2018-12-19

Learning and Performance in Serial Crowdfunding

Hosseini Amereei, Seyed Abbas

UNIVERSITY OF CALGARY

Learning and Performance in Serial Crowdfunding

by

Seyed Abbas Hosseini Amereei

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF BUSINESS ADMINISTRATION

GRADUATE PROGRAM IN MANAGEMENT

CALGARY, ALBERTA

DECEMBER, 2018

Abstract

Entrepreneurship scholars have long been interested in serial entrepreneurs who engage in multiple entrepreneurial ventures. The opportunity to learn from experience and find ways to systematize entrepreneurship is intriguing, and new technological developments such as the availability of crowdfunding platforms provides new possibilities in this direction. Various theories have been suggested for why past experience may have both positive and negative effects on the subsequent performance of entrepreneurs. In this thesis, I ask: do the theories about the positive and negative effects of past entrepreneurial experience on subsequent performance apply to the crowdfunding context? Do positive effects prevail over negative effects in aggregate? What are the specific mechanisms through which the effects of past crowdfunding experience on subsequent crowdfunding performance are realized? Building on a comprehensive data collection effort, I find that with experience, crowdfunders tend to adjust their goal levels downward, which results in lower pledge amounts for their campaigns (although it increases their chances of success). They also learn through experience to design better campaigns by including more visual elements, more reward tiers, and lengthier descriptions, and these in turn improve subsequent performance. The evidence in this research generally supports the proposition that after controlling for these mediation effects as well as social capital, crowdfunding experience still has a positive direct effect on performance.

Keywords: Serial Crowdfunding, Serial Entrepreneurship, Learning by Doing, Goal Adjustment, Crowdfunding Campaign Design

Dedication

I dedicate my thesis work to my wonderful family. A genuine thank you goes to my parents for their tremendous support and motivation they gave to me during this journey. I would like to give a big shout out of thankfulness to my wife, Narges, for her unconditional love and support. A special feeling of gratitude to our phenomenal children, Sadra and Sarah, who have made me stronger, more fulfilled and patient than I could have ever imagined.

Finally, and most importantly, I thank God, for letting me through all the difficulties. I have experienced Your guidance day by day.

Thank you.

Table of Contents

List of Tables

List of Figures and Illustrations

List of Symbols, Abbreviations and Nomenclature

Symbol	Definition
API	Application Programing Interface
EERD	Enhanced Entity-Relationship Diagram
JSON	JavaScript Object Notation
ReST	Representational State Transfer

Chapter 1: Introduction

Motivation

Digital technologies are rapidly changing the nature of entrepreneurship (Nambisan, 2017). These new technologies present both a threat and an opportunity for research. On the one hand, there is a threat of the increasing obsolescence of previously accumulated knowledge on entrepreneurship, which may no longer be readily applicable to the technologically transformed business environment. On the other hand, many digital technologies are tracking, measuring, and producing analyzable data on entrepreneurial activities on an unprecedented scale, providing researchers with the opportunity to study entrepreneurship in new ways.

An example of such a transformative technology are crowdfunding platforms like Kickstarter.com, Indiegogo.com and GoFundMe.com which have reduced barriers to entry, increased access to innovation, and provided entrepreneurs with new ways of raising funds, engaging stakeholders, marketing, and generating sales (Best & Neiss, 2014; Mollick, 2014; Short, Ketchen, McKenny, Allison, & Ireland, 2017). Crowdfunding technology transforms certain aspects of entrepreneurship. It provides new affordances and imposes new constraints on entrepreneurs that did not exist before (Leonardi, 2011), but it also produces mass amounts of publicly available data on entrepreneurial activity through the web pages of crowdfunding campaigns and their associated creator profiles. Not surprisingly, researchers are taking advantage of this opportunity and a rapidly flourishing literature has spawned around crowdfunding as a subject of study (e.g., Agrawal, Catalini, & Goldfarb, 2015; Anglin, Wolfe, Short, McKenny, & Pidduck, 2018; Crosetto & Regner, 2018; Cumming, Leboeuf, & Schwienbacher, 2014; Du, Li, & Wang, 2018; Gerber & Hui, 2013; Oo, Allison, Sahaym, &

Juasrikul, 2018; Short et al., 2017; Stevenson, Ciuchta, Letwin, Dinger, & Vancouver, 2018; Yu, Johnson, Lai, Cricelli, & Fleming, 2017).

