigns). Using insights generated from our exploratory analysis and drawing upon general laws of motion for stochastic processes, we introduce a new dynamic model for predicting crowdfunding outcomes. Our model incorporates the history and dynamics of the focal crowdfunding campaign as well as that of other campaigns to predict outcomes. We compare our model to other parametric and semi-parametric benchmark models showing substantial improvements.
Introduction

In the recent years, crowdfunding (individuals collectively contributing money to back different goals and projects through the internet) has proven to be a viable alternative for raising funds (Kuppuswamy and Bayus 2014). Businesses, entrepreneurs, and individuals have used this alternative fundraising mechanism to raise finances to support their businesses, creative projects, or personal goals. Evidence of very successful fundraising campaigns (e.g. Pebble smart watches on Kickstarter.com) and unsuccessful fundraising campaigns (e.g. Meatballs LLC in Ahlers et al., (2015)) exist. Different factors have been attributed to driving fundraising campaign outcomes - goal size, fundraising duration, creator’s network size, and signals of quality (Mollick 2014). Despite the growing importance and popularity of the crowdfunding mechanism, most platforms still do not provide analytics tools for creators and backers beyond simple aggregates. For instance, a major crowdfunding platform provider like Kickstarter has not provided analytics tools to track projects (Wired.com 2012). Reports from Huffington Post (2013) and Wired.com (2012) show that creators and backers are interested in tools that can help them forecast fundraising outcomes and make more informed decisions.

To the best of our knowledge, there are no known or proposed approaches for forecasting crowdfunding outcomes using granular day-by-data data, making the approach described here a first attempt.

In this paper, we: (1) explore the dynamics of contributions during crowdfunding campaigns drawing upon the laws of motion, (2) compare the nature and heterogeneity of contribution dynamics in successful and unsuccessful crowdfunding campaigns, (3) propose a novel method of forecasting crowdfunding outcomes based on the contribution dynamics of the focal fundraising campaign derived from our exploratory analyses, and compare our method
against other parametric and semi-parametric forecasting methods. Our study provides several insights on the crowdfunding phenomenon and offers practical advantages while contributing to the growing literature on crowdfunding and forecasting. Theoretically, we present insights into the nature and differences in backers’ contribution patterns in successful and unsuccessful crowdfunding campaigns. Practically, our approach offers advantages to several stakeholders in crowdfunding campaigns. First, it benefits crowdfunding platforms by presenting a forecasting model that can be used to provide up-to-date analytics to users. Second, it provides creators a method for forecasting fundraising outcomes before the end of their campaigns. Creators will be able to (1) know in time if they have to shore up promotion efforts by aggressively seeking donors outside their networks or persuasively pitching to and closing on investors to meet their funding goals. (2) Knowledge of probable outcomes can help creators in planning. For instance, creators who need to deliver rewards in a short time to backers can use their forecasts to plan. (3) Backers looking for a better way to cherry-pick winners or make better contribution decisions can benefit from our method.

The rest of this paper is organized as follows. In the next section, we present a short introduction to crowdfunding and its mechanisms, followed by our study context and data. Next, we present our methodology and then round up with the discussion and conclusion.

**Crowdfunding**

Crowdfunding refers to a fundraising campaign where a creator issues an open call through the internet to the public to raise funds in the form of donations or in exchange for some reward, equity and voting rights to support initiatives for specific purposes (Belleflamme et al. 2014). It has proven to be a practical way for fledgling entrepreneurs seeking early stage funding (Kuppuswamy and Bayus 2014) and has been generating a lot of interest in academic circles.
In the past few years, the number of platforms supporting crowdfunding has grown. Crowdfunding platforms like Kickstarter, GoFundMe, and IndieGoGo now handle millions of dollars’ worth of fundraising transactions. It is estimated that over a million projects were successfully funded by crowdfunding platforms in 2012 raising about $2.7 billion (Massolution 2013). Recently, crowdfunding has drawn the attention of policymakers and regulators as seen with the Jumpstart Our Business Startups Act (JOBS Act) signed into law in the United States. Further, with local governments and non-profits turning to crowdfunding to finance civic projects and programs designed for the common good (Lindsay 2015), crowdfunding analytics tools can provide insights that can benefit their fundraising.

Factors Affecting Crowdfunding Success

Prior studies have identified a number of factors associated with successful crowdfunding campaigns. These aspects include the project or campaign goal (Kuppuswamy and Bayus 2014; Mollick 2014), crowdfunding campaign duration (Mollick 2014), project creator’s network size (Kuppuswamy and Bayus 2014; Zheng et al. 2014), contribution frequency (Burtch et al. 2013), and outstanding amount to campaign goal (Burtch et al. 2013; Kuppuswamy and Bayus 2014). Mollick (2014), and Kuppuswamy and Bayus (2014) found that projects with higher campaign goals had a lower probability of being successful and that the average goal for unsuccessful campaigns is five times that of successful ones. Hou et al (2015) suggest that this goal size effect may be as a result of relatively large funding goals requiring relatively large amounts of contributions from backers to meet the set target. Further, when individuals observe a campaign’s goal, they may use it as a proxy for the project's complexity and feasibility and can decide whether or not to fund the campaign based on the goal (Frydrych et al. 2014; Koch and Siering 2015).
Researchers have established that the social networks of individuals play a significant role in fundraising success (Shane and Cable 2002; Shane and Stuart 2002; Zheng et al. 2014). Not only does the project creator’s network serve as an early pool of backers to the project campaign (Mollick 2014), they also provide endorsements which can serve as quality cues and lead to more external backers (Shane and Cable 2002). Hence, a project creator’s network should impact his chances of success positively.

Also, it has been documented in the crowdfunding literature that the duration of fundraising can impact the success of campaigns (Cordova et al. 2015; Zvilichovsky et al. 2015). Cordova et al. (2015) documents that project’s fundraising duration positively impacts the chances of success of crowdfunding campaigns. This effect may be because fundraising campaigns running for longer periods of time are more likely to be exposed to a higher number of potential funders and as such may eventually reach their goals.

Burtch et al. (2013) showed that contribution dynamics which they conceptualized as *contribution frequency*\(^2\) mattered in predicting crowdfunding outcomes. In the same hand, Kuppuswamy and Bayus (2014) and Burtch et al. (2013) showed that the outstanding amount left to reach funding goal also predicted outcomes. Table 1 provides a summary of these factors that we use as predictors and their sources. Our work focuses on using the contribution dynamics of the focal crowdfunding campaign to forecast future values or outcome. Though similar to Burtch et al. (2013) in that we include dynamic properties of crowdfunding campaigns, we conceptualize dynamics in a different and more nuanced way. For instance, we avoid using aggregates as Burtch

\(^2\) This measure was operationalized by Burtch et al. (2013) as the total number of contributions standardized by the days during which the campaign took place.
et al. (2013) in our conceptualization but rather rely on the natural information flow happening during a crowdfunding campaign, albeit discretized at the daily level.

Table 1: Summary of Factors Affecting Crowdfunding Success

<table>
<thead>
<tr>
<th>Factor</th>
<th>Effect</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Project Goal</strong></td>
<td>Negative</td>
<td>(Beier and Wagner 2015; Cordova et al. 2015; Hou et al. 2015; Koch 2016; Koch and Siering 2015; Mollick 2014; Zvilichovsky et al. 2015)</td>
</tr>
<tr>
<td><strong>Project Duration</strong></td>
<td>Positive</td>
<td>(Cordova et al. 2015; Koch 2016; Mollick 2014; Zvilichovsky et al. 2015)</td>
</tr>
<tr>
<td><strong>Number of Funders</strong></td>
<td>Positive</td>
<td>(Colombo et al. 2015; Cordova et al. 2015; Etter et al. 2013; Greenberg et al. 2013)</td>
</tr>
<tr>
<td><strong>Network size</strong></td>
<td>Positive</td>
<td>(Koch 2016; Mollick 2014; Zvilichovsky et al. 2015)</td>
</tr>
<tr>
<td><strong>Average contribution/average daily contribution</strong></td>
<td>Positive</td>
<td>(Burtch et al. 2013; Cordova et al. 2015)</td>
</tr>
</tbody>
</table>

Study Context and Data

In this section, we briefly describe the context and structure of data used in this study. Our data was collected from Kickstarter.com, one of the oldest, largest, and popular crowdfunding platforms (Kuppuswamy and Bayus 2014). Since a lot of empirical work on crowdfunding have used data from Kickstarter (Kuppuswamy and Bayus 2014; Mollick 2014), we follow in the same direction by using data from the platform in building our forecasting model. However, our approach can be readily adapted to other platforms.

Kickstarter

Kickstarter prides itself on helping "bring creative projects to life." The platform has successfully provided funding for projects that eventually led to thriving companies including
Pebble\textsuperscript{3} technology and Ouya\textsuperscript{4}. As of September 2014, Kickstarter has raised more than $1.3 billion for 69,530 projects (KickStarter 2014). Figure 1 shows a typical Kickstarter crowdfunding campaign homepage. Projects on Kickstarter are broadly grouped into various categories [See Figure 2].

Participating on Kickstarter requires that individuals join the community at no cost through free registration. Members can create projects for funding, contribute to projects financially, and comment on projects. There are no geographic restrictions on membership though creators can only be from certain countries. Backers can pledge a maximum of $10,000 or its equivalent. Projects on Kickstarter typically run from 1 to 60 days with 30 days being the recommended time frame.

Kickstarter has a few factors that set it apart from other crowdfunding platforms. First, it operates on an “all-or-nothing” fundraising model. This means that a project must fully meet its funding goal within its fundraising period otherwise funds are returned to backers. Second, contributors on Kickstarter do not receive equity in the projects that they fund but may receive modest “rewards” (e.g. a thank you note).

**Data**

We extracted information for about 2000 projects posted on Kickstarter between April 1st, 2014 and May 2nd, 2014. We visited the website using automatic web agents extracting key information on campaigns over their fundraising cycle. After collecting the data, we embarked on data cleaning and preprocessing. During the data cleaning process, we found that some creators canceled their campaigns within the funding cycle; as a result, such campaigns did not run their

\footnotesize{\textsuperscript{3} www.getpebble.com \\  \textsuperscript{4} www.ouya.tv}
full course. We dropped such campaigns from our sample. Because we are interested in predicting fundraising campaigns that seek to raise a sizeable amount of money, we restricted our sample to campaigns seeking at least $5000. This further led to a reduction in our sample size. Since we are interested in modeling and predicting the dynamic process of an ongoing crowdfunding campaign, we restricted our analysis to projects that had at least one backer (projects with zero backers will not contribute any information to our model). We restrict our model building to projects with fundraising campaigns running for at least ten days (as this allows for dynamics which is a key feature of our model to build). Typically, when creators launch fundraising campaigns, they will want to observe it for a bit before deciding on what actions to take to improve the campaign outcome. After completing the data cleaning and preprocessing, we obtain 618 usable projects.

5 Although we are not interested in predicting whether or not a crowdfunding campaign will receive at least one backer, we used the inverse probability weighting (IPW) technique (Haneuse et al. 2009; Pan and Schaubel 2008) to check for the performance consistency of our proposed dynamics based forecasting model as compared to other models when campaigns with zero backers are accounted for. There was no significant difference in performance consistency.

6 Appendix A also presents detailed instruction about how to collect and process Kickstarter data.
Figure 1. Sample Crowdfunding Campaign Home page on Kickstarter (Original Music Workshop Start Up Funds!⁷) that was successfully funded. Table 2 shows descriptive statistics of our sample and Figure 2 shows the distribution of campaigns across different categories in Kickstarter.

⁷ https://www.kickstarter.com/projects/paolaprestini/original-music-workshop-start-up-funds
Table 2. Descriptive Statistics of Sample (N=618)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>25th Quantile</th>
<th>75th Quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Campaign Goal ($)</td>
<td>23655</td>
<td>10500</td>
<td>47791.27</td>
<td>5000</td>
<td>58000</td>
<td>7000</td>
<td>25000</td>
</tr>
<tr>
<td>Amount Raised ($)</td>
<td>19672</td>
<td>5742</td>
<td>141325.3</td>
<td>1</td>
<td>3401361</td>
<td>699</td>
<td>12853.3</td>
</tr>
<tr>
<td>Number of Backers</td>
<td>198.7</td>
<td>58.5</td>
<td>664.4</td>
<td>1</td>
<td>11855</td>
<td>11</td>
<td>154.75</td>
</tr>
<tr>
<td>Average Contribution per backer ($)</td>
<td>96.53</td>
<td>66.91</td>
<td>114.19</td>
<td>1</td>
<td>1013.41</td>
<td>37.6</td>
<td>114.9</td>
</tr>
<tr>
<td>Percent of Campaign Goal Raised (%)</td>
<td>91.52</td>
<td>55.8</td>
<td>297.74</td>
<td>0</td>
<td>6802.72</td>
<td>5.3</td>
<td>108.9</td>
</tr>
<tr>
<td>Number of Facebook Friends</td>
<td>833.2</td>
<td>506.5</td>
<td>920.23</td>
<td>0</td>
<td>4861</td>
<td>252.8</td>
<td>1031.3</td>
</tr>
<tr>
<td>Funding Duration (days)</td>
<td>29.84</td>
<td>30</td>
<td>4.3</td>
<td>14</td>
<td>45</td>
<td>30</td>
<td>30</td>
</tr>
</tbody>
</table>

Figure 2. Distribution of campaigns across categories
Methodology and Results

We present our method and results in this section. Figure 3 provides a flow of our study with the implementation of our technique. We start by introducing functional data analysis (FDA) (Silverman and Ramsay 2005) techniques used to develop our forecasting model, and then we recover the underlying contribution patterns of the crowdfunding campaigns in our data. We apply functional principal components analysis (fPCA) and continue with an exploratory analysis of the patterns. Finally, we incorporate dynamic features into the model and compare it with relevant benchmarks.

Functional Data Analysis (FDA)

Functional data analysis (FDA) is a relatively new statistical technique that has been applied to studying and understanding phenomena that exhibit various types of dynamics by capitalizing on the phenomena’s dynamic attributes. The key feature of FDA is in its ability to examine curves, shapes, or more generally, functional observations (Silverman and Ramsay 2005). These functional observations can be functions of time and/or space, etc. FDA has been applied in diverse domains such as medicine and human biology (Ramsay and Silverman 2002; Zhou et al. 2010), finance (Hays et al. 2012), marketing (Foutz and Jank 2010; Sood et al. 2009), among others. Hays et al (2012) applied FDA in modeling the yield curves, an instrument used for portfolio management and in pricing securities. Sood et al (2009) used FDA to model the diffusion and market penetration of new products and demonstrated that it outperformed other models such as the Bass diffusion model (Bass 1969). Foutz and Jank (2010) proposed an FDA-based shape approach to forecasting movie box-office performance using the price patterns of movies in a virtual stock market. Similarly, Hui et al (2014) developed a Bayesian functional model to understand consumer judgment of TV show pilots using consumer moment-to-moment response
data. Consistent across these studies is that the underlying dynamics or pattern of the process generating the phenomena under study was exploited; it contributed to or improved the overall explanatory or predictive power of the results respectively.

Crowdfunding exhibits different forms of dynamics (e.g. contributions, backers, online buzz) and these can have implications on the outcome. The dynamics of contributions in a crowdfunding campaign has peaks and troughs over time with intervals of high activity and low activity (Kuppuswamy and Bayus 2014). Hence, the crowdfunded amount may not just be related to the contribution \( c \) at time \( t \) by the average contribution \( \bar{c}(t) \), but also by the dynamic variations in contributions \( c \) during the crowdfunding process. FDA allows us to model some of the dynamic properties that define these variations (e.g. velocity and acceleration) through the use of derivatives. Similarly, because the crowdfunding process can generate high-frequency and dimension data, FDA is useful for reducing such high dimensionality data without losing much information. Following these arguments and consistent with prior studies, we adopt FDA in developing our forecasting model on the basis that the dynamics of contributions in the process can lead to better forecasts.

FDA treats each function (curves, shapes, etc.) as the unit of observation clearly distinguishing itself from traditional statistical models that use data vectors as input and output variables. As a non-parametric approach, it assumes only smoothness and permits as much flexibility as is required by the data (Xiong and Bharadwaj 2014). It also offers other advantages like (1) it does not assume or fix the number parameters (such as those related to mean and variance) nor does it specify fixed parameters upfront (Silverman and Ramsay 2005). (2) Moreover, it does not require a stationarity assumption and therefore is best suited for the analysis of non-stationary time series (Ramsay and Dalzell 1991). A typical FDA process involves (1)
recovering the functional objects (known as smoothing e.g. using penalized splines), (2) computing the dynamics and/or recovering the functional principal components (fPC), followed by (3) modeling via e.g. functional regression analysis. Figure 3 gives an overview of the steps taken in this analysis.

