Archetypes of Crowdfunders' Backing Behaviors and the Outcome of Crowdfunding Efforts: An Exploratory Analysis of Kickstarter

Abstract

Crowdfunding is an emerging online mechanism for sourcing capital to support entrepreneurial ventures and innovative projects and it is becoming a viable alternative to traditional fundraising models. Due to the novelty of the phenomenon, the literature devoted to crowdfunding is nascent and scanty. As a result, many important questions have yet to be addressed. In particular, our understanding of how different the crowdfunders' backing behavior is from one another's is limited. Further, we have little knowledge of how the composition of different types of the crowdfunders is associated with the outcome of crowdfunding efforts. Using a large data set collected from Kickstarter, we attempt to address these questions. We conceptualize a typology of four archetypes of crowdfunders' backing behavior based on backing frequency and category concentration. These archetypes are category enthusiasts, portfolio masters, focused supporters, and casual wanderers. The results of our cluster analysis identify five clusters, four of which are aligned with the proposed typology and one of which represents one-time triers. Further, our logistic regression and OLS regression results show that the greater the ratios of casual wanderers and focused supporters, the greater the likelihood of fundraising success and the ratio of fund raised to initial goal. Interestingly, we also find that category enthusiasts and portfolio masters have the opposite effects on the fundraising outcomes. We discuss the implications of these findings and conclude this paper by discussing research limitations and recommending future research directions.

Keywords: crowdfunding, crowdfunder, typology, cluster analysis, crowdfunding outcome, backing frequency, category concentration

1. Introduction

Crowdfunding is an important, emerging online mechanism for sourcing capital to support entrepreneurial ventures and innovative projects. Crowdfunding is defined as the financing of a project or a venture by a group of individuals instead of professional parties (Schwienbacher and Larralde 2010). Crowdfunding allows individual founders of for-profit, cultural, or social projects to request funding from many individual funding backers, often in return for future products, equity, or some form of recognition (Mollick 2013). Typically, crowdfunding is implemented on an online platform, often with social network capabilities, for easy access and efficiency (Schwienbacher and Larralde 2010). Contrast to traditional capital sourcing models such as venture capitalists, crowdfunding can be characterized by unskilled crowdfunders, collective evaluation of proposed projects, greater transparency of investors and funding status, greater social influence, a wide variety of goals and rewards, and little or no geographical constraints. Crowdfunding has helped new ventures to raise billions of dollars (Massolution 2012) and the volumes and amounts of transactions have continued to increase. As the Jumpstart Our Business Startups (JOBS) Act passed in April 2012 in the US, crowdfunding efforts now may give funders equity stakes in return for their funding. Some of the notable crowd-funded platforms include Kickstarter, IndieGoGo, Crowdfunder, RocketHub, Crowdrise, Somoland, AngelList, to name a few.[1] Crowdfunding is inspired by micro-finance (Morduch, 1999) and crowd sourcing (Poetz & Schreier, 2012) and has become a viable alternative to traditional fundraising models. For example, of the fifty highest funded projects on Kickstarter, 45 have turned into ongoing entrepreneurial firms.

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[1] http://www.forbes.com/sites/chancebarnett/2013/05/08/top-10-crowdfunding-sites-for-fundraising/