Within the crowdfunding literature, comparatively little attention has been given to serial or repeat crowdfunders, although a number of seminal contributions have initiated this sub-area of study (Butticè, Colombo, & Wright, 2017; Butticè, Orsenigo, & Wright, 2018; Skirnevskiy, Bendig, & Brettel, 2017; Yang & Hahn, 2015). Why is it important to study serial crowdfunding? This line of research is based on the premise that there is something to be learned about entrepreneurship by studying people who engage in entrepreneurial activity multiple times. This point was made forcefully in an editorial paper by Ian C. MacMillan in the first volume of the Journal of Business Venturing, written at the suggestion of an anonymous but "extremely successful" serial entrepreneur (Macmillan, 1986). The key argument is that most entrepreneurs, being single-instance entrepreneurs, have only experienced one entrepreneurial journey, whereas serial entrepreneurs can learn to systematize the practice of entrepreneurship into a social technology (Nelson & Nelson, 2002).

Many scholars embarked on this endeavor and an extensive literature has followed (Eggers & Song, 2015; Gompers, Kovner, Lerner, & Scharfstein, 2010; Ucbasaran, Wright, & Westhead, 2003; Westhead, Ucbasaran, & Wright, 2009; Wright, Robbie, & Ennew, 1997), sometimes with conflicting empirical results (Westhead & Wright, 1998). Interest in the study of serial entrepreneurship does not seem to have waned over the years and continues to remain high. Despite theories on why past entrepreneurial experience may have both negative and positive impacts on future entrepreneurial performance, empirical findings have mostly indicated an overall positive effect (Gompers et al., 2010; Lafontaine & Shaw, 2016; Paik, 2014; Ucbasaran, Westhead, & Wright, 2009), although conflicting results continue to be reported (Gottschalk, Greene, & Müller, 2017; Li, Schulze, & Li, 2009).

In general, the study of serial entrepreneurship has been fraught with difficulty. Serial entrepreneurs are comparatively rare, and for most of them the process of launching multiple ventures spans an entire career. Therefore, collecting reliable data on a decent-sized sample of serial entrepreneurs and their entrepreneurial activity over time is immensely difficult (Macmillan & Katz, 1992). That is why most empirical research that studies the effect of entrepreneurial experience does not actually track data on those entrepreneurial experiences, but rather resorts to self-response measures through surveys asking respondents to identify whether or not they have any previous business start-up experience, and sometimes also ask about the number of previous startups and whether or not they were successful (Starr, 1996).

The context of crowdfunding provides an excellent opportunity to learn about the patterns and effects of engaging in multiple entrepreneurial actions over time. It is not uncommon for serial crowdfunders to engage in multiple crowdfunding campaigns within the span of just several years, and data on each one of their campaigns is recorded and publicly available. Referring to Kim B. Clark's notion of "fast history", Clayton Christensen suggests that such contexts where developments occur in more compressed time frames are ideal for research that aims to investigate longitudinal patterns (Christensen, 1997).

Research Questions

As it is a very young area of research, there are still many questions to be answered about serial crowdfunding. In this thesis, we ask: do the theories about the positive and negative effects of past entrepreneurial experience on subsequent performance apply to the crowdfunding context?

Do positive effects prevail over negative effects in aggregate? What are the specific mechanisms through which the effects of past crowdfunding experience on subsequent crowdfunding performance are realized?