Figure 3. Flowchart for exploratory analysis and implementation of forecasting model

**Recovering Contribution Evolution Curves**

Since our focus is on the contribution dynamics during a campaign, we start by estimating the underlying functional process as a continuous curve $S_i(t)$ that characterizes each campaign.
Once estimated, these curves are then explored to understand their dynamics. A variety of methods exist for data-smoothing and recovering underlying curves; however, we focus on the penalized smoothing spline because it offers great flexibility for 1-dimensional smoothing problems, such as the one presented in this work, and convenience in estimating curve rates of change (derivatives). Second, prior literature has shown the effectiveness of this technique in the recovery of the underlying curves of processes from discrete observations (Reddy and Dass 2006; Silverman and Ramsay 2005) even in the presence of noise in the raw data. If $t_i$ represents the $i^{th}$ time period in a campaign and $C_{ji}$ represents the amount contributed to project $j$ at period $i$, the aim of penalized smoothing splines is to identify a continuous smooth function $f_j$ that minimizes a penalized residual sum of squares (similar to least squares minimization in regression) based on the equation

$$PENSS_j = \sum_{i=1}^{n} (C_{ji} - f_{ji})^2 + \lambda(PEN_m)$$  \hspace{1cm} (1)

where $(C_{ji} - f_{ji})^2$ measures the fit of the function and $PEN_m$ measures the roughness (variability) of the function $f$ based on its $m^{th}$ derivative and the smoothing parameter $\lambda$ provides the tradeoff between fit and roughness. Figure 4 shows plots of the recovered functional curves for the project campaigns (both successful and failed). While the functional curves in Figure 5 show the contribution trajectories of different crowdfunding campaigns, we also calculate the first and second derivatives of the contribution trajectories to obtain estimates of their “velocities” and “accelerations.” Velocity here refers to the rate at which the contribution amount is changing while acceleration refers to the rate at which the contribution velocity is changing. These derivatives are used in further describing the nature and heterogeneities in the contribution dynamics of successful and unsuccessful campaigns in section 4.2.
Both velocity and acceleration help determine how fast a campaign’s current amount (amount raised so far in the campaign) is moving towards its final outcome. To further understand velocity in the fundraising context, assume that $x$ amount of dollars is contributed by individual $i$ after an interval $\Delta t$ from the last contribution, the velocity of contribution within the interval $\Delta t$ is the amount contributed per unit time $\dot{x}$ in that interval and is given by $\frac{x}{\Delta t}$. This velocity $\dot{x}$ is subject to change since different time intervals elapse between contributions similarly to the findings presented in (Kuppuswamy and Bayus 2014), and different individuals contribute different amounts even for the same intervals between contributions. These variations are bound to affect the rate at which a campaign approaches its final funding outcome. Potential backers can also use these variations in rates as signals to decide on either contributing to a campaign or not. Similarly for acceleration, assume that more individuals $j, k, l$ contribute the amounts $x_j, x_k$ and $x_l$ sequentially in decreasing time intervals $\Delta t_j, \Delta t_k, \text{ and } \Delta t_l$, and that $\Delta t_j + \Delta t_k + \Delta t_l \leq \Delta t$, resulting in velocities $\dot{x}_j, \dot{x}_k, \text{ and } \dot{x}_l$; even if the contributed amounts by the individuals are the same, the change in velocity will be as a result of the decreasing times thereby leading to an increasing acceleration. The acceleration, therefore, measures how much the velocities are changing over time (which could be decreasing or increasing) and will reflect the variations in both the number of new contributions and amounts contributed in a given time interval. It will show a surge or decline in activity in a campaign over a given interval. Intuitively, a “viral” campaign should see an increasing acceleration during the period in which the campaign experiences “virality” providing evidence of exponential-type growth in contributions throughout the time period.
Figure 4. Normalized Contribution Dynamics of Crowdfunding Campaigns
(The black line represents mean contribution trajectory and green line is the campaign goal; the red line correspond to successful campaigns; the blue lines correspond to unsuccessful campaigns)

**Functional Principal Components Analysis (FPCA)**

Having recovered the heterogeneous contribution curves and their derivatives, it is important to identify the distinguishing basic shapes that characterize these curves. Functional Principal Component Analysis (FPCA) helps in identifying these basic shapes which can then be used to create functional principal component scores (PCScore) for the curves making them more amenable to numerical analysis (Silverman and Ramsay 2005). FPCA is analogous to ordinary principal components analysis (PCA) in that it can extract key features from repeated measurement data by projecting the original data to a new space of reduced, and orthogonal dimensions. Let $f_i$ represent each curve of interest from a sample of $j$ curves measured at $p$ discrete time points, then all the $j$ curves of interest $F^{all} = [f_1, f_2, ..., f_j]$ can be denoted by a $[j \times p]$ matrix. Its $[p \times p]$
correlation matrix, $M = \text{Corr}(F^{all})$, can be represented in spectral form as $M = P^T \Lambda P$, where $\Lambda$ is the diagonal matrix of eigenvalues $[\lambda_1, \lambda_2, \ldots, \lambda_p]$ and $P = [e_1, e_2, \ldots, e_p]$ is the corresponding matrix of eigenvectors. In this example, each $e_t$ is a $[1 \times p]$ vector, which will in reality represent a continuous function in time that captures a unique characteristic of the curves of interest (Foutz and Jank 2010). Since each $e_t$ captures a percentage of the variability of $F^{all}$ like the conventional PCA, the $e_t$'s represent the principal components. In theory, $j$ different principal component curves are required to perfectly represent all $j$ curves in each dynamics class – trajectory, velocity, and acceleration and so forth. However, in practice, only the first few principal components (i.e. the ones which explain most of the variation) are chosen, effectively resulting in a reduction of our high-dimensional feature space. In our case, we use the first two principal components because they account for about 98% of the variability in the curves.8

These first two principal components are used to generate the PCScore. The PCScore represents how much weight each curve of interest $f_i$ has when decomposed into the corresponding principal components. For instance campaign $i$'s contribution trajectory $f_i$ PCScore will be the result of an inner product of $f_i = [f_{i1}, f_{i2}, \ldots, f_{ip}]$ and the selected principal components matrix $P_{selected} = [p \times 2]$.

**Exploring the Dynamics of Successful and Unsuccessful Fundraising Campaigns**

After determining the different PCScores for the contribution dynamics (trajectory, velocity, and acceleration), we investigate the natural groups of successful and unsuccessful fundraising campaigns and compare their dynamics. Using both visual and statistical techniques, we compare the contribution dynamics of the groups based on the differences in their trajectories,

---

8 We do not rotate the principal components (PC) generated using the singular value decomposition algorithm since we are not looking to interpret the PCs based on an axis of rotation.
velocities, and acceleration. Figure 5 and 6 show plots of these comparisons. Our goals are: 1) to understand the nature of the dynamics exhibited by successful and unsuccessful campaigns and 2) to determine if there are significant differences between the two groups. To achieve the first goal, we estimated the normalized mean (population average) trajectory of the crowdfunding campaigns in each group (successful and unsuccessful). And for each point of interest (funding level or time), we extracted the corresponding normalized funding level or time coordinate. To achieve our second goal, we compared the means of the trajectories of the two groups using functional analysis of variance (fANOVA) (Silverman and Ramsay 2005).

Insights generated from the exploratory analysis include the following: On the average, the contribution trajectory of successful campaigns start out with higher contribution to funding goal ratio compared to unsuccessful campaigns. Similarly, the average successful fundraising campaign will reach its goal by the 80% mark of the campaign period. The average successful campaign reaches 25% of its funding goal at 4.8% into the campaign period, hits 50% of funding goal at 28.2% into the campaign period, and reaches 75% of funding goal at 57.1% into the campaign period. In contrast, the average unsuccessful campaign raises just 14.8% of the funding goal over the entire period of the campaign. Over the 25% period mark of the campaign, the average unsuccessful campaign raises just about 6.65% of its funding goal.
Figure 5. Plots of dynamics

(a) Contribution trajectory, (b) Velocity, and (c) Acceleration. The black lines represent the average dynamics in each panel. The green, aquamarine, and yellow lines represent the 100%, 75% and 50% contribution lines respectively.
And by the time 50% and 75% of the campaign period have elapsed, the average unsuccessful campaign will have raised just 9.5% and 12% of its funding goal respectively. An analysis of the groups to determine difference in means using ANOVA and Welch’s t-test show that there are significant differences in mean trajectories of successful and unsuccessful campaigns with the contribution trajectories of successful campaigns being typically higher than those of unsuccessful campaigns. The box plot in Figure 6 (a) shows the differences between the contribution trajectories of the two groups.

![Box plots](image)

**Figure 6. Box plots**

Box plots showing comparisons between the means of the dynamics of successful and unsuccessful campaigns. “0” represents unsuccessful campaigns while “1” is successful campaigns.

For the contribution velocities shown in Figure 5(b), we see that the magnitude of the average contribution velocity for successful campaigns is higher than the average contribution velocity of the unsuccessful campaign. An analysis of the groups using ANOVA and Welch’s t-test show that there are significant differences in the mean contribution velocities as seen in the boxplots of Figure 6(b). It is also interesting to note that the contribution velocity for successful campaigns follows a "U" shape which is similar to the one identified by Kuppuswamy and Bayus (2014) in their study of backers rate. For successful campaigns, the shape of the mean velocity shows that velocities near the end are higher than the velocity at the start of the campaign. This
flurry of contributions near the end of the fundraising campaign can be explained by the classic
goal-gradient effect (Hull 1932) recently revamped by Kivetz et al. (2006) in the context of
consumer behavior and empirically investigated in the crowdfunding context by Kuppuswamy and
Bayus (2017). This suggests that individuals tend to be more energized to attain a goal when it is
in sight. On the average, successful crowdfunding campaigns show their minimum velocities
around the 40% period mark. On the other hand, unsuccessful fundraising campaigns lose
momentum early and often show weak last minute burst that is not enough to reach the goal.

Both successful and unsuccessful fundraising campaigns show nearly non-existent
accelerations. Figure 5(c) shows a plot of the contribution accelerations. The magnitude of the
acceleration for both clusters is close to zero. An analysis of the clusters using ANOVA and
Welch’s t-test show that there are significant differences in mean contribution acceleration and is
shown in Figure 6(c). The plot also suggests that on the average successful campaigns decelerate
before accelerating towards the goal and generally decelerate after the goal has been reached. The
deceleration at the start could be explained as a natural consequence of the early-stage contribution
velocity that the average successful campaign starts up with which it is not able to maintain further
in the campaign. On the other hand, unsuccessful campaigns maintain a constant low level of
acceleration. In other words, unsuccessful campaigns do not exhibit the acceleration patterns that
appear to be a distinguishing feature of successful campaigns. From the exploration of
crowdfunding projects' contribution dynamics, we can inductively infer crowding in and crowding
out effects which have been documented in the literature (Burtch et al. 2013; Kuppuswamy and
Bayus 2017); leading us to believe that dynamics provides rich information which when modeled
with more flexible semi-parametric approaches may prove useful for forecasting.
A Prediction Model for Crowdfunding Campaigns

Drawing from our exploration of the dynamics of crowdfunding campaigns, we now build a model for forecasting fundraising outcomes. Figure 7 shows an illustration of our forecast scheme where dynamics information from other earlier campaigns is combined with that of the focal campaign to predict outcomes.

Figure 7. Illustration of forecasting scheme used for outcome predictions

From our exploratory analysis, the contribution trajectory, velocity, and acceleration are important in the formation process of the outcome of the fundraising campaign over the campaign period. For this reason, we base our prediction model on a functional differential equation capturing the relationship. We propose a non-homogenous second order linear differential equation of the form
\[ \beta_0(t)f(t) + \beta_1(t)f'(t) + f''(t) + k = 0 \]  

(2)

Where \( f(t), f'(t), \) and \( f''(t) \) represent the contribution trajectory, velocity and acceleration respectively and \( k \) represents the funding goal. Our model is a plausible model for describing the funding outcome of a crowdfunding campaign because it is likely that there are forces proportional to the position, velocity, and acceleration affecting each campaign similar to those proposed by the laws of motion. In fact, functional differential equation models are believable for many processes that exhibit varying but predictable dynamics (Wang et al. 2008). In our model depicted by equation 2, \( \beta_0(t) \) reflects the force(s) acting the on-contribution trajectory at time \( (t) \) when the campaign has achieved a particular level of contribution. For instance, at a time very close to the funding goal, the goal-gradient effect or a crowding-out effect can become the driving force.

Similarly, \( \beta_1(t) \) reflects forces that are proportional to the contribution velocity at time \( (t) \). For instance, a campaign could go “viral” as a result of media mention or celebrity support triggering a flurry of contributions.

Rearranging equation (2) so that \( k \) (which is the project’s goal or outcome) is on one side of the equation and the dynamic parameters on the other side, and drawing on insights from our exploratory analysis of the fundraising campaigns, we obtain our final functional forecasting model (FDM):

\[ \text{Outcome}_T = \beta_0 + \sum_{p=1}^{\Delta} (\beta_p \text{PartialDynamics}_{T-x,p}) + \epsilon_j \]  

(3)

Where \( \text{PartialDynamics}_{T-x,p} \) represents the functional principal component scores (PCScores) generated for a project campaign’s contribution curves and derivatives up to the time \( T - x \). As you may recall from our analysis in section 4.1.2, we use functional principal components analysis (FPCA) to generate PCScores that is analogous to principal component scores in conventional
Principal Component Analysis (PCA). The PCScores allow us to make our curves amenable to numerical analysis. For the partial dynamics, the PCScores for each project campaign is generated not from the project’s complete contribution curve and its derivatives going from time $t = 0$ to time $t = T$ but from the project’s partial contribution curves and its derivatives which go from time $t = 0$ to time $= T - x$. Hence, we can use information on a contribution curve up to time $t = T - x$ to predict the outcome at time $t = T$.

Note that for each of the dynamic components of a project campaign – contribution trajectory, contribution-velocity, and contribution acceleration - we use only the first two functional principal components since they account for about 98 percent of the variations in the curve. Hence, for each curve in our sample, there are two PCScores for each dynamic component (i.e. Two PCScores for contribution trajectory, etc.). However, in our model shown in equation (3), we drop the acceleration parameters for the following reasons. First, our exploratory analysis showed that acceleration is almost zero for both successful and unsuccessful campaigns and will not add much performance to our forecasting model. Second, we can in this way obtain a parsimonious model with comparable or higher predictive capabilities which is often preferred (Shmueli 2010).

Our FDM model derived from equation (2) can be considered an inverse differential equation problem where the dynamic functions $f(t), f'(t)$, and $f''(t)$ are known and we interesting in estimating the coefficients $\beta$s from the data and can then use them as predictors of the outcome, $k$. Since our model maintains the linearity in the response equation (2), it can be estimated by least squares method.
**Benchmarks: Alternative Model Specifications**

To fully understand the advantage of our approach, we compare our FDM model to other reference models. Note that these models use the most recent dynamics information without incorporating historical or past dynamics information unlike our FDA based model - FDM. However, all of these other models are very popular in the context of forecasting (De Gooijer and Hyndman 2006; Stock and Watson 1998): the normal parametric linear model (Stock and Watson 1998) and the generalized additive model (GAM (Hastie and Tibshirani 1986)). The variables used as predictors in our models are drawn from the extant literature on crowdfunding, which has identified them as determinants of success as discussed in section 2.1. These include project goal, creators’ network size, the amount already contributed, and the number of backers (Table 1 shows the sources of these predictors). Further, to allow for fair comparison between these models with our dynamics based model, we use the most recent dynamic information of the variables to estimate the models. However, unlike the FDM model, these models are not able to incorporate historical or past dynamics information of the variables. The benchmark models are:

**Normal parametric linear model** – this is a simple model that fits a line in the estimation sample by minimizing the sum of squared errors and uses the equation of this line to predict the holdout sample. For example, to predict the outcome of a fundraising campaign at the time $T - x$, where $T$ is the period of the campaign and $x$ is the time before the end of the campaign, we use information from campaigns in the estimation sample at time $T - x$ to fit the model. The model estimates can then be used to predict the outcome of the holdout samples. Specifically, the prediction model is given by

$$
\text{Outcome}_T = \beta_0 + \beta_1 \text{SocNetsize}_{T-x} + \beta_2 \text{Goal} + \beta_3 \text{NumCont}_{T-x} + \beta_4 \text{AmtCont}_{T-x} + \epsilon_j
$$

(4)
Where \( \text{SocNetsize} \) is the creator’s network size on Facebook, \( \text{Goal} \) is the amount the creator is seeking to raise, \( \text{NumCont}_{T-x} \) is the number of individuals that have contributed to the campaign at time \( T - x \), and \( \text{AmtCont}_{T-x} \) is the amount that has been raised at time \( T - x \).

**Generalized additive model** – this model is similar the normal parametric linear model in its estimation technique, but it incorporates the nonlinearities in the data in its predictors. That is, it uses smooth functions to capture the distribution of the predictors and then uses these non-linear forms as predictors. Similar to the normal parametric model, we fit the estimation sample containing information about the predictors at time \( T - x \) and the outcome of the campaign, then use the fitted model to predict the outcome of the holdout sample. Specifically, the prediction model is given by

\[
\text{Outcome}_T = \beta_0 + \beta_1 \text{SocNetsize}_{T-x} + \beta_2 \text{Goal} + f(\text{NumCont}_{T-x}) + f(\text{AmtCont}_{T-x}) + \epsilon_j \quad (5)
\]

Where \( f(*) \) implies that the parameters in parenthesis have been smoothed and the definition of variables are the same as for Equation (4).

**Model Estimation**

We divide our data (618 campaigns including outliers) into a training set (518 campaigns) for estimation and a holdout set (100 campaigns) for validation. Since our data varied over the time period in which it was collected and we are interested in making predictions in the future, the training set consisted of crowdfunding campaigns that started earlier in the data collection period and the validation set or hold out sample consisted of campaigns that started later. We chose the hold-out sample consisting of campaigns starting on later dates to allow for additional exogenous variation with respect to the training set useful when testing competing models (Ebbes et al. 2011).
Because our dynamic model (FDM) is a functional regression model, we estimated it using least squares estimation techniques similar to those in other regression models (Silverman and Ramsay 2005). Figure 8 shows fit statistics of the models. FDM consistently fit better than other models. Model fit is dependent on the length of time $x$ before the end of the crowdfunding campaign. The smaller the time $x$ (i.e. time before the end of the campaign), the better the $R^2$ value, the Akaike information criterion (AIC (Akaike 1974)), and the Bayesian information criterion (BIC (Schwarz 1978)). AIC and BIC measures how much a model fits the data and the smaller the AIC and BIC, the better the model fit. Intuitively, since forecasting further into the future should be harder, longer time intervals to the end of the campaign should not perform as well.