Due to the novelty of the phenomenon, researchers have only recently begun to investigate crowdfunding. Accordingly, the literature specifically devoted to crowdfunding is nascent and scanty. Burtch, Ghose, and Wattal (forthcoming) investigated the antecedents and consequences of crowd-funded journalism projects and found that crowdfunding backers experience a decrease in their marginal utility from making a contribution when the amount previously pledged by other backers is already high. Similarly, Kuppuswamy and Bayus (2013) found that the likelihood a reward-based crowdfunding project receives additional backer support is negatively related to its past backer support and that this negative effect is positively moderated by time in the project's funding cycle. Agrawal, Catalini and Goldfarb (2010) examined whether crowdfunding is less influenced by geographic constraints on fundraising that are typical of traditional venture capital firms. Belleflamme, Lambert, and Schwienbacher (2012) compared two different forms of crowdfunding: individuals are offered either to pre-order the product, or to advance a fixed amount of money in exchange for a share of future profits and found that the entrepreneur prefers pre-ordering if the initial capital requirement is relatively small, and profit-sharing otherwise. Mollick (2013) examined the underlying dynamics of success and failure among crowdfunded ventures. He found that personal networks and underlying project quality are associated with the success of crowdfunding efforts, and that geography is related to both the type of projects proposed and successful fundraising. While these early studies have attempted to tackle some aspects of the dynamics of crowdfunders and project founders, many important issues around crowdfunding are yet to be addressed as even basic academic knowledge of its dynamics and structures is lacking (Mollick, 2013).

In particular, while prior research has examined how crowdfunding backers are influenced by past backers (Burtch, Ghose and Wattal, forthcoming; Kuppuswamy and Bayus, 2013), we have little understanding of how different the crowdfunders' funding behavior and strategy are from one another's. For example, some might focus on funding a specific category of projects while others might fund a wide range of categories. Further, some might be aggressive in that they fund a greater number of projects whereas others might be selective and fund a smaller number of projects. Understanding such differences in funding behavior and strategy among crowdfunders and identifying distinctive archetypes of the crowdfunders are important steps toward understanding how crow-funded markets function and how they can be designed effectively.

Another important question to address is how the composition of different types of the crowdfunders is associated with the funding outcomes of the proposed projects. While prior research has examined how project quality is associated with the success of crowdfunding efforts (Mollick, 2013), little is known about the association between crowdfunder composition and funding outcome. Do successfully funded projects tend to attract a particular type of the crowd? Or, do they attract a balanced mix of different types of the crowd? Does a composition of the funders signal the crowd certain information about the proposed project thus influence prospective funders' decision making? Answers to these questions may help the creators of projects effectively target the crowd to increase the likelihood of the success of their projects and also help the creators to predict the likelihood of the success of their projects based on the composition of the crowdfunders at any given time. This study intends to address these questions.

We investigate Kickstarter (http://www.kickstarter.com/), one of the leading crowd-funded markets. Kickstarter offers an online platform for the crowd to both create projects and fund them in exchange of some form of rewards. Following a tradition of exploratory studies about new phenomena in entrepreneurship (Rice, 2002; Tan, Shao and Li, 2012), this research attempts to make a first few steps towards an analytical understanding of crowdfunders and funding outcomes. Using a large data set collected from the Kickstarter platform, we aim to explore differences in funding behavior and strategies among individual funders and identify distinctive types. We also attempt to explore relationships between the composition of the individual funders of a given project and its funding outcome. Due to largely unknown nature of crowdfunders, this study is intended to be exploratory rather than confirmatory. The results of this study would help develop a framework of different types of crowdfunders and generate the agenda of future research on crowdfunding.

We first provide a brief description of Kickstarter to provide the study context. We then present our research methods and report data analysis results. We conclude with the discussion on the implications of this research for future crowdfunding research.

2. Study Context

Kickstarter is an online crowdfunding platform that provides tools to raise funds from the crowd for creative projects. In this platform, people known as creators create creative projects and seek funds from other people known as backers. Kickstarter offers 13 categories of projects, such as art, comics, dance, design, fashion, film & video, food, games, music, photography, publishing, technology, and theater. Since its launch in 2009, at the time of this writing, 4.2 million people pledged more than $638 million, funding more than 42,000 projects (www.kickstarter.com). Some of the high profile projects funded by Kickstarter include the Pebble[2] (an e-paper watch for iPhone and Android), Ouya[3] (an innovative video game console),

[2] http://www.kickstarter.com/projects/597507018/pebble-e-paper-watch-for-iphone-and-android
[3] http://www.kickstarter.com/projects/ouya/ouya-a-new-kind-of-video-game-console

and 3Doodler[4] (a 3D printing pen), which have raised $10.26M, $8.59M and $2.34M from initial funding goals of $100K, $950K and $30K, respectively.