Outline and Summary

In Chapter 2, we first provide a brief background on crowdfunding as a recent technological phenomenon, and then move on to review some of the existing literature on serial entrepreneurship and serial crowdfunding. Building on theories of learning by doing, goal adjustment, behavioral decision making, and aspiration-feedback, we develop hypotheses regarding the effect of crowdfunding experience on subsequent crowdfunding performance, and specific mechanisms through which this effect is mediated.

Chapter 3 provides an extensive overview of our data collection process, data collection software architecture, and its components. It also describes the resulting dataset, the subsample used for this thesis, and the variables used for analysis in later chapters. Chapter 4 provides some initial descriptive analysis of the data including summary statistics, correlation matrix, as well as various data visualizations. I also describe a number of illustrative cases in order to provide more tangible examples of the underlying data.

Chapter 5 gets into econometric regression analysis to test the hypotheses developed in Chapter 2. The methods used are mostly based on Ordinary Least Squares (OLS) regression analysis. The chapter includes extensive robustness checks following the initial results. Chapter 6 provides a summary of the overall findings and some concluding remarks including suggestions for future research.

Chapter 2: Background, Theory and Hypotheses

Background on the Phenomenon of Crowdfunding

The rise of the internet and information technology has brought about a new age of computer mediated economic transactions (Varian, 2010) in which new forms of economic contract have become possible, and a variety of barriers to economic activity across time and space are increasingly removed. Entire forms of economic exchange previously deemed infeasible or inefficient are now possible with the help of various technologies that reduce production and transaction costs (Coase, 1937) and allow for more efficient operation of entrepreneurs in the economy in creating new opportunities as well as discovery of existing opportunities. This has resulted in novel forms of business models around which entire new categories of businesses have formed (Afuah & Tucci, 2001). Clear examples of this phenomenon that have started to change our way of life in a matter of a few short years include collaborative consumption (i.e. the sharing economy) models such as Uber, RelayRides, DogVacay and Airbnb, online marketplaces such as eBay, Alibaba, Craigslist and Kijiji, as well as crowdfunding platforms such as Kickstarter, IndieGoGo, GoFundMe, PledgeMusic and ArtistShare.

Crowdfunding in particular has been a transformative technology for entrepreneurs. It substantially expands the scope of people who can become entrepreneurs thereby contributing to the democratization of entrepreneurship (Bannerman, 2013). Crowdfunding compresses the value chain, allowing individuals, teams or organizations to take their offerings directly to market, when otherwise they would have to incur considerably higher costs in making payments (typically without sharing in risk and uncertainty) to players and intermediaries in other segments of the value chain before getting a product out to market.

However, the value of crowdfunding is not limited to the supply side. On the demand side, crowdfunding provides consumers with access to innovations otherwise unavailable in the market, lower prices due to removed intermediaries, and new ways to co-create value with suppliers and support non-profit causes and civic common goods projects they care about, among other benefits (Gerber & Hui, 2013). Nevertheless, crowdfunding as a novel mode of business is still in somewhat of an experimental stage, and involves significant risks for both funders and fund recipients (Hughes, 2013; Wells, 2013). Legal frameworks that regulate crowdfunding are still in their infancy but evolving around the globe (Coke, 2017). Canada in particular has been lagging behind leading countries in crowdfunding regulation by about half a decade to a decade (NCFA, 2016).

Background on Serial Entrepreneurship: The Impact of Previous Entrepreneurial Experience on Subsequent Performance

As discussed in the introduction, MacMillan suggested that the study of serial entrepreneurs can provide valuable insight into the nature of entrepreneurial action, because repeat entrepreneurs can learn and develop a systematic methodology of entrepreneurship (Macmillan, 1986). While MacMillan used the term "habitual entrepreneur," the term "serial entrepreneur" has become standard in the literature to refer to habitual entrepreneurs who launch multiple ventures sequentially, typically exiting one before they start the next, and is sometimes distinguished from portfolio entrepreneurs who do not necessarily exit and run multiple new ventures at the same time (Wright et al., 1997).