![Figure 8](image)

Plots showing (a) normalized time to end of campaign vs the $R^2$ value and (b) normalized time to end of campaign vs the AIC and BIC

**Prediction Results and Performance**

After estimating our model, we check its prediction performance on the holdout set. We measure the prediction performance of our model at five different periods during the crowdfunding
campaign and compare it with the benchmark models at the same period. The periods used are 10%, 30%, 50%, 70%, and 90% into the total campaign duration. To measure the prediction performance, we use the mean absolute percentage error (MAPE) metric. For each time period $t = T - x$, in the holdout sample, we compute

$$MAPE(T - x) = \frac{1}{n} \sum_{i=1}^{n} \frac{|Y_{T-x,i} - \hat{Y}_{T-x,i}|}{|Y_{T-x,i}|}$$

For instance, a prediction model with a forecast error (MAPE) of 0.06 at 30% time periods into the campaign implies that on the average the true funding outcome will lie within ±6% of the forecasted value. In forecasting, the goal is to have prediction models with smaller forecast error which in turn means better prediction performance. Table 3 and Figure 9 shows the results for all the models across the different time periods. Whereas Table 3 shows the numerical values of the forecasting error across different stages of the crowdfunding campaign, Figure 9 illustrates the errors across the various stages. The x-axis in Figure 9 shows the time from the beginning of the campaign while the y-axis shows the forecasting error.

Not surprisingly, we see that as we predict closer to the end of the campaign (i.e. as time interval x gets smaller), the predictive performance of all the models gets better (i.e. MAPE decreases).
Table 3: MAPE results for competing models

<table>
<thead>
<tr>
<th>Stage of Campaign (in %)</th>
<th>Parametric Regression</th>
<th>GAM</th>
<th>FDM</th>
<th>FDM with Covariates</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
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<td>0.0211</td>
<td>0.0210</td>
<td>0.0127</td>
<td>0.0126</td>
</tr>
</tbody>
</table>

Figure 9. Prediction Performance

The prediction result shows that the dynamics based model is better than all alternative models. At 10 percent into the fundraising campaign period, the prediction error for the dynamics based model is about 6.29% and at 90 percent into the fundraising campaign, the prediction error drops to 1.27%. The benchmark models were fairly competitive between themselves in performance, but considerably lagging with respect to our proposed model. The GAM model, for
instance, was generally better than the linear model, but the latter became almost as good towards the end of the campaign. All the models generally had a prediction error of less than 12% indicating that they are generally good models. It is interesting to note that our model performed very well at the very early stages of the campaign implying that users of the model can have fairly good predictions at the onset of their crowdfunding campaign. An explanation for the superior performance of our model could be that it incorporates information about the dynamics (i.e. contribution trajectory and velocity) of the focal crowdfunding campaign and that of other campaigns to predict outcomes compared to the other models, which use last state information. Further, as shown from Figures 8 and 9, including covariates in our dynamics model further improves the predictive performance, albeit marginally.

**Performance Quality Check**

To further probe the quality of the FDM model, we perform a performance quality check on a subsample of the crowdfunding project campaigns. This subsample consists of the 134 crowdfunding project campaigns with the most outcome uncertainty; that is, crowdfunding project campaigns with overlapping contribution trajectories (overlapping red and blue lines) but different outcomes (see Figure 10). We select this subsample by including only those campaigns that have raised at least 15 percent of their goal and have not reached 30 percent of their target goal by the time the campaign has been run for 20 percent the campaign duration. This yields the 134 crowdfunding trajectories in Figure 10. We split that subsample such that 104 campaigns are used to train the model, and 30 campaigns are used for testing. Table 4 shows the performance for all models. We can see that the FDM model performs consistently better than the GAM and linear regression model. Further, adding covariates increases the predictive performance of the FDM model. Interestingly, the FDM model performs better compared to the results on the full sample
(Table 3). One possible explanation could be that campaigns in the subsample have more consistent dynamics compared to those removed from the sample, leading to better predictions of our functional model.

Overlapping successful and unsuccessful crowdfunding campaigns that have not reached 30 percent of their goal after 20 percent of campaign duration. Red curves represent successful campaigns, blue curve represents unsuccessful campaigns, and the green line is the 100 percent threshold contribution.

Figure 10: Campaigns with most uncertainty in outcome
Table 4: MAPE Results for Campaigns with most Uncertainty

<table>
<thead>
<tr>
<th>Stage of Campaign (in %)</th>
<th>Parametric Regression</th>
<th>GAM</th>
<th>FDM</th>
<th>FDM with Covariates</th>
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<tbody>
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<td>0.0105</td>
<td>0.0101</td>
</tr>
</tbody>
</table>

*We start from 30 percent time point mark into the campaign because the sample selection criteria are based on campaign status at 20 percent time point mark.

Discussion

Forecasting the outcomes of crowdfunding campaigns is increasingly becoming important because of the growth and use of crowdfunding mechanisms by fledgling entrepreneurs, businesses, and individuals. Users have shown interest in having forecasting tools at their disposal (HuffingtonPost 2013; Wired.com 2012). However, there has been little work developing forecasting models for the crowdfunding context, and most crowdfunding platforms are yet to implement such tools despite having large amounts of crowdfunding data. To the best of our knowledge, we demonstrate and assess the merits of the first crowdfunding forecasting model using the contribution histories and contribution dynamics of other comparable crowdfunding campaigns together with that of the focal crowdfunding campaign. FDA is an innovative statistical technique that has gained popularity recently allows us to carry out this task of modeling and quantifying dynamics.

Moreover, we explore and analyze the contribution dynamics of crowdfunding campaigns in terms of contribution trajectory, contribution velocity, and contribution acceleration. Again,
FDA proves useful in helping glean key intuitions on the contribution dynamics of the crowdfunding phenomenon. Comparing the natural clusters of successful and unsuccessful fundraising campaigns against each other, our analyses lead to the following important insights. First, on the average, successful crowdfunding campaigns reach their target goals long before the campaign is over. The average successful campaign will reach its target goal at about 80% into the duration of the campaign compared to the average unsuccessful campaign which will be at about a misery 12.3% after the same time period. Second, successful campaigns start out with high contribution velocities compared to unsuccessful campaigns. This could mean that prior to the launch of the campaign, creators engage in some offline awareness building that can help their campaigns take off. Kuppuswamy and Bayus (2014), for instance, suggest that this early awareness is usually among family and friends. The high contribution velocity can also act as a signal of quality to external backers who are not in the creator’s social circle but who are looking for projects to back. Potential creators should try to build offline awareness before launching their crowdfunding campaigns because it will increase their likelihood of success. Third, both successful and unsuccessful campaigns tend to have little or no contribution acceleration. While this insight looks surprising, it highlights that campaigns "going viral" are not a norm in the crowdfunding environment. Creators should rather not bank on a “viral effect” when launching campaigns to drive them to success but do the diligent work in steering backers to their campaigns to contribute.

On the forecasting front, we show that our dynamics based model - FDM - developed using FDA techniques perform better than standard alternative models. Insights generated from the forecasting model include: (1) using FDA techniques provide superior forecasting power for dynamic processes that evolve over time. Not only does our model perform better because of its
basis in the laws of motion, but FDA also provides higher flexibility by removing parametric assumptions, which can lead to improvements in predictive power. For instance, relaxing the parametric assumptions on the normal linear model with the GAM model led to predictive improvements with respect to the linear model. FDA's key strength lies in its ability to capture the variety of patterns in the different campaign contribution dynamics without overfitting through its use of principal components. Though this increased flexibility can lead to a disadvantage of variability in estimates, using a large number of subject observations reduces the problem of variability (Xiong and Bharadwaj 2014). 

(2) Principles of dynamics from the physics literature can be applied to predictions in the crowdfunding context. This approach is novel because the concept of using the second order equation of motion has not been extended into forecasting in the business literature. The concept lets us leverage on ideas that have been well established in the physical sciences literature and applying to crowdfunding prediction problems. 

(3) Incorporating information about the history and the evolution of the process that leads to the outcome of the fundraising exercise leads to better forecasting performance.

From a managerial perspective, our model proves to be very useful because of its ability to accurately forecast funding outcomes from the very early stages of the crowdfunding campaign. This ability to forecast funding outcomes well in advance allows sufficient time for campaign creators to make the necessary adjustments to their crowdfunding campaigns, engage in solicitation activities for more funds, and make post-funding plans (e.g. production plans for crowdfunded products) and arrangements for their crowdfunding campaigns. Further, with various crowdfunding platforms still not providing forecasting tools and with third-party platforms springing up to help campaign creators monitor, track and forecast their campaigns outcomes (e.g.
kicktraq.com), our model is a good forecasting tool which can easily be implemented by these platforms to provide more accurate and reliable forecasts.

**Conclusion**

Our explorations and developments contribute to the crowdfunding and forecasting domains in several ways. First, understanding and forecasting outcomes in the crowdfunding context is a non-trivial task, important to stakeholders in crowdfunding – platform owner, creators, and backers. Our method shows the effectiveness of using the contribution dynamics in campaigns as a forecasting measure and provides evidence that it leads to superior forecasts. Second, we provide insights into the nature of contribution dynamics as it relates to successful and unsuccessful crowdfunding campaigns. Our method has at least three clear practical implications: (1) it can be used to make more accurate predictions of crowdfunding outcomes. While outcomes at the end of campaigns are forecasted in this study, one can also use our model to forecast outcomes at any future time in a campaign by estimating our model with the future time as the focal end time. (2), we show that adding relevant covariates to our dynamics model allows for greater prediction accuracy. (3) Our technique can be adapted to other forecasting contexts that exhibit dynamics like the diffusion of products/services and in the forecasting of stock prices.

Finally, as the crowdfunding continues to grow and offer fundraising opportunities, we hope that our work not only provides a forecasting tool but raises interest and brings to visibility the need to build predictive models that will better fit the crowdfunding context.
CHAPTER 3: HOW STRATEGIC CROWDFUNDING DESIGN DECISIONS AND FINANCIAL SLACK AFFECT FUNDING AND POST-FUNDING OUTCOMES

Abstract

Recently, crowdfunding has become an alternative mechanism for financing new product development. However, most studies on crowdfunding have focused on the fundraising phase where they have explored strategies that can lead to successful funding. In this paper, we go beyond the fundraising stage by examining how these strategic funding decisions affect product shipment – a post-funding outcome. Based on the marketing-operations interface model, we conjecture that strategic crowdfunding campaign design decision can impact both funding and post-funding outcomes. We show that these strategic decisions have differential effects on both phases (fundraising and post-funding) of crowdfunding. That is, decisions that positively impact funding success may negatively affect the time to shipment of crowdfunded products. Further, and contrary to speculations, we find that overfunding (a fundraising phase outcome) provides financial slack and is associated with lower delays in product shipment. Finally, we provide implications for these findings.
Introduction and Motivation

“Funding isn’t everything” - Robert Strohmeyer (PCWorld 2013)

Crowdfunding has become an important mechanism for fledgling entrepreneurs and firms to finance new products and/or ventures (Belleflamme et al. 2014; McCormick 2015). Especially for fledgling entrepreneurs, the crowdfunding mechanism provides them with early stage capital that might otherwise have proven difficult to raise through more traditional channels like angel investors and venture capitalists (VCs). As a financing mechanism, it allows project teams or creators to raise funds to finance the creation and commercialization of products by issuing an open call, usually through the internet, to potential funders. However, crowdfunding is not just about raising money for product development. It provides a new method of bringing products to the market which differs from traditional product development process. First, crowdfunding is a community-driven product development method that allows for and enhances the selection of product ideas; a crucial step in innovation and new product development (Kornish and Hutchison-Krupat 2016; Urban et al. 1993). Second, it allows the crowd (funders) to get involved in the product design and development process which can help improve the final product while also giving funders a sense of empowerment. This is possible for the former because crowdfunding also allows creators to capture instantaneous customer response and feedback which is often not possible in traditional product development methods. Third, crowdfunding allows creators to gauge and measure the market readiness of a product often without a developed version of the

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9. It is reported that some of the most successful crowdfunded ventures were turned down by venture capitalists (Jeffries, 2013) and that the difficulties in raising early stage capital through traditional channels are often a result of the steep requirements for application (Carey, 2014), higher uncertainties than early stage investors are willing to bear, and unproven products

10. We use creator and project team interchangeably in this study

11. Individuals who support the venture or idea by contributing with financial resources, often a promise to pay a certain amount.
product. This is different from traditional product market research where a minimum viable product is often required. Finally, crowdfunding provides early champions and advocates for the product in the form of funders who not only finance the product but also market and advertise it to their peers. All these suggest that crowdfunding as a product development mechanism is different.

Extant academic research on crowdfunding has significantly expanded our knowledge of the workings of the phenomena; from identifying factors that affect fundraising success (Belleflamme et al. 2014; Kuppuswamy and Bayus 2014; Mollick 2014) and optimal design strategies for fundraising campaigns (Belleflamme et al. 2014; Hu et al. 2015) to understanding funder(s) behavior in the crowdfunding context (Burtch et al. 2013). However, these studies have extensively focused on the fundraising phase with little attention paid to the post-funding phase and its deliverables. From a product development perspective, these phases are tied together and define the complete process from idea to product delivery.

The introductory statement in quotes by Strohmeyer (2013) in a PCWorld article on crowdfunding brings to light the argument that the product crowdfunding process for product development does not end at getting successfully funded. In essence, a product crowdfunding venture cannot absolutely be considered completely successful unless it delivers on its pre-funding promises or has positive post-funding outcome(s). For instance, a fully funded product crowdfunding venture promising to develop and deliver a 3D printer for mobile devices is not "truly successful" unless it produces a finished product to the funders who financed its development and production by participating in the fundraising phase. Mollick (2015) based on self-reported survey data, perhaps surprisingly, points out that there are no clear indicators at the time of funding that can ultimately predict post-funding outcomes including product delivery.
Further, post-funding outcomes can subsequently affect other long-term post-funding events in a crowdfunded venture’s life cycle like product sales, access to outside funding, and transition to a viable business. Put together, these suggest that for crowdfunded products, there is a need to go beyond just the funding phase and to explore some of the factors that might impact not only funding but also outcomes in the post-funding phase, and to shed light on them.

In this paper, we tackle this problem by investigating factors that affect both funding and post-funding outcomes and by providing a comprehensive overview of the crowdfunding process and product development. To the best of our knowledge, this is the first work analyzing crowdfunding in such an integrative way.

Specifically, we focus on the following research questions:

1. Does the strategic funding phase decisions affect both funding and post-funding outcomes? If so, then how?

2. What is the impact of potential slack resources (measured in our study as excess funding) on the short-term post-funding outcome (measured in our study by the delay in product shipment)?

We focus on the post-funding outcome product delivery for the following reasons: First, when funders finance products in crowdfunding campaigns, they expect the products to be delivered especially when they are funding the product by pre-purchasing or pre-ordering it. Second, there is evidence suggesting that the shipment of most crowdfunded products are either significantly delayed or never shipped at all. For instance, 75 percent of crowdfunded products on Kickstarter, one of the largest crowdfunding platforms are delayed while another 10 percent never deliver (Mollick 2014; Mollick 2015). This suggests that creators may need fundamental insights on strategies to manage the entire process of product crowdfunding from fundraising to product
shipment and to maximize their probability of [economic] success. Third, the shipment of products can act as signal for a crowdfunding project team’s preparedness and capabilities, provide visibility and legitimacy for both development team and product, increase the likelihood of being financed by more traditional investors (e.g. venture capitalists), as well as increase its likelihood of survival as a venture (Mollick and Kuppuswamy 2014; Schoonhoven et al. 1990).

The outcomes of the two sequential phases are throughout influenced by a mix of marketing- and operations-related strategic decisions (Belleflame et al., 2013). Hence, we base our exploratory analysis upon theoretical perspectives from their respective academic literature. More specifically, we explore propositions relating to marketing-operations interface (MOI) models (Swink and Song 2007; Tang 2010).

Although our work is rather exploratory, we do propose some hypotheses in our investigation of the crowdfunding empirical setting. Schoonhoven et al. (1990, pp 178) suggest that in the absence of a single sufficient theory, logic and good knowledge of the experimental setting can inform the development of hypotheses. The assumptions, though mostly grounded in marketing and operations literature outlines our logical expectations of the effect of the identified strategic decisions.

**Stated Contributions**

Our work makes the following contributions.

1. First, using a significant sample of crowdfunding projects, for which we track their signs of progress beyond the funding phase, we develop an empirical framework allowing us to simultaneously estimate the impact of strategic decisions on funding and post-funding outcomes. Interestingly, we find evidence that strategic decisions that favor funding may hurt product shipment, a post-funding outcome.
2. Second, we highlight some of the factors that affect post-funding performance, a phase in crowdfunding that has otherwise received limited attention. Although success in the fundraising phase is important for product crowdfunding, the “ultimate” success is in the post-funding phase where both backers and the project team or creators can be winners when things work out well.

3. Third, we extend the literature on the effects of slack resources (financial slack in this case) to post-funding outcomes in the crowdfunding context. We present some empirical evidence that financial slack (overfunding) might be good for crowdfunding, especially in the case of new product development.

4. Finally, given that crowdfunding suffers from the potential moral hazard problem arising from funders’ inability to observe project team’s post-funding actions, we show that some observable design and funding indicators can help funders and other stakeholders determine more informed conclusions about a particular product’s delivery potential and interpret possible shipment delays that may otherwise arise.

5. In light of 1-4, we provide some design implications to crowdfunding platforms derived from the insights generated from our findings.