Each project posted on Kickstarter is independently created, giving the creator full control over, responsibility for, and full ownership of his/her project. Project creators set a funding goal and deadline. If people like a project, they can pledge money and become a "backer." However, projects must reach their original funding goals in order to receive money pledged by backers. To date, 44 percent of projects have reached their funding goals.[5]

Project creators offer rewards to their backers. However, these rewards tend not to be monetary per se, but rather take non-monetary forms such as a copy of the finished book, a private screening of a film, and early access to a finished product. However, some of the art or humanitarian projects view their backers as patrons or philanthropists and provide them with nothing in return. Project creators are allowed to customize funding levels and corresponding rewards in any way they want as long as they conform to the guidelines of the platform.

3. Typology of Crowdfunders

Before we explore different clusters of crowdfunders with empirical data, we propose a framework that classifies them into distinctive types (see Figure 1). This framework helps guide our data analysis so that results are conceptually meaningful and interpretable.

We propose two dimensions that are deemed important to classify individual funders: backing frequency and category concentration. Backing frequency indicates how actively individuals back projects. Individual funders can infer the baking frequency of an individual

[4] http://www.kickstarter.com/projects/1351910088/3doodler-the-worlds-first-3d-printing-pen
[5] http://www.kickstarter.com/help/stats

funder based on his/her backing history and time he/she joined the site. As a result, backing frequency may influence other individuals when they make their backing decision. Category concentration refers to the extent to which an individual concentrate his/her funding on one or several categories. This information can be inferred by other individuals based on an individual's backing history. The degree of category concentration indicates whether an individual backer is a specialist or a generalist. Furthermore, it also indicates if she tends to exploit one particular category of project or to explore many different categories. This exploitative or explorative funding behavior of an individual backer may send a signal to other prospective backers how knowledgeable and experienced she might be in certain categories (March 1991). Taken together, these two dimensions – backing frequency and category concentration – not only inform who the individual backer is but also socially influence other backers.

By juxtaposing the two dimensions, we define four distinctive types of individual backers in terms of their backing behavior and strategy. We name them *category enthusiasts*, *portfolio masters*, *focused supporters*, and *casual wanderers*. Category enthusiasts back many projects in one or a few categories. They are more likely to be a specialist than a generalist. By exploiting a small number of project categories, they become knowledgeable and experienced. Portfolio masters back many projects in a wide range of categories. They are more likely to be generalists than specialists and are not afraid of exploring different categories of projects. Both category enthusiasts and portfolio masters take crowdfunding very seriously and use it as an important channel to invest in creative ventures. Focused supporters back a small number of projects in one or a few categories. They are interested in certain categories but are not quite dedicated to funding many projects. Finally, casual wanderers back a smaller number of projects scattered in a broad range of categories. They are unlikely to be a specialist in any one particular category.

Neither focused supporters nor casual wanderers take crowdfunding as a primary channel for investing.

Backing frequency	High	Portfolio master	Category enthusiast
	Low	Casual wanderer	Focused supporter
		Low	High
		Category concentration	

Figure 1. Typology of Crowdfunders

4. Data and Methods

4.1. Data Collection

Data for this study was collected using a software crawler. The crawler software traversed the Kickstarter.com website to collect data on a random sample of completed projects and backers to those projects. Care was taken so that the sample data collected was representative of the population of projects.

Our dataset includes 6,880 projects with USD as the primary currency. Descriptive statistics on the sample of projects is shown in Table 1. Overall, the product development category (especially the games and technology subcategories) attracted the most number of backers but also showed the lowest successful funding rate. Projects in the comics subcategory exhibited the highest success rate, while in general the performance art category (including dance, film and video, theater subcategories) exhibited high success rates.