There are many ways in which prior entrepreneurial experience can improve the subsequent performance of an entrepreneur. Some of these mechanisms are as follows:

- One of the key mechanisms proposed in the literature is "learning by doing" (Audia, Locke, & Smith, 2000) whereby prior experience helps the entrepreneur develop their skills and expand their knowledge base, better preparing them for the next venture. Various areas in which the entrepreneur learns include learning about one's own strengths and weaknesses as well as those of the venture, learning about the environment and networks, learning about management methods, and learning about relationships (Cope, 2005).
- Venturing experience also exposes the entrepreneur to feedback from others, especially the market, thereby providing the entrepreneur with valuable information on what products and business processes may or may not work in the future (Ucbasaran et al., 2009).
- Prior experience also helps entrepreneurs develop their social capital and expand their network of relationships through which they may access or acquire valuable knowledge or resources in the future (Butticè et al., 2017).

It was established early on that the impact of previous experience on subsequent performance is not always necessarily positive, and that negative effects may also be at play (Parker, 2013; Starr, 1996). Some of the mechanisms through which prior entrepreneurial experience may have zero or negative effects on subsequent performance are as follows:

- Each venture is different, old experience may not apply to new context, and may even bias the entrepreneur's view based on small unreliable sample. Entrepreneurs may get fixated on what they deem to be the factors of success or failure in their previous experience, whereas those factors may no longer be relevant in the new context (Levinthal & March, 1993).

- Cognitive heuristics and biases and the complexities of the situation may result in the entrepreneur not correctly identifying the reasons for previous success or failure, and making poor judgments based on these incorrect or biased causal attributions (Eggers & Song, 2015).
- Given the immense difficulties of the entrepreneurial journey and the amount of financial and social pressures that it puts on the entrepreneur, there may be a fatigue effect whereby the entrepreneur is no longer motivated to work as hard, invest as much time, energy and resources, or to take as much risks as before (Wright et al., 1997).

There is also much discussion in the serial entrepreneurship literature on whether or not the impact of prior experience on performance differs if the previous experience was successful or failed. Here, the arguments and results have been widely conflicting. Some argue that entrepreneurs learn better from failed experience than successful experience (Kim, Kim, & Miner, 2009; Rerup, 2005), pointing out that failure is more likely to spark serious re-evaluation and modification of mental models and behaviors, and that success may lead to hubris and competency traps whereby the entrepreneur becomes overconfident and over-reliant on their existing knowledge and skills (March, 1991; Shepherd & Griffin, 2006). On the other hand, others argue that failed experience can have more damaging effects than successful experience. For example, the entrepreneur may suffer from social stigma and reputation loss (Cardon, Stevens, & Potter, 2011), loss of self-esteem, or misattribute the reasons for failure to external causes (Eggers & Song, 2015).

In terms of empirical results, most studies to date have found a generally positive effect of previous entrepreneurial experience on subsequent performance (Gompers et al., 2010; Lafontaine & Shaw, 2016; Paik, 2014; Ucbasaran et al., 2009). While a number of studies have found zero or insignificant effects (Gottschalk et al., 2017; Li et al., 2009), almost no studies have demonstrated the effects to be negative in aggregate. Two studies have found curvilinear effects: Toft-Kehler, Wennberg, and Kim (2014) found that positive effects only arise after experience reaches an expert level, and negative effects are observed before that. Parker (2013) found the effect of previous entrepreneurial experience to be positive overall but diminishing over time.

As stated earlier, collecting dynamic data over time on serial entrepreneurs and their activities has been difficult. Thus, much of the existing conflicting arguments have not been tested properly and conflicting empirical findings have not been reconciled. Parker (2013, p. 653) summarizes the state of affairs as follows:

> "Much of what we know about serial entrepreneurship comes from cross-section studies of entrepreneurs which often focus on the entrepreneur's current or most recent business … Analyses of the performance of serial entrepreneurs therefore embody something of a static character … it is becoming increasingly widely recognized that we need to move beyond simple snapshots of serial entrepreneurs and to look instead at the dynamics of their venturing spells in general and their venture performance trajectories in particular."