Background and Hypotheses

Literature on Crowdfunding

Recently, crowdfunding as a concept and mechanism has been receiving a lot of attention in both practice and academic circles. In the latter, a stream of research has begun investigating some its workings and dynamics. Extant literature has examined the incentives for creators and funders to participate in crowdfunding and have found various reasons (Agrawal et al. 2013; Gerber et al. 2012). For instance, these studies find that while creators participate due to the ability
to raise low-cost capital, pre-sell products, build new relationships, and garner market information; funders are motivated to participate in order to support great products or ideas, have early access to new products, and enjoy participation benefits. In addition, Schwienbacher and Larralde (2010) confirm these findings on creators’ motivations and further suggests that funders may also be motivated by altruism.

Another stream of the crowdfunding literature has focused on determinants and strategies for successful fundraising, what we will later refer to as the first phase of the process. Studies in this area dominate the crowdfunding literature. Mollick (2014) investigates the factors related to successful fundraising and finds that social network size, goal amount, duration of fundraising campaign, and signals of quality affect fundraising success. Li and Duan (2014), using a structural model, show that seeding a fundraising campaign can lead to successful funding. Hu et al (2015) analytically show how strategic product and pricing decisions can impact a crowdfunding campaign. Additionally, Belleflame et al (2014) model the effects of pre-selling versus fixed contributions during fundraising on the overall success of a crowdfunded product. They show that when there is a limited market for the crowdfunded product, pre-selling the product is optimal for the project creator.

Other studies investigate the types of funders (Lin et al. 2014), and funder behavior (Burtch et al., 2013; Kuppuswamy and Bayus, 2014). While Burtch et al. (2013) finds that there is often a crowding-out behavior by funders in the public goods funding context, Kuppuswamy and Bayus (2014) find evidence of increased funding as a campaign nears its goal. This difference in findings may be a result of the different contexts examined in the two studies and leads us to believe that funders react differently to private and public goods. In the public goods context, there is bystander effect whereby funders assume that other funders will provide the necessary funds required for a
project to reach its goal when the goal is close. Additionally, Kuppuswamy and Bayus (2014) find that backers are influenced by how much of the goal has been pledged rather than the number of backers.

Consistent across these studies is the focus on factors related to the fundraising phase of crowdfunding with minimal attention to the post-funding phase and its related implications to product development. From a strategic perspective, although we have insights on factors that affect funding success in the first stage in general, it will be interesting to understand which strategies spillover into the second stage and how, given that the post-funding phase is fraught with logistical challenges (Stanko and Henard 2016). Further, though a factor like overfunding has been attributed to leading to product shipment delays in the post-funding phase anecdotally (e.g. Masterton, 2013), the literature lacks a systematic and rigorous empirical analysis. This study addresses the identified knowledge gap while suggesting that the literature on product crowdfunding can be enriched when the phenomenon is viewed as a multi-stage process.

**Crowdfunding Mechanism and New Product Development**

Although the crowdfunding mechanism has primarily been viewed as a vehicle for fundraising, entrepreneurs and businesses are embracing it as a vehicle to take products from the idea stage, through funding, to commercialization. For instance, Sony Inc launched its own crowdfunding platform simply to facilitate product development through the crowdfunding process (McCormick 2015; Russell 2015). Crowdfunding is valuable to new product development in that it drives innovation (Mollick and Kuppuswamy 2014; Stanko and Henard 2017). According to Stanko and Henard (2017) crowdfunding drives radical product innovations by promoting open search through conversations and inputs from backers. Similarly crowdfunding is playing a central role in increasing the development of niche and often forgotten product areas. For instance, virtual
reality (VR), the technology of the moment, was largely ignored by traditional financiers until the success of the Oculus Rift VR headset, a product of the crowdfunding process (Mollick 2016a). Further, as a mechanism for launching new products, crowdfunding is valuable in that it quickens the product idea selection process (Kornish and Hutchison-Krupat 2016), cuts production costs because backers provide the needed capital, and the backer community inputs lead to quick product improvements and refinement.

Marketing-Operations Interface Models

Operations and marketing arguably have two of the most opposing goals from a functional perspective when it comes to new product development (Swink and Song 2007; Tatikonda and Montoya-Weiss 2001). Whereas marketing tends to be externally focused and customer oriented (Tang 2010), operations tend to focus more internally on efficiencies, capabilities, and capacity. Marketing-operations interface (MOI) models where developed to examine the issue of coordination and collaboration between the marketing and operations functions (Tang 2010) with the aim of aligning the two functions towards the firm’s goals and success (Singhal and Singhal 2002; Tang 2010). Research on MOI has highlighted the benefits of tight integration of the marketing and operations functions to the firm. Hausman et al. (2002) show that well integrated MOI can improve firm competitive advantage and profits. In the same light, Sawhney and Piper (2002) find that a high quality of coordination at the MOI can enable firms to reduce product defect rates, production costs and product delivery delay. With respect to MOI and product development, Calantone et al. (2002) emphasize the need for tight marketing-operations integration. Further, Swink and Song (2007) show that the tight integration of marketing and operations can lead to greater product success which they measure in terms of new product development time and new product competitive advantage. Consistent across these studies is the focus on the coupling of the
marketing and operations functions albeit in the context of traditional product development in firms. In the product crowdfunding context, marketing and operations activities are loosely coupled, if at all.

In product crowdfunding, creators may make marketing decisions that enable them meet their funding goals but compromise their ability to deliver products on schedule after funding. On the other hand, they can make operations decisions benefiting their delivery capabilities, but, at the same time, minimizing the chances of getting fully funded. Thus, the way these strategic decisions affecting both funding and post-funding outcomes are chosen requires careful consideration. Also, these strategies should align to ensure maximum overall success.

**Product Decisions and the crowdfunding process**

When creators decide to crowdfund a product, they make product decisions about their crowdfunding campaign design which should ensure ultimate success and is in tandem with their long-term goals for the product. On the one hand, creators need to make financing decisions to raise enough money. That is, they need to make product decisions that allow them to meet their funding goals. On the other hand, creators need to make decisions on products and production levels that help product delivery and fulfillment.

Hence, when creators design crowdfunding campaigns, they not only make product decisions that affect the overall fundraising performance, they make decisions that affect product delivery as well. Product decisions in crowdfunding include specifying the line or menu of products (variety of products with different qualities or features) offered at different reward tiers (Hu et al, 2015) and limiting the quantity of products available for advance selling\(^\text{12}\) or pre-

\(^{12}\) This is part of fundraising. People may pledge in return to get finished products.
purchasing. We expect these product line decisions – menu of products offered and limiting the quantity available for advance selling – to not only affect creators' ability to successfully raise funds but also affects their ability to meet their predefined product shipment timelines.

The marketing literature suggests that a high product variety stimulates sales and also increases the probability of satisfying the needs of a heterogeneous consumer population (Bayus and Putsis Jr 1999; Xia and Rajagopalan 2009). Consistent with this line of argument, Hu et al (2015) showed that having a menu of products in the crowdfunding design incentivizes funders with different valuation and preferences to choose goods and / or reward tiers optimal for them and can drive funding success. However, the operations management literature argues that increasing the variety of products leads to a reduction in operational performance and difficulties in inventory management (Alfarao and Corbett 2003; Ton and Raman 2010; Wan et al. 2012). Creators are often inexperienced in production and manufacturing processes (Wheelright 1988), and may be too occupied with getting successfully funded that they ignore the drawbacks of offering multiple varieties of the product during fundraising. In line with these perspectives, we argue that offering a broad range of the crowdfunded products will boost the chances of funding success. However, the wide variety of products at many reward tiers will lead to difficulties in the management of production complexities associated with new product development. Hence, will ultimately result in higher delays in product shipment in the post-funding phase.

Consequently, we postulate that:

**H1a: With respect to product decisions, the larger the variety of products offered during the crowdfunding campaign, the higher the likelihood of meeting the funding goal.**
H1b: With respect to product decisions, the larger the variety of products offered during the crowdfunding campaign, the longer the delay in product shipment.

From marketing literature, limiting the quantity of product available for advance-selling can potentially affect the overall sales revenue when there is a high initial demand for a product. In other words, by limiting the quantity of product available for pre-order, creators may be leaving surplus orders on the table by not matching funder demand. This should imply crowdfunding campaigns with limited product availability should have fewer chances of being funded compared to those with unlimited product availability. However, in the crowdfunding context where the target is to meet a specific funding goal, creators can limit the quantity of product available for pre-order without compromising on their chances of being fully funded or reaching their goal. Belleflamme et al. (2014) show that this strategy is possible even when it is used to price discriminate. Further, because funders are constantly looking for signals of competence and preparedness on the part of the creators, they may see the limiting of products available for pre-order as a sign of careful planning and preparation. Hence, they may gravitate towards such product crowdfunding campaigns by supporting it, thereby leading to its funding success. Putting the arguments as mentioned earlier together, since product availability can be limited in such a way that a campaign reaches its funding goal, we do not expect to see a significant difference between the effect of limiting product availability and not limiting product availability on funding success. We, therefore, hypothesize:

H2a: Compared to not restricting the quantity of product available for pre-orders, limiting the number of products available for pre-orders will have no significant effect on the likelihood of meeting the funding goal.
Limiting the quantity of products available for pre-purchasing or preorders should also facilitate delivering products on time. Operations literature suggests that having unlimited advance sales or preorders is only good when a seller has sufficient capacity (Xie and Shugan 2001; Yu et al. 2015). Creators who do not limit the quantities of product available for preorder may not only be overestimating their capacity to produce and deliver but also will be setting themselves up for increased product shipment delay. Further, because of the uncertainty in demand during the fundraising phase, potential manufacturing problems and capacity issues, we argue that creators are most likely to reduce product shipment delays when they limit or cap the number of products available for preorder.

This leads us to hypothesize that:

\textit{H2b: Compared to not limiting the quantity of product available for pre-orders, limiting the quantity of products available for pre-orders will reduce the delay in product shipment.}

\textbf{Fulfillment Time and the crowdfunding process}

As part of the requirements to launch crowdfunding campaigns, creators need to specify a time frame for the delivery or fulfillment of the crowdfunded product. The fulfillment time, therefore, includes the time the creator will spend to develop, manufacture, and deliver the product after being successfully funded. Fulfillment times can either be long or short. It not only serves to inform funders on when the products will be delivered, but also may be used by funders in deciding which competing crowdfunding campaign to fund. However, creators can use fulfillment time as a strategy to steer funders into funding product campaigns or to psychologically manage funder waiting experience (Ho and Zheng 2004) such that funders do not perceive long product development times as delays.
Marketing literature suggests that short fulfillment and turnaround times are better than long fulfillment times, and can help businesses grow market share and profits (Ferdows et al. 2004; Stalle Jr and Hout 1990). For instance, by providing shorter fulfillment times, LeatherTECH a furniture company grew sales by about 60 percent (Hensel 1996). Further, long fulfillment times can dissuade a category of funders who are time sensitive from supporting a product campaign. Hence, from a marketing perspective, to meet funding goals in the face of competing for crowdfunding campaigns, it is better to provide short fulfillment times. In essence, long fulfillment times should increase the chances of a product campaign not being fully funded.

However, operations research suggests that there is often a trade-off between short fulfillment times and delivery performance unless capacity is expanded accordingly (Ho and Zheng 2004; Shang and Liu 2011). Short fulfillment times are usually hard to meet especially in the case of new product development; hence long fulfillment times might be more beneficial. Short fulfillment times can also be costly (Elhafsi 2002; Kalai et al. 1992) and can negatively affect customer satisfaction if fulfillment is not on-time as promised or is unreliable (Kumar et al. 1997). Further, short fulfillment time does not provide some benefits of long fulfillment times like helping hedge against the uncertainties of production (Whybark and Williams 1976), and helping psychologically to manage the waiting experience of funders (Ho and Zheng 2004). For instance, specifying long fulfillment times and actually fulfilling on-time can increase customer satisfaction (Kumar et al. 1997).

In the crowdfunding context creators are often inexperienced; and because the process of developing innovative new products often involves a lot of uncertainties, and implies that plans may be modified as new knowledge is gained (Kirsch et al. 2009; Shah and Tripsas 2007),
specifying long fulfillment times will be more beneficial and will have a positive effect on a creator’s ability to ship without delay.

Putting these all together we hypothesize the following concerning promised fulfillment time on both phases of crowdfunding:

\( H3a: \) **Product crowdfunding campaigns with long promised fulfillment times are less likely to meet their funding goal.**

\( H3b: \) **Crowdfunded products with long promised fulfillment times will experience lower product shipment delay**

**Financial slack and crowdfunded product shipment**

Financial slack in the crowdfunding context refers to funds more than what a product creator has requested for during the crowdfunding campaign. It is not unusual for fully funded crowdfunding campaigns to receive funding beyond what creators sought for. However, the funding structure of crowdfunding campaigns can affect post-funding performance (Jung et al. 2014). Further, there are debates on if a funding structure that introduces slack through overfunding affects the delivery of crowdfunded products (Masterson 2013).

The literature on slack resources suggests that slack can be good especially in the face of uncertainties (Cheng and Kesner 1997; Hendricks et al. 2009). Hence we argue that slack is important in the delivery of crowdfunded products because crowdfunding is used to fund the development of novel and innovative projects. Innovation involves a considerable level of uncertainty (Nelson and Winter 1977), and liabilities of newness (Schoonhoven et al, 1990) which is especially true for the development of new and innovative products where the optimal way to carry out development may not be apparent.
For creators of crowdfunded products who have not proven the workability of their ideas or who might be inexperienced in the workings of large scale product manufacturing, they may experience unplanned product development disruptions, manufacturing problems, shipping complexities, and changes in scale and scope that might ultimately affect their shipment timelines. It is not uncommon for innovators to be oblivious of some of these issues about product development especially the role of manufacturing in innovation (Wheelwright 1988). However, with sufficient slack, creators will have the leeway to manage such changes by either reallocating resources to meet predefined production timelines. Cheng and Kesner (1997), point out that ventures with slack are more likely to respond with new actions to shifting environmental demands. This view of the benefit of sufficient slack is supported by Hendricks et al (2009) who find that slack reduces the negative effects of disruptions in supply chains and slack functions as a good shock absorber.

Research focusing on financial slack has linked it to positive outcomes (Latham and Braun 2008; Lee 2011). Creators who seek product development funds via crowdfunding usually do not have credit lines or cash positions like established ventures. We expect that the excess funds that the creator gets during the funding phase will come a long way in reducing any product delivery delays that might arise due to unforeseen circumstances. Further, even when there is no potential for shipment delay, the extra funds may be invested in expertise that can help in speeding up development and subsequently shipment time.

Putting it all together, financial slack is good for crowdfunded products and can help speed up shipment. Accordingly, we hypothesize the following:

**H4: Higher financial slack is associated with lower product shipment delays.**
Figure 11 shows a visual description of our research model and hypotheses and how these are related to the three different phases considered in this work: strategic design decisions, funding phase, and post-funding phase.

Research Methodology

Data and empirical context

Our empirical context is Kickstarter, one of the world’s largest crowdfunding platforms. As of September 2014, Kickstarter has raised more than $1.3 billion for 69530 projects, representing about 41.3% of the projects launched on its platform since inception in April 2009 (KickStarter 2014). It has successfully provided funding for innovative products that eventually transitioned to thriving businesses including Pebble Wristwatch and Ouya. Further, it has consistently produced the highest number of post-funding VC-backed products and ventures
among crowdfunding platforms (Insights 2014). Being an all-or-nothing platform where product creators set their fundraising goals and get nothing if they do not reach their funding goals at the end of the fundraising cycle, Kickstarter allows product creators sell their products as a way of raising funds typically through discounted pre-orders (Hong et al. 2015a) in order to meet their goal.

To investigate our proposed hypotheses, we collected data on successfully funded and unsuccessfully funded private goods projects on Kickstarter platform in the product design and technology categories launched on the platform from January 2012 through May 2014. We select these categories because they pertain tangible products and are treated somewhat special by Kickstarter. In essence, Kickstarter requires campaigns in these categories to produce a development and/or manufacturing plan and provide a fulfillment timeline when setting up their fundraising campaign (Mollick 2014). Further, these categories provide some of the innovative products on Kickstarter and a significant percent of those successfully funded raise over $100 thousand (Lin et al. 2014). Our sample consists of projects seeking a minimum funding goal of $500013, a non-trivial amount. Additionally, we manually collected data on the shipment status and shipment dates for the successfully funded projects; and only included projects with clearly defined and identifiable shipment timelines, shipment status, and delivery dates in our final sample. Our overall sample consisted of a total of 2011 projects, out of which 806 projects were successfully funded and are used in our analysis. Figure 12 shows two sample Kickstarter pages with some of the variables of interest highlighted.

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13 This has been used as an operationalization for large crowdfunding projects in other studies (e.g. Mollick 2014)
Panels (a) and (b) are examples of two typical crowdfunding campaigns page on Kickstarter.com. Panel (c) shows snapshots from the two campaigns highlighting the variety of products offered based on pledge tiers, promised fulfillment time, and whether products are of limited availability during the funding campaign.

Figure 12. Kickstarter page with strategic decisions highlighted
Variables

**Product Shipment Delay (Ship_Delay):** The product delivery delay was measured as the number of months from the month and year a crowdfunded project promised to deliver until the month it shipped its first batch of products. The data is recorded in months because project creators are expected to specify the expected month and year of delivery. This data was collected manually by extracting shipping dates from creator updates to funders and from other Internet-related sources. For firms that are right-censored in our analysis, meaning they did not deliver within the promised time and we do not observe any effective delivery, the waiting time is calculated as the number of months since month and year of promised delivery till the month of final data collection. 667 projects have shipped their products at the time of final data collection.