Category	Subcategory	*N*	Avg Goal	Avg Duration	Avg Backers	Success Rate
Exhibit	Art	550	11331.92	39.21	52.75	18.00%
	Comics	205	10284.04	40.62	168.07	35.12%
	Photography	223	11083.05	41.09	41.91	13.90%
	Publishing	644	11023.88	40.62	68.64	11.34%
	Subtotal	***1622***	***11042.96***	***40.21***	***72.15***	***16.95%***
Performance	Dance	72	7937.97	37.69	34.44	25.00%
	Film & Video	2093	26528.90	40.70	113.40	25.75%
	Music	967	8902.98	41.42	84.65	19.96%
	Theater	237	9940.76	39.03	45.47	24.89%
	Subtotal	***3369***	***19905.51***	***40.72***	***98.69***	***24.01%***
Product	Design	556	32011.79	38.62	171.81	12.41%
	Fashion	190	15973.29	37.47	108.77	21.58%
	Food	342	21307.86	40.29	77.73	9.36%
	Games	502	57005.73	37.36	814.33	20.92%
	Technology	299	39898.68	38.60	325.44	15.05%
	Subtotal	***1889***	***36351.17***	***38.47***	***343.51***	***15.46%***
Total		**6880**	**22331.50**	**39.98**	**159.65**	**20.00%**

Table 1. Sample Descriptive Statistics

Figure 2 shows the distribution of projects by project funding goal as well as the average success rates by funding goal. The vast majority of projects sought between $5,000 and $100,000 in project funding (note the x-axis is in log scale), while several ambitious projects sought over $1M. Interestingly, we observe that the success rates of projects by funding goal exhibits a U-shaped distribution, with projects seeking limited funding (< $500) or extremely large amounts of funding (> $1M) being more successful than those in the moderate funding goal range. It seems that although more involved projects experience greater difficulties in fund raising, those with ambitious goals may be of higher quality and are thus able to successfully attain their fund raising objectives.

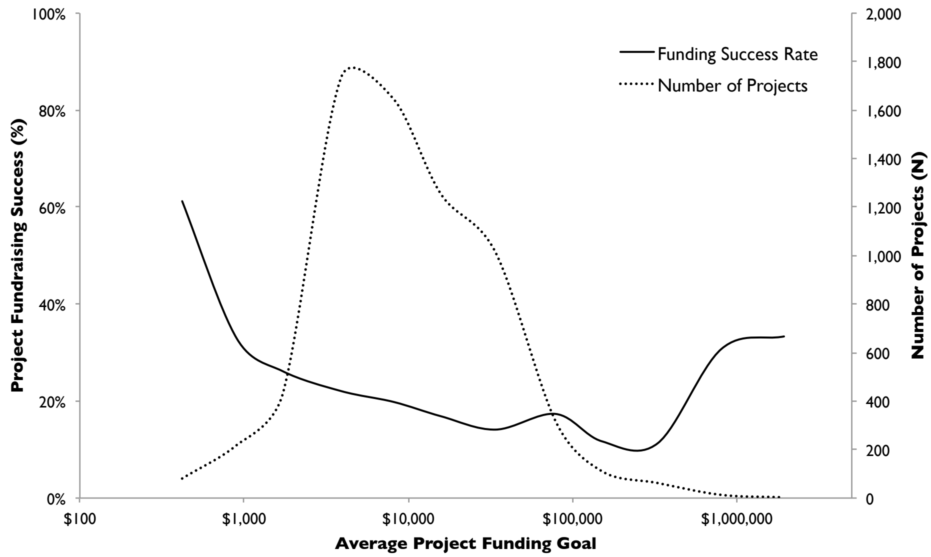

Figure 2. Success Rate by Project Funding Goal

Our dataset also includes 414,737 users / crowdfunders who are backers of the sample of projects. The backers on average have been with Kickstarter for 18.7 months and have backed an average of 6.02 projects. Also, 11,537 users (or 2.8% of the sample) were also project creators. It seems that many creators are also participating in funding other users' projects.