The Context of Serial Crowdfunding

The context of serial crowdfunding provides us with an excellent opportunity to examine the longitudinal patters of serial entrepreneurial activity over time. However, the context of serial crowdfunding has some unique characteristics and features as well, meaning that the same theories may not as readily apply, and that the findings may not be fully generalizable to the broader entrepreneurship context.

Butticè et al. (2018) identify three key characteristics that distinguish the serial crowdfunding context from the serial entrepreneurship context:

- First, much more information about crowdfunding campaigns (whether failed or successful) is available online publicly compared to information about private entrepreneurial ventures. Hence, there is a lot of opportunity to learn indirectly by observing other campaigns, rather than being only able to learn through experience. Therefore, they posit that the learning advantages of serial crowdfunding are heavily diluted compared to the serial entrepreneurship context.
- Second, the serial crowdfunding context lowers the cost of community building through social networks on a larger scale, but also involves networks with generally weaker ties such that these networks are unlikely to improve the serial crowdfunder's access to valuable and rare physical resources.
- Third, crowdfunding is generally a context of higher information asymmetry compared to traditional venturing. Many backers are often asked to pledge money before it is even clear that the product can be manufactured. This is because crowdfunders typically do not need to pass through rigorous due diligence and screening processes to engage in fundraising, unlike traditional entrepreneurs who approach venture capitalists and other investors. Furthermore, given the typically earlier stage of development of their projects, crowdfunders may not be able to disclose detailed information on their offering, or may

fear that doing so would expose them to threats of imitation and problems with intellectual property protection.

In addition, I suggest that there are further aspects of serial crowdfunding that make it unique. For example:

- Crowdfunding campaigns have specific design elements that all crowdfunders have an ability to manipulate within the rules of each specific crowdfunding platform, and with the design options provided by those platforms. Learning to improve these specific design elements is a unique factor in serial crowdfunding.
- Crowdfunding campaigns typically need to announce a public goal level for the amount of money they want to raise, and this goal level has an impact on their chances of success. Many platforms such as Kickstarter have an all-or-nothing rule whereby crowdfunders only receive money if the total amount pledged by backers exceeds the goal level before the deadline of the maximum campaign length (60 days on Kickstarter). Some platforms allow for the goal level to change, but others like Kickstarter do not. Learning the optimal goal level to set for a crowdfunding campaign is an important and unique factor in serial crowdfunding.

The Impact of Previous Crowdfunding Experience on Subsequent Crowdfunding Performance

To date, I have only been able to identify five published studies (Anglin, Short, et al., 2018; Butticè et al., 2017; Butticè et al., 2018; Skirnevskiy et al., 2017; Yang & Hahn, 2015), one unpublished working paper (Leboeuf, 2016), and two doctoral dissertations (Fan-Osuala, 2017;

Yang, 2017) on serial crowdfunding and the impact of previous crowdfunding experience on subsequent crowdfunding performance. Skirnevskiy et al. (2017) and Butticè et al. (2017) emphasize the role of accumulated social capital as a key mechanism through which previous crowdfunding experience has a positive impact on future performance. Leboeuf (2016) however, finds that in the case of previously failed projects, the social stigma effect hurts the performance of the crowdfunder's subsequent campaigns.

Butticè et al. (2018) find that the advantage of previous crowdfunding experience is most salient in contexts characterized by higher information asymmetry such as the video game, technology, and design categories in the Kickstarter platform. Yang and Hahn (2015) find that serial crowdfunders learn from their past failures, but not past successes, and they learn most when they learn both from their own previous campaigns and through the indirect experience that comes with backing other crowdfunding campaigns.