**Funding Success (Fund_Succ):** This measures if a crowdfunding campaign reaches its funding goal during the fundraising phase. It is coded as a binary variable, with a value of 1 if the campaign reached its funding goal and 0 if it does not.

**Financial Slack (Fin_Slack):** This was measured as the percentage to which the project goal was overfunded. Hence, a project with a goal of $1000 that received $1200 in funding will have a 20 percent financial slack.

**Promised Fulfillment Time (Fulfill_Time):** This is measured as the number of days after the products fundraising cycle required to ship the product. Thus if a fundraising cycle ended on May 31st, 2013 with a shipment date of June 2013, then promised fulfillment time will be calculated as 30 days.
**Product Variety (Prod_Var):** This is measured as the number of distinct product variants in terms of size, materials, colors, features. These terms are the same used in creating stock keeping units (SKU) which has been used in the literature to measure variety (cite).

**Product Limit (Prod_Lim):** This is coded as a binary variable, with a value of 1 if the creator capped the number of products that can be preordered and 0 if there is no cap.

**Control variables.** **Amount Pledged (Amt_Pleg):** The total amount raised in the products crowdfunding campaign.

**Number of backers (Num_Backers):** Total number of funders who contributed to the total amount pledged to a funding campaign.

**Product Rewards (Prod_Var):** This is measured as the number of distinct product reward tiers offered in a crowdfunding campaign.

**Funding Duration (Fund_Dur):** The number of days a product’s crowdfunding campaign was available for funding.

**Funding Goal (Fund_Goal):** The amount which the creator intends to raise from the product’s crowdfunding campaign.

**Product Category (Prod_Cat):** The category in which the product belonged. This is coded as a binary variable, with a value of 1 if the product belongs to the product design category and 0 if it belongs to the technology category.

**Riskiness guidance (Risk):** This measures the level of risk detailed by the creator reflecting her assessment of the risk involved in developing the product. This was measured as a count of the
number of words used by a creator to describe the risk involved in the project. The larger the number of words, the higher the detail and the assessment of risk.

Team Type (Team): This is coded as a binary variable; with a value of 1 if the crowdfunding campaign is a team effort and 0 if it is an individual effort.

Crowdfunding Experience (CF_Expe): This is coded as a binary variable; with a value of 1 if a creator has launched a crowdfunding campaign before on the platform and 0 if the creator has not.

Product Design Experience (Prod_Des_Expe): This is coded as a binary variable; with a value of 1 if a creator on a team member has a prior product design or manufacturing experience and 0 if the no one has.

Product Development Stage (Dev_Stage): This is coded as a binary variable; with a value of 1 if the creator has gone beyond product development and funds raised is to be used for production and commercialization of product (e.g. tooling, molding, and first production runs), and 0 if funds raised are to be used to either start or continue product development.

Video (Video): This measures whether a video was included in a crowdfunding campaign or not. This is coded as a binary variable, with a value of 1 if the campaign had included a video and 0 if it does not.

All the non-categorical explanatory variable in our analysis are log transformed because of their right high skewness and variability, and the descriptive statistics of our sample is reported in Table 5. The pairwise correlations are reported in Appendix B
Table 5. Descriptive Statistics

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*Log transformed variables

Empirical Analysis: Methodology

Since we are interested in the effects of strategic crowdfunding design decisions at two different stages of crowdfunding, we estimated two models. Our dependent variable of interest in the first stage is crowdfunding success. That is, whether a crowdfunding campaign got fully funded or not. Hence we estimate a probit model14 with the crowdfunding design decisions as the key independent variables.

---

14 We focus on the Probit model due to its good small sample properties (Griffiths et al, 1987) in the case of cross-sectional data. Importantly, the Probit model, in contrast with the Logit Model, does not satisfy the Independent of Irrelevance Alternative assumption (IIA) that is hard to entertain with cross-sectional data. Moreover, the presence
Our dependent variable of interest in the post-funding phase (second stage) is the length of time a crowdfunded product is delayed before shipping, hence we use the statistical framework focused on duration analysis, an event-history approach (Allison, 1984). This approach takes both the occurrence and timing of an event (shipment in this case) into account while estimating for the exogenous factors. In line with the related literature, we use the proportional hazards (PH) regression (Cox 1972) model to investigate the product shipment delays. The PH model is appropriate because it is the most robust model, and allows for the estimation of the factors impacting the hazard rate without assuming any prior underlying distribution for product shipment delays. The hazard rate, \( h(t) \), approximates the probability of product delivery in period \( t \) given that the product has not been shipped in period \( t - 1 \). Further, the model assumes proportional hazards where the baseline model is a function of time \( t \) and does not involve the explanatory variables. Helsen and Schmittlein (1993) provide an extensive discussion of this model and its implication for marketing response models.

It is important to notice that since all the projects used in this stage were successfully funded, selection bias in the second stage could be present. Our proposed solution to address this endogeneity concern relies on the inverse probability weighting (IPW) procedure which can be used for addressing sample selection bias in PH models (Pan and Schaubel 2008; Seaman and White 2013; Wooldridge 2007). This is a two-stage procedure where the probability of being successfully funded is first estimated (first stage) and then the inverse of the probabilities generated from this first stage model are passed into the second stage (PH model) as weights. Essentially, in the IPW procedure, all projects that make it to the second stage (i.e. were successfully funded) are of normally distributed errors allows for an exact correction for the selection bias as is discussed below. See Maddala (1983) for a discussion about the differences between the Probit and Logit models.
"discounted" appropriately with a factor proportional to the inverse of the probability of being successful.

The Cox Proportional Hazard (CPH) with IPW model is fit by maximizing a weighted partial likelihood, where each crowdfundng campaign \( i \) that shipped at time \( t \) from the baseline contributes the term

\[
\left\{ \frac{\exp(\beta X_i(t))}{\sum_{j \in R(t)} \tilde{w}_j(t) \exp(\beta X_j)} \right\} \tilde{w}_i(t)
\]

Where \( R(t) \) is the set of crowdfunding campaigns that have shipped at time \( t \), \( X \) is the vector of explanatory variables, \( \beta \) the parameter to be estimated and \( \tilde{w}_i(t) \) the estimated weight. We follow Allison (1984) by not modeling unobserved heterogeneity by means of random effects, since we only analyze non-repeated events, and the covariates are not time varying. However, we include additional fixed effects by means of year and product category dummies to address any unobserved time trends or shocks.

**Empirical Analysis: Results**

The results of our analyses are reported in Tables 6 and 7 where we obtained estimates using the maximum likelihood scores and we compute robust standard errors to address model misspecification for the funding phase. Table 6 shows the results for the funding phase with funding success as the dependent variable. Model 1 is the base model (control variables) and Model 2 is the base model plus creator characteristics variables. We focus on Model 3 in highlighting the results for the funding phase. Table 7 shows the results for the CPH models with IPW (post-funding phase). Model 5 is the base model plus creator characteristics, while Model 6 includes the
product decision variables and model & is the full model including financial slack. Again, we focus on Model 7 in highlighting the results for the post-funding phase.

Table 6. Analysis Results for Funding Phase

<table>
<thead>
<tr>
<th></th>
<th>Model 1 (Probit)</th>
<th>Model 2 (Probit)</th>
<th>Model 3 (Probit)</th>
<th>Model 4 (Logit)</th>
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<td></td>
<td></td>
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<td>0.5700***</td>
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</tr>
<tr>
<td></td>
<td>(0.0447)</td>
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<td>(0.0950)</td>
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<tr>
<td></td>
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<td>(0.3780)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0010)</td>
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Note: * p<0.1, ** p<0.05, ***p<0.01; Robust standard errors in parentheses
Table 7: Analysis Results for Post-funding Phase

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<td>-7478.9</td>
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Note * p<0.1, ** p<0.05, *** p<0.01 ; Standard errors in parentheses
Model 3 shows the results from the full Probit model used in estimating funding success (fundraising phase). The results indicate that the model is a good fit, with a highly significant log likelihood value -261.7 and pseudo $R^2$ of 0.81.

Model 7 is the results from the full CPH model with correction for sample selection bias. Recall the all the estimates for the CPH models are in the log-hazard format and thus they need to be interpreted in a careful way. For example, a negative coefficient implies a decreasing hazard rate; namely, a decreasing hazard rate implies that the (instantaneous) probability of delivering the product on time increases. Overall, the model is significantly better than a baseline non-parametric model with no covariates (Kaplan and Meier 1958) - the log-likelihood of -7478.9 with $p<0.001$ in indicate that the model is identifying significant covariates.

Hypothesis 1A predicts that there is a positive relation between the variety of products offered and funding success. We find support for this hypothesis ($Prod\_Var = 0.3103, p<0.01$) indicating that crowdfunded campaigns offering products with various configurations are more likely to experience funding success. However, hypothesis 1B posits that a wider product variety can lead to increased shipment delay. We also find support for this hypothesis ($Prod\_Var = -0.1266, p<0.001$) indicating that a wider product variety can negatively affect operations and lead to shipment delays.

Hypothesis 2A predicts no significant effect on the association between having a limited number of the crowdfunded product for pre-order during the fundraising campaign and funding success and shipment delay. Again, we find that this hypothesis is supported ($Prod\_Lim = -0.1644, p>0.10$) indicating that products campaigns with a set number of products available for order during the funding phase do not significantly affect funding success. On the other hand, hypothesis 2B posits that having a limited number of the crowdfunded product for pre-order during the
fundraising campaign can lead to lower shipment delays. We find that this hypothesis is also supported \((\text{Prod\_Lim} = 1.085, p<0.01)\).

Hypothesis 3A suggests a negative association between longer promised fulfillment time and funding success. We find support for this hypothesis \((\text{Fulfill\_Time} = -0.0013, p<0.05)\) indicating that having longer specified fulfillment times can reduce the chances of funding success. However, hypothesis 3B predicts a negative association between longer specified fulfillment time (note that this includes development and manufacturing times) on shipment delay. Again the estimate is significant \((\text{Fulfill\_Time} = 0.0006, p<0.01)\), and we do find support for the hypothesis.

Hypothesis 4, in contrast, postulates a negative association between slack funding (level of excess funding) and product shipment delay. We find support for this hypothesis \((\text{Fin\_slack} = 0.0985, p<0.05)\) indicating that the more the percentages of excess funding a crowdfunded product receives during the fundraising phase, the less the likelihood of shipment delays.

Moreover, by inspecting some of the results related to the control variables we can gather interesting insights. First, we observe that providing detailed guidance and risk information can greatly increase the chances of funding success \((\text{Risk} = 0.4806, p<0.01)\). Further, we observe that \text{Prod\_Dev\_Stage} is positive and significant \((0.2489, p<0.01)\) in the post-funding phase analysis, indicating that crowdfunding campaigns seeking funds for production runs and commercialization are more likely to ship products early than campaigns seeking to fund for product development. Also, we find that prior product design experience is significant in both phases of the crowdfunding process.

As a form of robustness check, we reiterated the analysis for the funding stage using logistic regression (Model 4). Similarly, for shipment delay in the post-funding phase, we fit three other
survival models with different parametric distributions for the baseline hazard rate (see Appendix B). Importantly, we note that the findings remain directionally consistent.

Discussion

The goal of this study was to empirically explore how crowdfunding campaign design decisions and funding structure affect both funding and post-funding outcomes, and to advance our understanding of the effects of these factors on the overall crowdfunding process. Considering crowdfunding as a two-stage process, our analyses show some major findings including an unexpected finding. First, we find that the effect of offering a wide variety of products is different for both funding and post-funding phases. While offering a wide variety of products can increase a campaign’s chances of being fully funded, it can hurt creator’s ability to ship on time. This finding is consistent with both marketing and operations literature. Operations management theories posit that increasing the variety of products can lead to reduction in operational performance and difficulties in inventory management (Alfaro and Corbett 2003; Ton and Raman 2010; Wan et al. 2012). Figure 13 illustrates this point by means of a numerical exercise in which we vary the amount of product varieties, while keeping all the other covariates set to their sample mean. It is possible to notice the tradeoff between increasing the probability of funding in the first stage and decreasing the likelihood of delivery on time in the second. For project teams and creators who are often inexperienced, this finding suggests that it may be better for them to maintain minimal product variations during crowdfunding as this will enable them ship with less delay, although this may come at the cost of being fully funded. However, for project teams and creators who want to maintain a wide variety of products, they can benefit from finding competent manufacturing partners early. These manufacturing partners should be able to seamlessly handle all the possible product variations offered during crowdfunding in order to minimize potential
shipping delays. Similarly, funders who observe that crowdfunding campaigns offering multiple variations of products being crowdfunded should expect that such products may experience delays.

Second, we find that the effect of limiting the quantity of products available for pre-order is different for funding and post-funding phases. Although the parameter estimate is negative, the effect is not significant. This can be attributed to the fact that success in the funding phase is measured based on a predetermined funding goal. Creators may be limiting the quantity of products available for pre-order such that by the time

![Plot of Probability of funding success superimposed with plot of relative likelihood of product delivery when product variety is varied and all other covariates set to their mean value.](image)

Figure 13: Product Variety against Probability of funding success and relative likelihood of product delivery

the available quantity is exhausted, they would have met their funding goals. On the other hand, crowdfunded projects with a limited quantity of products available for pre-order during the
fundraising phase are less likely to experience shipping delays. For project teams and creators, not limiting the quantity of products available products for pre-order may be considered a trivial oversight in crowdfunding campaign design. However, our finding analysis suggests that such an oversight may have significant effects on their shipping timeline. Further, it also highlights the importance of capacity planning and management for creators and project teams who intend to crowdfund for their products. While it may appear beneficial to have an unlimited quantity of products available in order to meet funding goals, it is better to limit the quantity of products available for pre-orders such that it allows the crowdfunding campaign meet its funding goals without going beyond the available capacity. Capacity expansion costs are often high when there is learning and uncertain demand (Cakanyildirim and Roundy 2002; Hiller and Shapiro 1986) as may be the case for crowdfunded products. Taking together, creators can benefit from limiting the quantity of products available for pre-orders by having fewer shipment delays in the post-funding phase without losing on their campaign's chances of being fully funded in the funding phase.

Third, we find crowdfunded projects with longer fulfillment time are less likely to be fully funded in the funding stage. This finding suggests that funders may be sensitive to product wait-time in the crowdfunding context. They will most likely fund a competing campaign offering a shorter product wait-time when given the choice. An implication of these is that creators who want to increase their chances of being successful may have to work on reducing the wait time. This could imply having to go from just ideation stage to the later stages of product development before launching a crowdfunding campaign. Additionally, we found that crowdfunded products with longer fulfillment times are less likely to experience longer delays in shipping.

Given that funders can benefit from any additional information about a crowdfunding campaign, an implication of our possible explanation is that crowdfunding platforms require
project teams and creators to disclose the current level of product development and whether it is an experimentation project; in addition to the risk and challenges disclosure required of them in order to launch crowdfunding campaigns. This will not only better inform funders’ investment decisions but prepare them for potential late shipment or total failure of the project.

Finally, we find that crowdfunded product campaigns that are overfunded have more financial slack and are more likely to experience less shipping delays. There has been calls and debates on whether crowdfunding platforms should ban overfunding or put controls that limits overfunding (Gabison 2015; Masterson 2013). Further, Gyalokay (2015) suggests that overfunding may not be good for crowdfunding because of the possibilities of it leading to increased project scope, among other reasons. Our finding provides an empirically grounded answer, suggesting that overfunding may actually be good for crowdfunded products as it provides creators with more financial slack thereby leading to fewer delays in shipment. This finding also suggests that overfunded projects which have failed to ship or are experiencing significant delays in shipping may be a small minority most likely from the pool of the few crowdfunding campaigns that experience "viral" funding. Further, there might be other reasons beyond overfunding that might have affected the creators’ ability to ship like overall poor project planning or sheer incompetence.

**Practical and Managerial Implications**

Our findings provide practical implications. First, prior literature suggests that creators offer a wider variety of products in order to ensure funding success (Hu et al. 2015); however, our finding puts a caveat on this strategy by highlighting its potential to hurt the crowdfunded project in the post-funding phase. Hence, there is the need for creators to balance product variety with capabilities. Second, theoretical models have suggested that limiting the quantity of products available for pre-selling during fundraising can benefit the creator if the crowdfunded product has
a potentially high post-funding market (Belleflamme et al. 2014). Our finding reinforces this proposition empirically. Hence, creators who expect their products to have a huge post-funding market will benefit from adopting this strategy of limiting the quantity of product available for pre-selling in addition to improving their chances of early shipment. Third, though not part of our hypotheses, we observe that the stage of development at which a crowdfunded product matters in determining its likelihood of shipment. Information on the development stage of a product can prove vital to funders and will help them better anticipate shipment. Hence, crowdfunding platforms focused on product development should require creators to provide more detailed information or explicitly disclose the stage of development at which their crowdfunded product is and what they intend to use the funds raised to do. For instance, a creator who has a working prototype and is raising money for tooling and production should not only disclose this information but also inform funders how long the tooling process will take and what it entails.

These findings highlight the need for a strong marketing related (fundraising) and operations related strategy in the crowdfunding context. Creators who want to maintain success over the entire crowdfunding process will have to integrate their fundraising plans with their production plans. For instance, creators may have to first estimate their production capacity and capabilities before setting up fundraising campaigns on crowdfunding platforms.