4.2. Analysis Approach

We use cluster analysis to classify the crowdfunders using their previous backing of projects in different categories and backing frequency. Cluster analysis allows researchers to discover empirically driven typologies or test theoretically developed ones (Punj and Stewart, 1983). We expect to find at least four clusters of crowdfunders (category enthusiast, focused supporter, portfolio master, and causal wanderer) with the typology of backers specified in Figure 1. More specifically, we perform K-means cluster analysis on the 400K+ unique backers. We started with a two-cluster solution and then increased the number of clusters until one of the following two conditions was met: (1) the added cluster contained an insignificant number of observations or (2) the added cluster was almost identical to one of the existing clusters (Moe, 2003).

Upon identifying distinctive clusters of crowdfunders, the association between the types of crowdfunders and project outcomes (e.g., project success, funds raised, etc.) will be explored using regression analysis. More specifically, the relative proportion of the different clusters of crowdfunders are regressed on project outcomes measures to determine which types of crowdfunders are strongest predictors of project outcomes.

5. Results

The results of the cluster analysis are summarized in Table 2. The final solution was with 5 clusters. Cluster 1 consists mainly of a large number of infrequent backers (60.1% of our sample). These backers have backed on average 1.9 projects and predominantly in one project category. Funders in this cluster have backed the performance art category (i.e., dance, film and video, music, and theater) most frequently, followed by the product development (i.e., design, fashion, food, games, and technology) category. As can be expected due to the infrequent backing activity, category concentration[6] is extremely high. We henceforth refer to these backers as "One-Time Triers". Cluster 2 represents the second largest cluster of backers (29.9% of our sample). These crowdfunders are characterized by relatively infrequent backing activities (i.e., backing frequency = 0.33 or approximately one project every 3 months) but their backing activity was spread across a variety of funding categories, as indicated by the low category concentration index. These backers are representative of the "Casual Wanderer" type in our classification. Cluster 3 consists of backers with relatively infrequent backing activity (i.e.,

[6] Category concentration was measured using the Herfindahl-Hirschman Index (HHI).

approximately 1.6 projects per month) that is focused on a limited set of funding categories (category concentration = 0.767), with the product development category being the most frequently sought funding category. These backers are representative of the "Focused Supporter" type in our classification. Cluster 4 consists of crowdfunders with very frequent backing activity (i.e., approximately 7 projects per month) that is highly concentrated on the product development funding category. These backers are representative of the "Category Enthusiast" type. Finally, cluster 5 consists of a small number (*N*=231) of crowdfunders that exhibit extremely high backing activity (approximately 21 per month) that is spread out across all funding categories (i.e., category concentration = 0.576). These crowdfunders are representative of the "Portfolio Master" type in our classification.

Cluster	**1** One-time Trier	**2** Casual Wanderer	**3** Focused Supporter	**4** Category Enthusiast	**5** Portfolio Master	**Total**
N	251,657	123,926	35,084	3,839	231	414,737
Total Projects Backed	1.94	6.94	23.10	73.57	241.57	6.02
Experience	17.30	23.06	14.11	13.10	11.63	11.63
Category (Performance)	50.05%	34.11%	14.80%	11.26%	16.85%	41.92%
Category (Exhibit)	14.60%	24.18%	12.22%	14.03%	20.51%	17.26%
Category (Product)	35.35%	41.71%	72.98%	74.71%	62.63%	40.81%
Category Concentration	0.998	0.546	0.767	0.702	0.576	0.841
Backing Frequency	0.15	0.33	1.61	5.63	20.99	0.39

Table 2. Five Cluster Solution

From this cluster analysis, there seems to be empirical support that the typology of crowdfunders offered in section 2 does exist. However, it seems that the results may be sensitive to scale of funding activity. In other words, given that when the number of projects backed is small, the concentration ratio (as measured by HHI) is inevitably high. In order to test the robustness of these five clusters, we repeated the cluster analysis while excluding the 172,528 backers with only 1 backing history and using the normalized HHI as the concentration index.[7] The results of the repeated cluster analysis were consistent with the ones presented before – a five-cluster solution emerged and the clusters exhibited the same patterns as those from the earlier analysis.