Total Effect

There are multiple reasons to expect that the performance of serial crowdfunders will increase as they launch more projects and become more experienced. First, serial crowdfunders typically launch multiple projects for very similar types of offerings over time. For example, a musician may raise funds for multiple albums, a theatre company may raise funds for multiple theatrical productions, a board game or card game designer will offer different varieties of their game, etc. therefore, we expect that the argument that previous experience will not apply to a "novel" subsequent context does not hold in the crowdfunding context, and instead the "learning by doing" effect is likely to improve the quality of the crowdfunder's offering and their ability to deliver.

Serial crowdfunders can also be expected to learn to better manipulate the modifiable design elements available to them in each subsequent campaign. Such design elements include the length of the campaign description, the language used and the pitching and storytelling capabilities employed in the description text, the number of level of reward tiers, the number and quality of visual elements such as pictures and videos used in the campaign description, the number and quality of updates, etc. We delve into this mechanism further below.

Another important element that the crowdfunder must make a decision on for each campaign is the goal level that must be publicly announced at the time of launch. When operating in an all-or-nothing rule system, the crowdfunder has to choose a goal level that is both satisfactory and feasible. Serial crowdfunders may learn to set more reasonable goal levels for their campaigns over time. We discuss this mechanism separately as well, below.

Information asymmetries are likely to be resolved over time for both the crowdfunder and backers. This can have positive effects as the crowdfunder figures out exactly what the costs of design, sourcing, production, and shipping will be. These are often not reliably estimable before the first campaign, resulting in many crowdfunders running into difficulty in delivering on their promises to backers. On the backer side too, it is easier to evaluate a crowdfunding campaign when its creator has a track record of previous campaigns.

Reduced information asymmetries may also have negative effects. Backers may be less willing to fund crowdfunders who have been demonstrably unsuccessful in previous projects (Leboeuf, 2016), although there is not much evidence that backers actually check the track record of projects they are interested in. Even if the crowdfunder has been previously successful, their subsequent campaigns are likely to have less of a “novelty” value for backers that have previously been exposed to the crowdfunder’s previous campaigns.

Since the complexities of a single crowdfunding campaign are less than a full launch of a venture, some of the arguments regarding the difficulty of learning from experience and understanding the causal factors that led to previous outcomes may not be as applicable in the crowdfunding context as the general entrepreneurship context. Furthermore, the level of fatigue caused by a single crowdfunding campaign may not be as much as a full venture. However, the possibility that these effects are still operative to some extent in the crowdfunding context cannot be ruled out.

Lastly, previous studies have focused heavily on the improvement of social capital as a mechanism through which experience benefits serial crowdfunders (Butticè et al., 2017; Skirnevskiy et al., 2017). Due to this factor being extensively studied before, in this study we control for this factor in order to focus on other mechanisms. Overall, even after controlling for social capital, we expect the positive effects of experience are stronger than the negative ones, and thus the aggregate total effect of crowdfunding experience on subsequent performance is predicted to be positive (see also Figure 1):

Hypothesis 1: Crowdfunding experience is positively associated with campaign performance.

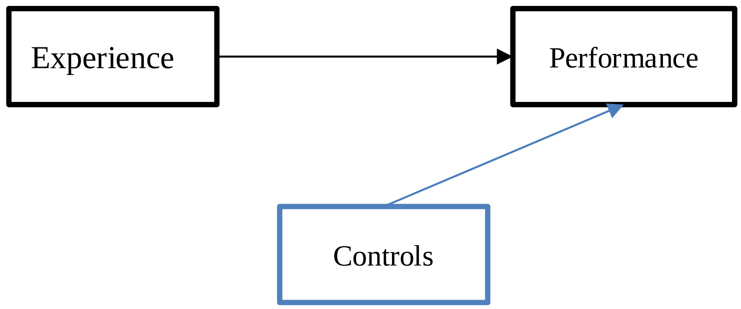

Figure 1. Base model of the impact of crowdfunding experience on performance

The Mediation Effect of Goal Level

Although traditional entrepreneurs are not required to publicly announce their target revenues at launch, setting goal levels is a key requirement in crowdfunding campaigns. When operating in an all-or-nothing rule system like that of the Kickstarter platform, setting the right goal can be the make-or-break factor in campaign success and performance. The crowdfunder has to choose a goal level strategically, such that is both satisfactory and feasible, and that it elicits a positive response from backers. Over time, serial crowdfunders are likely to improve their goal setting skills. As information asymmetry is reduced and crowdfunders gain a better understanding of the scale and costs associated with their projects, they are also better able to identify ways to save on costs in the future and improve the efficiency of their work. This allows them to set lower goal levels to maximize their chances of success.