**Conclusion**

This study joins a body of literature that has been examining the marketing-operations interface and integration (Calantone et al. 2002; Ho and Zheng 2004; Swink and Song 2007), and a more recent body of literature that has begun investigating post-funding outcomes in crowdfunding, especially the delivery of crowdfunded projects. Among the latter, Mollick (2015) that uses survey methods to investigate project delivery rates is most notable. We empirically
investigate some of the factors that affect both funding and post-funding outcomes. More specifically, we focus on strategic decisions that affect both funding success and the shipment of crowdfunded private products. Crowdfunded products have been known to be plagued with shipping and delivery delays (Mollick 2014; Pepitone 2012) and factors that may impact product shipping delays or indicators that may convey valuable information on product delivery capabilities or outcomes can benefit all stakeholders. Our study though exploratory shed some light on the differential effects of these factors on both outcomes in crowdfunding and further provides some implications for practicing.

However, our study is not without limitations. First, we consider only two categories of crowdfunded products – product design and technology. Thus, our findings are generalizable only to these categories. Future studies could extend the study to other categories such as film, music, and crafts among others in other to see if these results hold. Second, our study focused on crowdfunded products that had fully successful fundraising campaigns (campaigns that reached their funding goal) raising a potential selection bias and further limits its generalizability to crowdfunded products with partially successful fundraising campaigns as is obtainable on some crowdfunding platforms. We do not know whether these factors apply to different sets of products. Additional research is needed to investigate how the factors investigated in this study apply to or are different in the partially successful campaigns. For instance, while we observed campaigns with positive financial slack in the case of fully successful fundraising campaigns, partially successful campaigns experience negative to no slack at all which may provide different dynamics or results. Finally, future research can go beyond shipment delivery event in the post-funding phase
to other equally important event like crowdfunded product exit\textsuperscript{15} or transition to viable business. These events may be affected by a different set of mediating and moderating factors.

\textsuperscript{15} According to an Inc.com article (Krasny, 2014) and Insights (2014), angels and venture capitalists (VCs) have begun monitoring crowdfunding platforms and using the overall performance of projects to identify viable candidates for investment. For instance, Insights (2014) reports that crowdfunded hardware projects received over $200 million across 23 deals in 2013 from VCs alone.
CHAPTER 4: POST-FUNDING RELATIONS-BUILDING EFFORTS, TEMPORAL PROXIMITY AND THE PERFORMANCE OF SUBSEQUENT CROWDFUNDING CAMPAIGNS

Abstract

Crowd-based platforms that allow project owners (individuals and organizations) harness the online crowd for projects have proven to be of value. However, a significant amount of them do not have reputation systems and as such members of the online crowd may have to rely on other metrics to reach a decision decide on whether to participate in a project owner’s future project. In this study, we focus on one of such platforms – reward-based crowdfunding platforms - which helps drive innovation and where the project owner’s purpose for harnessing the crowd is to fund her projects. Viewing the project owner’s harnessing of the crowd for fundraising (crowdfunding campaign) as an exchange situation, we examine whether her efforts in building relations with the crowd from a prior crowdfunding campaign through the delivery on the prior crowdfunding campaign’s project expectations and regular communications will impact the performance of her subsequent crowdfunding campaign and how. We find that project owners’ relations building efforts positively impacts their subsequent crowdfunding campaign performance and discuss its implications.
Introduction

In recent years, there has been a proliferation of online platforms that provide individuals and organizations (hereafter project owners) with the ability to harness or engage the online crowd for various purposes (e.g. crowdfunding platforms for fundraising and crowdsourcing platforms for tasks). The ability to harness the crowd via online crowd-based platforms has proven to be beneficial to project owners as the online crowd often provide cost-efficient solutions to project owners’ problems (Boudreau and Lakhani 2013; Boutin 2006). Moreover, the availability of a ready pool of individuals (crowd) on the platforms as well as the ease of accessing the crowd also makes it appealing to project owners (Fallon 2015; Spinelli 2017). As a result, project owners flock to these crowd-based platforms to harness and often re-harness the crowd for their projects whenever they have the need. Although project owners harnessing the crowd mimics market exchange similar to those on other online market platforms, where exchange parties transact with one another and often have expectations from each one another, a significant amount of these crowd-based platforms do not have reputation systems (e.g. reviews and star ratings) on which the crowd can evaluate the “characteristics” and credibility of project owners. For instance, popular crowd-based platforms like Amazon mTurk, Kickstarter, and Indiegogo do not have reputation systems where the members of the crowd can observe the credibility of project owners based on their prior exchange with other members of the crowd.

Given that reputation systems provide proxy metrics for determining a project owner’s characteristics (e.g. credibility and quality) based on her past exchange behavior, which also helps in revealing information about the project owner and her ability to act opportunistically (Pavlou et al. 2007), the absence of reputation systems will imply that members of the crowd will have to

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16 We use crowd-based to reference online platforms used in harnessing the crowd.
rely on some other mechanisms in making their decisions about project owners and whether to engage in a future exchange with them. Considering that repeat exchanges between the same transacting parties are often interrelated and that the exchange history between the same transacting parties can affect their willingness to commit to future exchanges (Anderson and Weitz 1992), it is possible that project owners actions and outcomes resulting from a prior exchange can affect the performance of a future exchange as members of the crowd may rely on them in lieu of reputation systems. Consider the two scenarios in Figure 14. In scenario A, the actions of the project owner from her prior exchange is positive that the members of the crowd are interested in participating in a future exchange, while the same cannot be said of scenario B.

We argue that in the absence of reputation systems, the members of the crowd will rely on the project owner’s relations-building efforts from a prior exchange and their recollection of these efforts in determining whether to engage in a future exchange with her. Additionally, given the importance of timing to sellers in online markets (Ebay 2005; Lucking-Reiley et al. 2007) and in the potential that relations-building efforts from a prior exchange affects subsequent exchange, we examine if the temporal proximity - time difference – between the prior exchange and subsequent exchange moderates the effect of relations-building efforts from prior exchange on subsequent exchange.

In this study, we ask the following research questions:

Does the project owner’s relations-building efforts from a prior exchange impact the performance of a future exchange on crowd-based platforms with no reputation systems? If yes, how? Is the impact of the project owner’s relations-building efforts on future exchange affected by the temporal proximity between the prior- and future exchange? To answer these questions, we situate our study in the online reward-based crowdfunding context. We do this for the following reasons.
First, online reward-based crowdfunding has become a go-to fundraising mechanism for fledgling entrepreneurs (Mollick 2014; Mollick and Kuppuswamy 2014; Overly 2013) and it is changing the entrepreneurial fundraising landscape (Raglin 2017; Rejcek 2016). Project owners flock to crowdfunding platforms to harness the crowd for fundraising. According to Massolution (2015b), about $17.2 billion was raised by entrepreneurs through crowdfunding within North America, and crowdfunding is estimated to

![Scenario A](image)

![Scenario B](image)

Figure 14: Scenarios from Two Different Crowdfunding Campaigns
outgrow the venture capital market by 2025 (Noyes 2014). Apart from providing funding, crowdfunding has generated significant social and economic impact including creating jobs and businesses (Mollick 2016b). Hence, from a practical significance standpoint, it is worthwhile to study online crowdfunding platforms. Second and particularly important is that unlike other online crowd-based markets, including like Upwork and CrowdSpring where reputation systems exist for project owners, such systems do not exist in the reward-based crowdfunding markets (e.g. Indiegogo, Kickstarter) despite the lack of rigorous vetting for project owners joining the platforms. Hence, if there is a setting where the members of the crowd may have to rely on a project owner’s relations-building efforts from a prior exchange to determine whether to engage in a future exchange with her, the reward-based crowdfunding setting will be one. Third, the nature of exchange in reward-based crowdfunding is different in the respect that it is not just transactional or purely economic motivated – based on utilitarian principles with participants guided by self-interest alone – but also, motivated by prosocial behavior (Gerber and Hui 2013; Lin et al. 2014; Ryu et al. 2016). Additionally, there are no enforceable rules or agreements between project owners and members of the crowd (backers\(^\text{17}\)) that govern exchange interactions. For instance, though backers may have certain expectations from project owners, no rule stipulates that backers "must” get something in return for financially supporting a project owner’s crowdfunding campaign, making the exchange non-contractual. Hence, backers should be more motivated to seek out ways to only enter into an exchange with credible project owners. Finally, despite the growing trend of serial crowdfunding by project owners in reward-based crowdfunding platforms (Kuppuswamy and Mollick 2016; Skirnevskiy et al. 2017; Yang and Hahn 2015); on the average project owners continue to record significant failure rates (Kuppuswamy and Bayus 2017). While

\(^{17}\) We use backers to identify members of the online crowd who participate in a crowdfunding campaign
prior successful crowdfunding campaign experience has been observed to not lead to success on subsequent crowdfunding campaign (Yang and Hahn 2015), it will be interesting to identify factors that lead to repeat crowdfunding campaign success and to provide alternative argument as to why prior successful crowdfunding campaigns may not translate to subsequent crowdfunding campaign success.

In building our conceptual model as depicted in Figure 15, we draw on concepts from relationship marketing (Morgan and Hunt 1994; Wulf et al. 2001), as it allows us to define the relations building aspects of an exchange and tease out how relations-building efforts can affect future exchange. Moreover, we introduce temporal proximity as a moderator to the effect of relations-building efforts on subsequent exchange. Put together, our conceptual model offers a new perspective on the actions that can lead to successful fundraising on crowdfunding platforms, and provides several implications for project-owners who would want to engage in serial crowdfunding campaigns on reward-based crowdfunding platforms. Although our study is set in the crowdfunding context, our findings have broader implications and can be extended to other crowd-based platforms with no reputation systems (e.g. Amazon mTurk).

Further, our work contributes to several streams of literature. First, we add to the literature on relationship marketing (Morgan and Hunt 1994; Wulf et al. 2001) in the context of crowdfunding. In addition to confirming the importance of project owners’ relations-building efforts on campaign success, we demonstrate the practical importance of engaging in relations building with backers on crowdfunding platforms. Second, we contribute to an emerging literature on crowdfunding (Agrawal et al. 2013; Schwienbacher and Larralde 2010). More especially, by considering the emerging trend of serial crowdfunding, which has taken off with the maturity of
the crowdfunding phenomenon. Our work allows us to identify factors that can lead to repeated crowdfunding campaign success in serial crowdfunding.

The rest of this paper is structured as follows. First, we present the theoretical background and hypotheses development. Next, we present our data and research methodology. Then, we present our results and discussion. Finally, we conclude with the contributions and limitations of our study.

**Theoretical Background and Hypotheses Development**

**Crowdfunding**

Raising funds for entrepreneurial initiatives from traditional channels (e.g. banks, angel investors and venture capitalists) have often proven difficult and challenging especially for
fledgling entrepreneurs (AngelBlog 2017; Rao 2013). However, crowdfunding has proven to be a viable and less challenging alternative. In crowdfunding, entities (fledgling entrepreneurs and organizations) turn to the online crowd, often through online communities and platforms, to request for funds to pursue their entrepreneurial initiatives. There are different models of crowdfunding including lending-based, equity-based, donation-based, and reward-based. Each model has its unique platform designs to facilitate the type of exchange that it facilitates since their goals and forms of exchange on vary. For instance, whereas lending-based crowdfunding focuses on peer-to-peer lending transactions where a backer lends money to a project owner, donation-based focuses on the crowd making charitable contributions to a project owner. We focus on reward-based crowdfunding, the largest and most popular form of crowdfunding. In reward-based crowdfunding platforms, the setting of our study, project owners often offer rewards or presale products to the crowd in exchange for funds which they can use to pursue their initiatives. Hence, the expectation of receiving either rewards or products incentivizes backers to finance the project owner (Ryu et al. 2016). Moreover, reward-based crowdfunding provides positive implications for innovation (Stanko and Henard 2017)

With crowdfunding becoming a mainstay for fundraising, the number and variety of crowdfunding platforms has continued to grow (Younkin and Kashkooli 2016). In 2015 alone, crowdfunding platforms collectively raised about $34 billion (Massolution 2015b), an amount greater than the total ($24.6 billion) angel investments in North America over the same period (Sohl 2016). For project owners seeking to raise funds for their initiatives through rewards and presales, reward-based crowdfunding platforms popularized by the likes of Kickstarter and Indiegogo offers the opportunity to reach a broad base of potential backers. In other word, these
platforms allow project owners to harness the crowd towards a specific task which in this case is raising specific amounts of funds.

**Serial crowdfunding** - Although the literature on crowdfunding have largely explored why individuals participate in crowdfunding (Agrawal et al. 2013; Gerber et al. 2012), backer(s) behavior (Burtch et al. 2013; Kuppuswamy and Bayus 2014), and the factors that lead to fundraising success (Beier and Wagner 2015; Mollick 2014); a new stream has started exploring the serial crowdfunding phenomenon (Kuppuswamy and Mollick 2016; Skirnevskiy et al. 2017; Yang and Hahn 2015). Kupusuwamy and Mollick (2016) examine gender differences in serial crowdfunding and find that men are more likely to engage in serial crowdfunding than women. Yang and Hahm (2015) argue that project owners learn from their prior crowdfunding campaign experience and show that different aspects of the crowdfunding experience have a differential influence on the funding outcome of a subsequent crowdfunding campaign. One interesting finding from their work is that a project owner’s *prior successful crowdfunding campaign experience* does not lead to success in a subsequent crowdfunding campaign. This result highlights that other factors can play important roles in driving fundraising success in subsequent crowdfunding campaigns beyond prior successful crowdfunding campaign experience. For instance, the project owner’s post-funding relations-building efforts with the crowd may matter; with the crowd avoiding the campaigns of project owners with whom they may have had bad post-fundraising experiences. Finally, Skirnevskiy et al. (2017) documents that social capital derived from a project owner’s prior crowdfunding campaign positively influences subsequent crowdfunding campaigns. However, they do not unpack the mechanisms through which project owners build social capital on crowdfunding platforms (and how these mechanisms can impact subsequent crowdfunding campaigns). On this issue, the project owner’s relations-building efforts may come in handy in
building the social capital which can be leveraged for the success of future crowdfunding campaigns and other post-campaign related activities like actual product development.

**Relationship Marketing**

Despite the absence of an all-encompassing theory of relationship marketing (Bagozzi 1995; Wulf et al. 2001), propositions from relationship marketing has proven to be valuable in explaining exchange relationships (Dwyer et al. 1987; Morgan and Hunt 1994). Relationship marketing refers to all the marketing actions and activities designed towards establishing, developing, and maintaining successful relational exchanges (Dwyer et al. 1987; Morgan and Hunt 1994). From the seller’s (project owner’s) perspective, it explicates how her actions and activities can drive long-term exchange relations including repeat purchase, positive word of mouth, and information sharing (Fruchter and Sigué 2004).

The relationship marketing literature argues that sellers need to invest in building relationships with customers as it makes customers become favorably disposed to them (Hart and Johnson 1999; Wulf et al. 2001). According to Wulf et al. (2001), such investments in relationship building either through time, effort, or other irrecoverable resources creates some sort of psychological bonds that encourage customers to stay in a relationship with the seller while setting an expectation of reciprocation. In essence, the norm of reciprocity which has been found to be a major factor in explaining long and stable exchange relations (Larson 1992), is what will keep the members of the crowd tied to a project owner because it evokes a sense of obligation towards the project owner on the basis of her past behavior (Gouldner 1960). In the same vain, the crowd will expect the project owners to reciprocate fairly by delivering on their expectations and investing in maintaining the relationship.
Although most studies in relationship marketing have been set in offline settings – with no explicit reputation systems for sellers, and in online settings where the traditional market exchange occurs, we extend the tenets of relationship marketing to the reward-based crowdfunding context with its unique exchange structure and lack of reputation systems for evaluating project owners.

**Relations-building Efforts and Crowdfunding Success**

Scholars have long understood that relationships are developed through specific sequential interactions in which participants carry out activities toward one another (Hallen et al. 1991; Klepper 1995; Lee and Kim 1999). And as a relationship develops over time, parties seek to increase their successful exchange outcomes through increased exchange benefits and interdependence (Dwyer et al. 1987). Further, reciprocity demands that actions taken by one party in a relational exchange will be reciprocated in kind by the other party.

In crowdfunding, project owners can increase the likelihood of exchange - financial contributions from backers – and successfully raise funds by attracting and engaging (potential) backers often using a mix of strategies including campaign promotion and communications (Hong et al. 2015b; Mollick 2014; Parhankangas and Renko 2017). However, to increase the likelihood of repeated exchange – contributions to subsequent crowdfunding campaigns - and build backer loyalty, project owners have to go beyond the short-term (initial) fundraising success thinking and take a long-term orientation by incorporating behavioral factors that demonstrate their reliability, trustworthiness, and commitment to backers. Hence, project owners need to exhibit a sequence of behaviors that helps in establishing, developing and maintaining good relations with backers after initial fundraising.

Prior literature has shown that relations matter for repeated exchange or commitment to occur among exchange participants (Anderson and Weitz 1992; Ganesan 1994; Mattila 2001;
Scheer et al. 2010). In the crowdfunding context, we argue that relations building efforts will matter and that backers will observe project owners' relations building behavior from past crowdfunding campaigns when deciding on whether or not to back their subsequent fundraising campaigns. Relations building efforts are trust and commitment building actions from project owners to backers. They demonstrate project owner's good faith and signal that the project owner desires that the exchange relationship continues into the future. We focus on two relations building efforts identified in Gruen et al. (2000) and Anderson and Weitz (1992): *pledge delivery performance* and *frequent communication*.