Thus far, we have not addressed the association between the types of crowdfunders and the outcomes of the crowdfunding projects. We explore this issue by combining the project outcomes with the composition of backers by type. Table 3 shows the results of the regression analysis. Model 1has project success (i.e., whether or not project funding goal was met) as the dependent variable, while Model 2 has the amount of funding raised (relative to initial fund raising goal) as the dependent variable. Given that the dependent variable in Model 1 is a binary outcome (i.e., 0 for unsuccessful and 1 for successful), we employ logistic regression. Since the amount of funding raised could exceed the initially set funding goal amount (i.e., percentage of goal raised > 1), we use OLS for Model 2. Also, given that the number of backers differs by project, we use the proportion of backers in each category as the main independent variable. The one-time trier category is used as the base case. Finally, we include as controls the projects initial funding goals, *Project Goal*, natural logged due to the skewed nature of this measure. We also control for the duration of the projects as longer projects have more time to meet the funding goals or raise more funds.[8] The results are summarized in Table 3.

[7] The normalized HHI is calculated as $(HHI - 1/N) / (1 - 1/N)$, where N is the number of projects backed. Normalized HHI ranges from 0 (completely evenly distributed across all categories) to 1 (completely concentrated in one category), whereas HHI ranges from $1/N$ to 1, and thus is sensitive to the scale of funding activity.

[8] We have also included a quadratic term for duration to see if there were any non-linear effects of duration. The quadratic term was not found to be significant.

	Model 1 Logistic Regression DV: Project Success	Model 2 OLS Regression DV: Percentage of Goal Raised
Constant	2.8502**	2.4073**
	(0.3257)	(0.1879)
ln(*Project Goal*)	-0.3693**	-0.1971**
	(0.0341)	(0.0190)
Duration	-0.0292**	-0.0059**
	(0.0026)	(0.0013)
Casual Wanderers (%)	1.9496**	0.5054**
	(0.2457)	(0.1460)
Focused Supporters (%)	4.8058**	2.1402**
	(0.4437)	(0.2566)
Category Enthusiasts (%)	-1.6808	-1.2392**
	(0.8640)	(0.4341)
Portfolio Masters (%)	-21.5169**	-3.6664**
	(2.0081)	(0.6405)
Number of Obs. (N)	6,343	6,343
Model Fit	$LR\ \chi^2 = 840.49^{**}$	$F = 16.16^{**}$
R^2	0.1437	0.0440

Significance Levels: $^{**}\ p < 0.01$, $^{*}\ p < 0.05$
Notes: 537 (= 6,880 – 6,343) projects which incomplete backer data was dropped from the analysis. Category dummies were included in the estimation but the results are not reported here for brevity.

Table 3. Association with Project Outcomes

As expected, the greater the fundraising goal, the less likely the project is to successfully meet its funding objectives (Model 1: $\beta = -0.369$ or odds ratio = 0.691, $p < 0.01$). Interestingly, it was found that the amount raised was also contingent on the extent of fundraising goals. In other words, projects with greater fundraising goals were not only less likely to reach its objectives but the percentage raised was likely to be less (Model 2: $\beta = -0.197$, $p < 0.01$). It seems that crowdfunders may be unconvinced by overly ambitious projects.[9] We also find that longer durations do not contribute to greater likelihood of project funding success or percentage raised. Actually, projects with longer durations were less likely to succeed (Model 1: $\beta = -0.0292$ or odds ratio = 0.971, $p < 0.01$) and resulted in less funds raised (Model 2: $\beta = -0.06$, $p <$

[9] We also estimated a model that includes a quadratic term for *Project Goal* to test for any non-linear effects (see Figure 2). The quadratic term was insignificant in Model 1 ($\beta = 0.0168$, ns) but positive and significant in Model 2 ($\beta = 0.057$, $p < 0.01$) indicating a U-shaped function of project funding goal (i.e., generally decreasing but increasing at high levels of project goals).