Backers are unlikely to contribute to a crowdfunding campaign if they evaluate its goal to be unreachable, because they would then see the campaign as unlikely to yield them the rewards described. On the other hand, if the goal level is too low, backers may doubt the feasibility calculations of the crowdfunder and by extension their capability to deliver on the campaign's promised rewards.

I argue that first-time crowdfunders are more likely to set overly optimistic goal levels for their projects because of psychological heuristics and biases such as availability effects (Tversky & Kahneman, 2004). Crowdfunding is often valorized in popular media, and cases of successful campaigns raising millions of dollars are overrepresented in public discourse compared to their actual statistical likelihood. Therefore, this is likely to engender a biased estimate in the minds of first-time crowdfunders, of the amounts of money that can be feasibly raised through crowdfunding. This effect is similar to the finding that people in the general population who have watched a movie about sharks overestimate the probability of being killed by a shark, because imagining cases of such deaths is more available to their memory (Hertwig, Pachur, & Kurzenhäuser, 2005). This availability heuristic compared with the general finding in the literature that entrepreneurs tend to be over-optimistic (Busenitz & Barney, 1997), suggest that first-time crowdfunders are likely to set higher-than-reasonable goal levels for their crowdfunding campaigns.

With experience, I suggest that serial crowdfunders will learn to set more reasonable goal levels for their campaigns. Ucbasaran, Westhead, Wright, and Flores (2010) suggest that the mechanism of optimism adjustment is an important way in which repeat entrepreneurs learn from failure. However, their arguments and results suggest that serial entrepreneurs are less likely to adjust their optimism than portfolio entrepreneurs, because they are too emotionally invested in each venture to elicit correct judgments about the reasons for failure. In the context of serial crowdfunding, since launching a new campaign after a failed one is relatively inexpensive and each crowdfunding campaign experiment is less involving, the barrier to learning suggested by Ucbasaran and colleagues is unlikely to be in effect.

Another theoretical framework supporting the notion of goal level adjustment over time is the aspiration-performance feedback theory, first formulated by Cyert and March (1963). Applying this theory to the entrepreneurship context, entrepreneurs have aspiration levels when engaging in entrepreneurial action, and continually evaluate their performance relative to this aspiration level. Failure to meet aspiration levels will result in either discontinuing the course of action, or adjusting the aspiration level accordingly. Serial entrepreneurs are likely to gain a better understanding of what goal levels are feasible and reasonable for crowdfunding campaigns as they gain experience, and are thus likely to downwardly adjust their goal levels in subsequent campaigns. Hence:

Hypothesis 2: Crowdfunding experience is negatively associated with campaign goal level.

Cases of enormous success where a crowdfunding campaign raises much more money than their goal level are statistically rare phenomena despite their apparent salience in media. Most successful crowdfunding campaigns barely manage to pass their goal level targets. Thus a downward adjustment of goal levels is likely to decrease the total amount of money pledged to the campaign, even if it increases the likelihood of that amount surpassing the goal level. Thus, if we measure performance as amount pledged, goal level is likely to partially and negatively mediate the relationship between experience and performance (See also Figure 3):

Hypothesis 3: The effect of crowdfunding experience on performance is partially and negatively mediated by goal level.