Positive exchange outcomes and relations lead to commitment in maintaining an exchange relationship (Brown et al. 2004; Lambe et al. 2001) through trust building. Since project owners use pledges, including product delivery schedules to facilitate backer participation in their crowdfunding campaigns, backers will maintain exchange relationship with project owners that maintain good pledge delivery performance by delivering on the specifics of their pledges. Since reciprocity is expected for exchange relationship to continue (Blau 1964), backers will maintain relations with project owners who deliver as promised by backing their subsequent crowdfunding campaign. Hence we hypothesize:

\textit{H1: Project owners with higher pledge delivery performance are more likely to be successful in a subsequent crowdfunding campaign.}

Prior exchange studies have shown that effective communication between participants is very important in exchange relationships (Anderson and Weitz 1992; Anderson and Narus 1984; Lee and Kim 1999). Regular and frequent communication between participants in an exchange should lead to all participants being better informed, and in turn foster more confidence among participants in the relationship leading them to be more willing to maintain their exchange relations
In the crowdfunding context, project owners providing backers with frequent updates after they have successfully backed their prior campaign can help earn their trust which in turn can lead to more exchange relationships. This is especially true if the project owner will delay or fail on their pledges delivery. Frequent communications from project owners will help keep backers informed, reduce their disappointments and, earn their trust while signaling project owner commitment to delivering expected outcome even if they have missed their promised deadline. Hence, we hypothesize:

**H2:** Project owners with higher post-funding communication (updates) frequency to backers are more likely to be successful in the subsequent campaign.

**Moderating effect of Timing and Temporal Proximity of Successive Campaigns**

The timing of an event is very crucial to the event’s performance. For instance, the timing of product launch affects new product performance (Bayus et al. 1997; Calantone and Di Benedetto 2012). Similarly, timing matters in the presentation of online recommendations to consumers as it determines if they will consider and accept it or not (Ho et al. 2011). For two related events (A and B) happening in succession, the timing of the latter event (B) creates a time difference (*temporal proximity*) between the events. The temporal proximity of two related events does not only affect the performance of the latter event (Moorthy and Png 1992), it can affect how individuals perceive the events (Peetz et al. 2010a; Peetz et al. 2010b), and how individuals react to the latter event (Kivetz et al. 2006). This effect of temporal proximity on individuals reaction to events has been documented across various disciplines, including marketing (Grégoire et al. 2009; Kivetz et al. 2006), and psychology (McCullough et al. 2003; Peetz et al. 2010b; Wohl and McGrath 2007), especially as it relates to individuals’ perception of the former event. Wohl and McGrath (2007)
document that individuals tend to be the more forgiving of a transgression as the event begins to feel far away in time. A finding which suggests that individuals may have diminishing sensitivity to an earlier event as time goes by and which supports the popular saying that *time heals all wounds*. Echoing this, Gregoire et al. (2009) find that customers’ desire to seek revenge from erring firms decrease with the passage time. In line with this thinking, temporal proximity may not just influence individuals’ perception towards a past event but can affect their actions towards a future event.

For crowdfunding campaigns by the same project owner, the *temporal proximity* of successive campaigns conceptualized as the time period between the delivery of the promises of the initial crowdfunding campaign and the launch of the subsequent crowdfunding campaign, may affect the performance of the subsequent campaign. This is because the temporal proximity between the campaigns will affect how the crowd perceives the actions of the project owner from the initial campaign, which will in turn affect how they contribute towards the success of her subsequent campaign. For instance, if the project owner failed to deliver on backers’ expectation, the absence of a reputation mechanism on the crowdfunding platform will imply that such transgression is not explicitly revealed in the project owner’s profile and over time, backers may “forgive” due to a diminishing sensitivity towards the transgression or even forget such transgression. Moreover, according to temporal construal theory (TCT) (Liberman and Trope 1998; Trope and Liberman 2003), events with higher temporal proximity will elicit concrete and low-level representations or details as compared with events with lower temporal proximity. Hence, the effect of the relations-building efforts from a prior campaign may not carry over to a subsequent campaign to a subsequent campaign as the temporal proximity between the campaigns decrease since its details of the campaign may have been lost. We therefore hypothesize:
$H3a$: The effect of pledge delivery performance from a prior campaign on a project owner’s subsequent campaign’s success is moderated by the temporal proximity between the campaigns such that the lower the temporal proximity the lower the effect of pledge delivery performance.

$H3$: The effect of post-funding communications frequency from a prior campaign on a project owner’s subsequent campaign’s success is moderated by the temporal proximity between the campaigns such that the lower the temporal proximity the lower the effect of post-funding communication frequency.

**Data and Methodology**

**Data**

To investigate our proposed hypotheses, we collected data on crowdfunding projects posted on the Kickstarter - one of the largest and most prominent reward-based crowdfunding platforms - in the product design and technology categories launched between January 2012 and May 2014. We select these categories because they deliver tangible products and are treated somewhat special by Kickstarter. Because we are interested in how relations from a prior crowdfunding impacts a subsequent crowdfunding campaign, we focus on project owners involved in serial crowdfunding. A significant amount of project owners are involved in serial crowdfunding (Briggman 2014; Janofsky and Loten 2015), with Stanko and Henard (2016) reporting as much as 15 percent in their study sample.

We take several steps to filter the initial dataset to arrive at the final sample which we used for analysis. First, we identified project owners who have engaged in serial-crowdfunding. Second, we identify their initial (prior) and subsequent campaign pairs. This resulted in a sample size of 864 containing two major groups of project owners – those whose initial campaign failed and those whose initial campaign succeeded. Because Kickstarter does not give the funds raised to project
owners whose campaigns failed – since it operates on the all-or-nothing principle, and because we are interested in post-funding relations, we cannot observe the relations building variables for project owners whose initial campaign failed. Hence we remove them from our sample although we do account for this sampling bias in our analysis. This left us with cases in which a project owner first experienced fundraising success in the initial campaign before a follow-up or subsequent crowdfunding campaign. Next, we remove cases were creators launched a second crowdfunding campaign before the end of the fundraising period of the initial crowdfunding campaign as these few cases could raise ambiguity issues on how the first campaign’s post-funding relations-building efforts is impacting the subsequent campaign. At the end of the filtering exercise, we end up with a final sample consisting of 372 observations of prior crowdfunding campaign-subsequent crowdfunding campaign pairs.

Measures

Dependent Variable - Since we are interested in the fundraising success of the subsequent crowdfunding campaign, that is if a subsequent crowdfunding campaign reached its funding goal or not, our dependent variable, Subsequent Campaign Success, is measured as a binary indicator. It takes the value of 1 if the subsequent crowdfunding campaign reached its fundraising goal, and 0 otherwise.

Independent Variables - Pledge Delivery Performance (PledgePerformance): measured as when a creator delivered the promised outcomes (usually rewards) to backers. It is coded as a binary variable with a value of 1 if the creators delivered the pledges on or before the promised time, and 0 otherwise.

Communication Frequency (CommFreq): measured as the weekly rate at which the creator updates her backers after a successful fundraising up until when the pledges are delivered (i.e. the
total number of updates up until reward delivery divided by the number of weeks from the end of the crowdfunding campaign to actual reward delivery).

Temporal proximity (TempProx): this is measured as the number of days between the shipments (delivery) of the products (expectations) promised from the prior or initial campaign to the launch of the subsequent campaign.

**Control Variables** - Several variables are included in the analysis to control for possible effects due to project specifics from both prior and subsequent crowdfunding campaigns – the number of rewards from prior campaign (PriorCamReward), the duration of prior campaign (PriorCamDuration), the funding goal of prior campaign (PriorCamGoal), the number of backers who contributed to the prior campaign (PriorCamBackers), the number of rewards for subsequent campaign (SubCamReward), the duration of subsequent campaign (SubCamDuration), the funding goal of subsequent campaign (SubCamGoal).

All non-categorical variables with high skewness and variability are log transformed while the descriptive statistics of all variables is presented in Table 1. The variable correlation matrix is provided in Appendix C.
Table 8: Descriptive Statistics

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</tr>
<tr>
<td>SubCampaignSuccess</td>
<td>372</td>
<td>0.707</td>
<td>0.456</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**Estimation approach**

We employ a Logit estimator to model our binary outcome, *Subsequent Crowdfunding Success*, as a function of our main independent variables and control variables. In order to examine the potential moderating effects of temporal proximity on the relationship between project owners’ relations-building efforts and subsequent crowdfunding success, we also examine models where temporal proximity is interacted with the relations-building efforts of interest. However, as is well-noted in the literature on non-linear models, “the interaction effect”, cannot be evaluated simply by looking at the sign, magnitude, and/or statistical significance of the co-efficient of the interaction term (Ai and Norton 2003). We follow the recommended approach by computing the average marginal effects of the relations-building efforts variables (*PledgePerformance* and
CommFreq) over the range of the moderating variable (Ai and Norton 2003; Norton et al. 2004; Pinzon 2016).

Since our primary analysis was conducted using only the sample (N=372) in which all project owners had an initial successful crowdfunding campaign before embarking on a subsequent crowdfunding campaign and in which we could observe their post-funding relations-building efforts, it raises the possibility of selection bias because it does not account for project owners whose initial crowdfunding campaign was a failure and whom we cannot observe their post-funding relations-building efforts. To address this endogeneity concern, we rely on the inverse probability weighting (IPW) two-stage procedure (Seaman and White 2013; Wooldridge 2007). In the IPW procedure, we first estimate the probability of a project owner’s initial crowdfunding campaign being successful and then use the inverse of the probabilities as a weighting factor in the second stage estimation - our model of interest (i.e. in estimating the likelihood of being successful in the subsequent crowdfunding campaign). Under the IPW procedure, the project owner’s prior crowdfunding campaign-subsequent crowdfunding campaign observation pairs in our sample used in the second stage for model estimation are “discounted” appropriately with a factor proportional to the probability of them being an observation with a successful prior crowdfunding campaign. IPW allows us to incorporate and use information for both types of project owners (those with initial crowdfunding campaign success and those with initial crowdfunding campaign failure) in our model.

As a form of further robustness check, we reran our analysis using a Probit models. The results remain qualitatively the same as the significance and directions of the parameter estimates did not change as seen in the results tables.
Results

To test our arguments in H1 and H2, we specified the following model:

\[ \Pr(\text{SubsequentCampaignSuccess}) = \beta_0 + \beta_1 \text{PledgePerformace} + \beta_2 \text{CommFreq} + \text{Controls} + \epsilon_j \]

We report the results for model estimation with and without IPW procedure. Although the magnitude of the co-efficients of the terms in the models with and without IPW vary, qualitatively the results remain consistent. Table 9 shows the results without IPW and Table 10 shows the results with IPW procedure for sample bias correction.

Table 9: Analysis Results (without IPW procedure)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 (Logit)</th>
<th>Model 2 (Logit)</th>
<th>Model 3 (Probit)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dependent Variable: Subsequent Campaign Success</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PledgePerformace</td>
<td>1.0293*** (0.2844)</td>
<td>0.5819*** (0.1590)</td>
<td></td>
</tr>
<tr>
<td>CommFreq</td>
<td>1.1811*** (0.4432)</td>
<td>0.5582*** (0.1988)</td>
<td></td>
</tr>
<tr>
<td>PriorCamGoal</td>
<td>0.1137 (0.1114)</td>
<td>0.1320 (0.1251)</td>
<td>0.0730 (0.0703)</td>
</tr>
<tr>
<td>PriorCamDuration</td>
<td>-0.0072 (0.0129)</td>
<td>-0.0112 (0.0155)</td>
<td>-0.0059 (0.0091)</td>
</tr>
<tr>
<td>PriorCamReward</td>
<td>-0.0262 (0.0209)</td>
<td>-0.0188 (0.0221)</td>
<td>-0.0116 (0.0130)</td>
</tr>
<tr>
<td>PriorCamBackers</td>
<td>0.6025*** (0.1137)</td>
<td>0.5769*** (0.1254)</td>
<td>0.3547*** (0.0739)</td>
</tr>
<tr>
<td>SubCamGoal</td>
<td>-0.5118*** (0.1101)</td>
<td>-0.4147*** (0.1241)</td>
<td>-0.2546*** (0.0711)</td>
</tr>
<tr>
<td>SubCamDuration</td>
<td>0.0148 (0.0113)</td>
<td>0.0121 (0.0128)</td>
<td>0.0080 (0.0074)</td>
</tr>
<tr>
<td>SubCamReward</td>
<td>0.0261 (0.0222)</td>
<td>0.0314 (0.0230)</td>
<td>0.0200 (0.0136)</td>
</tr>
<tr>
<td>Log PseudoLikelihood</td>
<td>-214.468</td>
<td>-185.061</td>
<td>186.147</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.096</td>
<td>0.178</td>
<td>0.173</td>
</tr>
</tbody>
</table>

Note * p<0.1, ** p<0.05, ***p<0.01 ; Robust Standard errors in parentheses

Model 1 is our base model (logit model without IPW procedure) and shows the result of the control variables in our analysis. Although not a focus of our study, we do note that the number of backers from the prior campaign (PriorCamBackers), one of our control variables, is a
significant predictor of subsequent campaign performance. This could be because backers tend to follow their favorite project owners and justifies the recent announcement of a "follow" feature on Kickstarter (Hurst 2016). Additionally, this result is interesting because it highlights the importance of backers to project owners concerning future activities that they may engage in after their initial crowdfunding campaign. It also lends credence to Stanko and Henard (2017) which reports that the number of backers is a good predictor of a crowdfunded product's future market performance.

Table 10: Main Effects Analysis Results (with IPW procedure)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 4 (Logit)</th>
<th>Model 5 (Logit)</th>
<th>Model 6 (Probit)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1.1199***</td>
<td>0.6267***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.3037)</td>
<td>(0.1613)</td>
</tr>
<tr>
<td>CommFreq</td>
<td>1.2304***</td>
<td>0.5591**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.5247)</td>
<td>(0.1851)</td>
<td></td>
</tr>
<tr>
<td>PledgePerformace</td>
<td>0.1205</td>
<td>0.1720</td>
<td>0.0012</td>
</tr>
<tr>
<td></td>
<td>(0.1227)</td>
<td>(0.1367)</td>
<td>(0.0088)</td>
</tr>
<tr>
<td>CommFreq</td>
<td>-0.0032</td>
<td>-0.0044</td>
<td>-0.0955</td>
</tr>
<tr>
<td></td>
<td>(0.0133)</td>
<td>(0.0148)</td>
<td>(0.0783)</td>
</tr>
<tr>
<td>PriorCamGoal</td>
<td>-0.0220</td>
<td>-0.0114</td>
<td>-0.0081</td>
</tr>
<tr>
<td></td>
<td>(0.0221)</td>
<td>(0.0253)</td>
<td>(0.0142)</td>
</tr>
<tr>
<td>PriorCamDuration</td>
<td>0.5493***</td>
<td>0.5016***</td>
<td>0.3137***</td>
</tr>
<tr>
<td></td>
<td>(0.1217)</td>
<td>(0.1329)</td>
<td>(0.0788)</td>
</tr>
<tr>
<td>PriorCamReward</td>
<td>-0.0220</td>
<td>-0.0114</td>
<td>-0.0081</td>
</tr>
<tr>
<td></td>
<td>(0.0221)</td>
<td>(0.0253)</td>
<td>(0.0142)</td>
</tr>
<tr>
<td>PriorCamBackers</td>
<td>-0.4545***</td>
<td>-0.3680***</td>
<td>-0.2273***</td>
</tr>
<tr>
<td></td>
<td>(0.1166)</td>
<td>(0.1280)</td>
<td>(0.0747)</td>
</tr>
<tr>
<td>SubCamGoal</td>
<td>0.0142</td>
<td>0.0121</td>
<td>0.0077</td>
</tr>
<tr>
<td></td>
<td>(0.0115)</td>
<td>(0.0121)</td>
<td>(0.0072)</td>
</tr>
<tr>
<td>SubCamDuration</td>
<td>0.0271</td>
<td>0.0332</td>
<td>0.0215</td>
</tr>
<tr>
<td></td>
<td>(0.0211)</td>
<td>(0.0238)</td>
<td>(0.0139)</td>
</tr>
<tr>
<td>Log PseudoLikelihood</td>
<td>-464.444</td>
<td>-402.362</td>
<td>-405.288</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.082</td>
<td>0.163</td>
<td>0.157</td>
</tr>
</tbody>
</table>

Note * p<0.1, ** p<0.05, ***p<0.01 ; Robust Standard errors in parentheses

Hypothesis 1 posits that project owners with higher pledge delivery performance were more likely to be successful in their subsequent crowdfunding campaign. Model 2 shows that pledge delivery performance is positively associated with subsequent crowdfunding campaign
success ($\beta=1.0293$, $p < 0.01$), providing evidence for hypothesis 1. Hypothesis 2 posits that project owners with higher post-funding communication frequency were more likely to be successful in their subsequent crowdfunding campaign. Again, Model 2 shows that positive higher post-funding communication frequency is associated with subsequent crowdfunding campaign success ($\beta=1.1811$, $p < 0.01$). Model 3, which is a Probit estimation without IPW also supports both hypotheses 1 and 2. Looking at the models estimated using the IPW procedure (Model 4, Model 5, and Model 6 in Table 10), we see that hypotheses 1 and 2 are supported.