0.01). One would presume that greater slack in time for funding may provide greater exposure to backers and as a result lead to greater success rates or funding pledged. However, it seems that this was not the case.

More pertinent to our study, we find that the composition of the backers also had a significant impact on project outcomes. The results showed that attracting a greater relative proportion of casual wanderers (cluster 2) and focused supporters (cluster 3) was positively associated with project outcomes (both success and percentage of funding goal raised), while the opposite was true for category enthusiasts (cluster 4) and portfolio masters (cluster 5). Recall that casual wanderers and focused supporters are characterized by relatively infrequent backing activity, whereas category enthusiasts and portfolio masters exhibited high frequency in project backing. It seems that projects in crowdfunding platforms are more likely to successfully attain their fundraising goals when they appeal more broadly to the mass / casual "crowd." An alternative explanation may be that frequent crowdfunders are highly supportive of the crowdfunding phenomenon and are unconditionally backing many projects. Also, their extensive experiences have rendered them more risk neutral compared to less experienced backers. Given that pledged funds are disbursed only when projects meet their funding goals, frequent crowdfunders may back projects without bearing any risks. Less experienced backers, on the other hand, may be more risk averse and more prone to network effects and as a result may exhibit herding behaviors.[10] Although, our exploratory analyses based on cross-sectional dataset does not allow us to test the causes and mechanisms of the observed effects, the

[10] Interestingly, Burtch et al. (forthcoming) observed crowding-out effect where funders are less likely to contribute to a crowdfunding project as the level of others' contribution rises. The crowdfunding context in Burtch et al. was for crowdfunded journalism, a public good. Our context differs in that for most projects, the returns to funding are private and excludable, and thus do not suffer from the tragedy of the commons problem.

observation that the composition of the backers may influence crowdfunding project outcomes call for further research.

5. Discussion and Conclusion

In order to gain a deeper appreciation for the crowdfunding phenomenon, we develop a typology of crowdfunders both conceptually and empirically. We conceptualize based on backing frequency and concentration of category backed a typology of four archetypes of crowdfunders consisting of category enthusiasts, portfolio masters, focused supporters, and casual wanderers. Cluster analysis of a large dataset of crowdfunders on Kickstarter identified five clusters, four of which are aligned with the proposed typology and an additional one representing one-time triers. Subsequent analysis also suggests that the composition of backer types may have implications for crowdfunding project outcomes. More specifically, we observed that the greater the ratios of casual wanderers and focused supporters, the greater the likelihood of fundraising success and the ratio of fund raised to initial goal. Interestingly, we also find that category enthusiasts and portfolio masters have the opposite effects on the fundraising outcomes.

This study is by no means a definitive analysis of crowdfunders' behaviors. Rather, it is an initial empirical exploration that raises more questions than answers. That being said, this study does highlight the inherent and pervasive heterogeneity amongst crowdfunders and that this heterogeneity does seem to have an impact on crowdfunding project outcomes. Future research should do well to recognize the heterogeneity among crowdfunders and incorporate this in the theorizing and subsequent empirical testing. For example, different types of crowdfunders may be more or less susceptible to peer effects and as a result herding effects (or alternatively crowding-out effects) may or may not occur depending on the types of crowdfunders that initially contribute to a crowdfunding project. How crowdfunders react to projects owners' marketing and management activities (e.g., project updates) during the course of a project could also differ depending on the type of backers.

This study has numerous limitations. Our initial data collection efforts focused on acquiring rudimentary data on backers and projects outcomes. Also, our dataset is cross-sectional and as a result cannot test for causality (e.g., whether backer types influence project outcomes or projects influence the types of funders that back the projects) or allow us to analyze the dynamic nature of crowdfunding behaviors (e.g., how different types of crowdfunders influence one another dynamically). We are currently in the process of collecting a more detailed longitudinal dataset from Kickstarter so that such research questions may be more adequately addressed.

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