To test our arguments in H3a and H3b, we specified the following model:

$$\Pr(\text{SubsequentCampaignSuccess})$$

$$= \beta_0 + \beta_1 \text{PledgePerformance} + \beta_2 \text{CommFreq} + \beta_3 \text{TempProx}$$

$$+ \beta_4 \text{PledgePerformance} \ast \text{TempProx} + \beta_5 \text{CommFreq} \ast \text{TempProx} + \text{Controls}$$

$$+ \epsilon_j$$
Table 11: Interaction Effects Analysis Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Without IPW</th>
<th>With IPW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 7 (Logit)</td>
<td>Model 8 (Probit)</td>
</tr>
<tr>
<td>PledgePerformace</td>
<td>0.8316** (0.3378)</td>
<td>0.4760** (0.1909)</td>
</tr>
<tr>
<td>CommFreq</td>
<td>1.3437*** (0.4471)</td>
<td>0.6784*** (0.2194)</td>
</tr>
<tr>
<td>TempProx*</td>
<td>0.0029** (0.0014)</td>
<td>0.0016 ** (0.0007)</td>
</tr>
<tr>
<td>PledgePerformace</td>
<td>0.0010 (0.0014)</td>
<td>0.0006 (0.0008)</td>
</tr>
<tr>
<td>TempProx*</td>
<td>-0.0020 (0.0015)</td>
<td>-0.0011* (0.0007)</td>
</tr>
<tr>
<td>PriorCamGoal</td>
<td>0.1178 (0.1412)</td>
<td>0.0610 (0.0810)</td>
</tr>
<tr>
<td>PriorCamDuration</td>
<td>-0.0093 (0.0157)</td>
<td>-0.0048 (0.0093)</td>
</tr>
<tr>
<td>PriorCamReward</td>
<td>-0.0203 (0.0225)</td>
<td>-0.0119 (0.0131)</td>
</tr>
<tr>
<td>PriorCamBackers</td>
<td>0.5674*** (0.1322)</td>
<td>0.3422*** (0.0758)</td>
</tr>
<tr>
<td>SubCamGoal</td>
<td>-0.4426*** (0.1329)</td>
<td>-0.2627*** (0.0766)</td>
</tr>
<tr>
<td>SubCamDuration</td>
<td>0.0119 (0.0131)</td>
<td>0.0077 (0.0076)</td>
</tr>
<tr>
<td>SubCamReward</td>
<td>0.0338 (0.0239)</td>
<td>0.0205 (0.0138)</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.197</td>
<td>0.193</td>
</tr>
</tbody>
</table>

Note * p<0.1, ** p<0.05, ***p<0.01 ; Robust Standard errors in parentheses

Again, we report the results for model estimation with and without IPW procedure in Table 11. As mentioned earlier, the results from an interaction effect cannot be interpreted by simply looking at the magnitude, direction, and significance of the co-efficients of the interaction terms. However, we need the results of the model to compute the average marginal effects of the relational action terms (PledgePerformace and
CommFreq) when they are moderated by temporal proximity (TempProx). The average marginal effects the relational factors are tabulated in Table 4.

Table 12: Computed Average Marginal Effects on Relations-Building Efforts

<table>
<thead>
<tr>
<th>PledgePerformance</th>
<th>CommFreq</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.00003***</td>
<td>-0.00056***</td>
</tr>
</tbody>
</table>

Although not hypothesized, we can see from Table 11 that lower temporal proximity is positively correlated with subsequent crowdfunding campaign success. Further, from the results presented in Table 12, we see that both relations-building efforts – pledge delivery performance and communication frequency - are associated with negative average marginal effects when moderated by temporal proximity, supporting both hypotheses that lower temporal proximity decreases the strength of the association between project owners’ relations-building efforts and subsequent crowdfunding campaign success. Put another way, the interaction between temporal proximity and pledge delivery performance is such that the effect of temporal proximity is more for project owners that did not meet their expected pledge delivery performance than those met it. Similarly, interaction between temporal proximity and communication frequency is such that the effect of communication frequency on subsequent crowdfunding campaign success decreases with lower temporal proximity.

Discussion

In this study, we set out to determine if project owners’ relations-building efforts from a prior crowdfunding campaign matters in the performance of their subsequent crowdfunding campaign, and to know if the temporal proximity of the project owner’s subsequent crowdfunding
campaign to her prior crowdfunding campaign may impact this relationship. Drawing from relational marketing literature, we find that the relations-building efforts of project owners from prior campaign matters for the success of their subsequent campaign and that the temporal proximity of the two campaigns affects the strength of this relationship. First, we find that project owners who have good pledge delivery performance by delivering on their pledges are more likely to be successful in their subsequent crowdfunding campaigns. This suggests that delivering pledges on time can be a commitment and loyalty building mechanism for project owners and may be a factor that motivates backers to contribute to their subsequent crowdfunding campaign. Hart and Johnson (1999) suggests that investing in actions, efforts and irrecoverable resources that help build trust with the customers, will make the customers favorably impressed and can engender true loyalty. Hence, project owners may need to take actions that improve their project implementation and delivery performance, especially if their pledges involve delivering tangible products at specific dates as this can ingratiate them with backers making them willing to support their subsequent crowdfunding campaign efforts.

Second, we find that project owners who provided regular updates after being funded and during the product development phase are more likely to be successful in their subsequent crowdfunding campaigns. This could be because regular communication serves as a trust-building mechanism (Anderson and Narus 1984; Mohr and Spekman 1994; Morgan and Hunt 1994); and could prove useful when projects owners have to delay on pledge delivery or fail on their projects. Further, project owners could use such communications to also inform backers about plans for subsequent crowdfunding campaigns and getting them primed.

Third, we find that the further apart in time (low temporal proximity) that the two sequential crowdfunding campaigns are from each other the less the strength of the effect of the project
owners relations-building efforts. In other words, as time goes by, the strength of the effect of a project owner’s relations-building efforts diminishes suggesting that the backers (crowd) may “remember” the relations-building efforts of a project owner for a short while. This is in line with studies that suggest that the passage of time can lead to individuals having a diminishing sensitivity to distant events or actions (Grégoire et al. 2009; Peetz et al. 2010b). Another possible explanation for the low temporal proximity effect on subsequent crowdfunding campaign success could be that with the passage of time, new backers who have no idea of project owners characteristics may have joined the crowdfunding platform. The absence of a previous interaction with the project owner may cause new backers on the crowdfunding platform to approach their subsequent crowdfunding campaigns unbiased by the project owners’ relations-building efforts from their prior crowdfunding campaign. So for project owners who may have engaged in relations-building in a prior campaign, they may want to capitalize on its effect by launching their subsequent crowdfunding campaigns as quick as possible while those who may have had negative relations with backers may want to wait a little longer before re-harnessing the backers.

**Implications and Limitations**

Theoretically, our study builds on and contributes to the information systems and marketing literatures in crowdfunding and relational marketing.

Our study extends concepts from relational marketing into the crowdfunding context by highlighting that relations-building efforts can be used to explain repeated success in crowdfunding campaigns. Prior works in relationship marketing have focused mostly on either offline settings (Adjei et al. 2009; Morgan and Hunt 1994; Samaha et al. 2014; Verhoef 2003) or online settings (Bilghihan and Bujisic 2015; Gan et al. 2007; Liang et al. 2008; Luo 2002) where exchanges are mostly contractual and have not considered crowdfunding a typically non-
contractual exchange setting. We contribute to the relational marketing and crowdfunding literatures by suggesting that relations-building efforts matter for project owners.

Further, our study expands on the emerging literature on serial crowdfunding (Kuppuswamy and Mollick 2016; Skirnevskiy et al. 2017; Yang and Hahn 2015), most notably Skirnevskiy et al. (2017), which reports that social capital built by project owners in prior crowdfunding campaigns positively impact the outcomes of their subsequent crowdfunding campaigns. Our work presents a possible rationalization on why building social capital on crowdfunding platforms matters by identifying the actions (relations-building efforts) through which project owners can build social capital and linking these actions to subsequent crowdfunding campaign success.

Moreover, Mollick (2016a) reports that the unique value of crowdfunding may be in the community. The findings we report in this study reiterate and evidence the importance of project owner’s relations-building efforts to backers and how it might influence backers’ actions towards project owners’ future events or activities. For instance, negative relations may lead to negative word-of-mouth from backers about a project owner’s product which might hurt future product sales in the case of product crowdfunding projects.

Practically, our study identifies relations-building efforts that might help creators build backers’ trust and loyalty which can pay off in their future crowdfunding campaigns. Hence project owners who may want to engage in future crowdfunding campaigns on specific crowdfunding platforms should invest in building positive relations with backers through their relations-building efforts. We highlight that the timing or temporal spacing of campaigns can be used strategically to achieve success in the subsequent crowdfunding campaigns. In essence, project owners who did
not invest effort relations building may have to wait a little longer before launching a subsequent crowdfunding campaign as that increases their chances of success.

Finally, although we focused on relations-building efforts in the crowdfunding context, the relations-building efforts identified in this study may also prove useful to entities that harness the online crowd for different tasks in other settings including crowdsourcing where there are possibilities of the crowd engaging in malicious behavior (Gadiraju et al. 2015).

Our study is not without its limitations. Our sample consisted of project owners who had experienced success in their initial crowdfunding campaign before embarking on their subsequent crowdfunding campaigns. Moreover, our sample is a convenient sample because we measure only the post-funding relations-building efforts of project owners who were successful in their initial crowdfunding campaigns as we can easily observe them. We do not measure the post-funding relations-building efforts for project owners who were unsuccessful in their initial crowdfunding campaign because we could not observe such actions. Together, these raise some potential bias and though we tried to correct for the selection issues with our estimation procedure, the generalizability of our findings can only be limited to those project owners who experienced prior crowdfunding campaign success before trying for a subsequent crowdfunding campaign. Future studies could survey a more general cross-section of project owners including those who failed in their initial crowdfunding campaigns to see if relations-building efforts will matter in determining the success of their subsequent crowdfunding campaigns.

Finally, although our study identifies project owners’ relations-building efforts as key factors from the prior campaign that can impact subsequent crowdfunding campaign outcomes, it is possible that there are other factors from project owners’ prior crowdfunding campaign which may impact the subsequent crowdfunding campaign which we may have omitted. Future studies
can identify and investigate these other factors and in so doing expand our knowledge of how activities from prior crowdfunding campaign may influence the performance of future ones.

Conclusion

Crowdfunding has been playing a significant role in our society and economy, driving innovation (Mollick 2016b; Stanko and Henard 2016; Stanko and Henard 2017), and creating new jobs and employment (Mollick 2016b). Given the emerging trend of serial crowdfunding and the high failure rates experienced by project owners on crowdfunding platforms, it is only appropriate that we examine if there are factors from the project owners’ prior crowdfunding campaigns that may impact the outcomes of their subsequent campaigns. This study identifies the post-funding relations-building efforts of project owners as a key factor and empirically shows that it does matter for the success of subsequent crowdfunding campaigns.
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CHAPTER 5: APPENDIX

Appendix A

Normal parametric linear model: The normal parametric linear model formulated was with variables that has been identified in prior literature as predictors of success. The model is a multivariate regression model and was estimated using the ordinary least squares (OLS). In OLS, the estimated coefficients $\beta$ minimizes the sum of squared errors in the model. The typical OLS equation is written as:

$$\mu'\mu = (y - X\beta)'(y - X\beta)$$

Where $\mu$ is the vector of errors, $y$ the vector out dependent variables, $X$ the matrix of independent variables, and $\beta$ the vector of estimated co-efficient. For our estimation, the outcome of the crowdfunding campaign at time $T$ ($\text{Outcome}_T$) is the dependent variable. The independent variables are the observed campaign creator’s social network size ($\text{SocNetsize}_{T-x}$) at a time $T - x$ before the target time $T$, the campaign goal ($\text{Goal}$), the observed number of contributors ($\text{NumCont}_{T-x}$) to the campaign at a time $T - x$ before the target time $T$, and the observed amount contributed ($\text{AmtCont}_{T-x}$) at time $T - x$ before the target time $T$. The estimation was done using R statistical package.

Generalized Additive Model (GAM): The GAM was modeled using the same predictor variables as was used in the normal parametric linear model. GAM typically incorporates the nonlinear forms that may exist in the predictors relationship with the dependent variable in order to have a better fit, especially in cases where simple transformation of the data way not capture
the relationship. GAM assumes that the relationship between the dependent variables is better captured by a functions of the predictor variable. Typical GAM model formulation is written:

\[ g(\mu) = \beta_0 + f(x_1) + f(x_2) + \cdots + f(x_n) \]

Where \( f(x_i) \) a smooth is function of the covariate or predictor \( x_i \) and \( \mu \) is the expected mean of the outcome. Our model uses the backfitting algorithm (Hastie 2015) to combine the smoothing and fitting methods. The predictors that varied with time (\( AmtCont_{T-x} \) and \( Cont_{T-x} \)) were fit with splines since they showed more nonlinear relationship to the outcome. We used the “gam” package in R for the estimation.

Data Collection Process

Our data was extracted from Kickstarter.com using web scraping agents.

To extract the data, we used Web Scraper\(^{18}\) a free chrome browser extension built for data extraction from dynamic web pages. Webscraper can be accessed at http://webscraper.io and an in-depth documentation of how to use the tool is also provided on the website. Data extraction using the scraper involves creating a plan or a sitemap of how the website for which data is to be extracted from should be traversed and what data and data types should be extracted. The documentation on the website covers this process in detail. The sitemap helps the scraper navigate the focal website for data extraction accordingly and extracts all the required data of interest which can then be exported as a csv file.

In order to extract campaign data from Kickstarter.com, we set up two data extraction agents to navigate the Kickstarter website at exactly 11.50 PM EST over the data collection period. The first data extraction agent is configured to extract the web links (URLs) of all new crowdfunding

\(^{18}\) The web scraping agent can be downloaded from webscraper.io
campaigns posted on the Kickstarter homepage on the given day up until the start time (11.50 PM EST) of the scraper. The extracted campaign URLs are converted into JavaScript Object notation (JSON) and provided to the second data extraction agent whose sitemap contains instructions on what data to extract while traversing the crowdfunding campaign websites associated with each URL. Once the scraping is complete for each day, the data is exported as a csv file and added to a database. This process was repeated daily until we gathered a sizeable amount of crowdfunding campaigns from which we then extracted the daily crowdfunding dynamics data from.

The data cleaning process involved removing all the cancelled projects and projects with no contributors. To remove cancelled projects, we identified all project campaigns that have the search word “Cancelled” in its title and removed such projects. Further, we removed projects that ran for a very short time and will not give creators the opportunity to make adjustments that can help them improve their chances of succeeding. We also removed projects that had funding goals of less than $5000 [chosen based on prior literature (Cordova et al. 2015; Mollick 2014)] as such amount is non-trivial.

References


19 To mark a project campaign as cancelled, Kickstarter includes “Cancelled” as part of the title of a crowdfunding campaign.
**FDM Model Pseudocode**

PROGRAM BuildFdmModel:

READ crowdfundingCampaignData

Sort crowdfundingCampaignData by start date of each crowdfunding campaign

FOR each crowdfunding campaign in crowdfundingCampaignData

  Sort observations in daily ascending order
  GET all dailyContribution
  FOR each dailyContribution

  COMPUTE logDailyContribution as log of dailyContribution

  END FOR

END FOR

FOR each crowdfunding campaign in crowdfundingCampaignData

  SET dynamics as logDailyContribution from time [0] to time [t]

  CALL rSmoothSplineFunction

  CALL rPredictFunction

  COMPUTE functionalDynamics from dynamics using rSmoothSplineFunction

  COMPUTE firstDerivative as first derivative of functionalDynamics using rPredictFunction

  COMPUTE secondDerivative as second derivative of functionalDynamics using rPredictFunction

END FOR

CALL rPredictFunction

SET all functionalDynamics to have equal knots using rPredictFunction

SET all firstDerivative to have equal knots using rPredictFunction

SET all secondDerivative to have equal knots using rPredictFunction

CALL rPrincipalComponentsFunction

GET all functionalDynamics

COMPUTE PcFunctionalDynamics using rPrincipalComponentsFunction

SET fdmFunctionalDynamicsPc as first 2 columns of PcFunctionalDynamics
GET all firstDerivative

COMPUTE PcFirstDerivative using rPrincipalComponentsFunction

SET fdmFirstDerivativePc as first 2 columns of PcFirstDerivative

GET all secondDerivative

COMPUTE PcSecondDerivative using rPrincipalComponentsFunction

SET fdmSecondDerivativePc as first 2 columns of PcSecondDerivative

FOR each crowdfunding campaign in crowdfundingCampaignData

COMPUTE functionalDynamicsPcScore as dot product of functionalDynamics and fdmFunctionalDynamicsPc

COMPUTE firstDerivativePcScore as dot product of firstDerivative and fdmFirstDerivativePc

COMPUTE secondDerivativePcScore as dot product of secondDerivative and fdmSecondDerivativePc

SET finalContributionAmount as logDailyContribution of final crowdfunding campaign day

END FOR

SET dynamicsData as a dataframe with functionalDynamicsPcScore and firstDerivativePcScore

SET fdmData as subset of dynamicsData for model building

SET subFinalContributionAmount as subset of all finalContributionAmount for model building

CALL rLinearModelFunction

COMPUTE fdmModel with fdmData as regressor and subFinalContributionAmount as predicted variable using rLinearModelFunction

END.

R Functions and Packages

rSmoothSplineFunction: is the smooth.spline() function in the “splines” package in R.

rPredictFunction: is the predict() function in the “splines” package in R.

rPrincipalComponentsFunction: is the prcomp() function in the “stats” package in R.

rLinearModelFunction: is the lm() function in the “stats” package in R.
### Appendix B

**Correlation Matrix for Variables in Chapter 3**

#### Pairwise Correlation Table

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**Number of observations in brackets.**

---

20 While number of backers and amount pledged are highly correlated as seen in correlation matrix and can bias our results through multicollinearity, as a robustness check we dropped each variable in the second stage model and re-estimated all parameter. The results remained qualitatively the same.
### Results for Post-funding Phase (chapter 3)

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<th>Product Characteristics</th>
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<td>0.1483*** (0.0189)</td>
<td>1.0415*** (0.1375)</td>
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<td>-1.2635*** (0.1174)</td>
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<td>-0.0017*** (0.0004)</td>
<td>-0.0065** (0.0026)</td>
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**Note**: *p<0.1, **p<0.05, ***p<0.01; Standard errors in parentheses*
### Appendix C

#### Correlation Matrix for Variables in Chapter 4

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