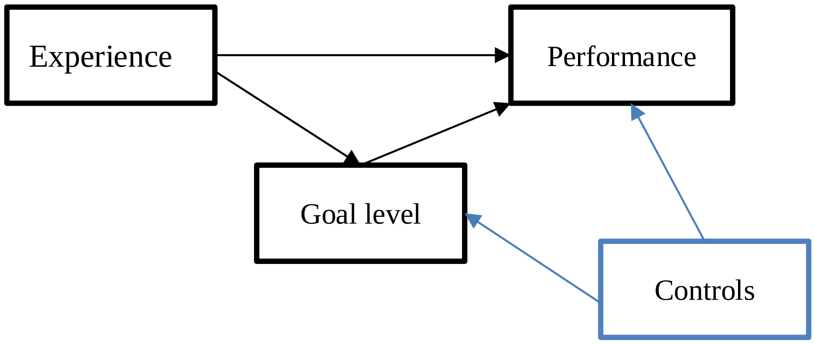

Figure 2. Goal level mediates the impact of experience on performance

The Mediation Effect of Campaign Design

Campaign design capabilities are very important factors in the performance of crowdfunders. Some studies employing machine learning techniques have shown that the success of crowdfunding campaigns can be predicted with relatively high accuracy rates (60%-80%) just by examining the computer-identifiable design features of the campaigns such as whether or not a video is present, number of reward tiers, length of campaign description, length of campaign blurb, campaign category, etc (Etter, Grossglauser, & Thiran, 2013; Greenberg, Pardo, Hariharan, & Gerber, 2013; Kamath & Kamat, 2018; Mitra & Gilbert, 2014). Many of these studies have found that the presence of visual elements such as pictures and videos is one of the strongest predictors of success.

Other studies have also confirmed that specific design elements are important. For example, Du et al. (2018) have found that when choosing the number of reward tiers, there is an inverted U shaped relationship indicating an optimal balance where the number is not too high and not too low. Multiple studies have shown that the language used in crowdfunding campaign descriptions is strongly associated with performance (Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018).

Overall, the existing literature suggests that campaign design is an important factor in the success and performance of crowdfunding campaigns, but no study has taken a longitudinal perspective to see whether or not campaign design improves over time in serial crowdfunding. We suggest that improved ability in campaign design is one of the key manifestations of learning by doing in the serial crowdfunding context. Hence, we posit that with additional experience, serial crowdfunders will improve the design of their campaigns:

Hypothesis 4: Crowdfunding experience is positively associated with improved campaign design.

Given the existing literature on the importance of campaign design in the performance of crowdfunding campaigns, we posit that when campaign design improves with experience, this in turn improves the performance of serial crowdfunders' campaigns. Since this is only one of the mechanisms through which experience impacts performance, we hypothesize a partial mediation relationship (See also Figure 2):

Hypothesis 5: The effect of crowdfunding experience on performance is partially and positively mediated by campaign design.

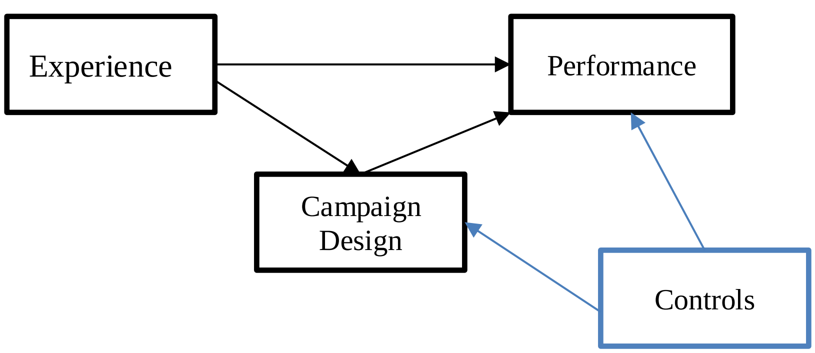

Figure 3: Campaign design mediates the impact of experience on performance

Decomposing Direct and Indirect Effects

Having identified two mediators of the relationship between crowdfunding experience and subsequent performance, it is interesting to hypothesize about the direct effect that would remain in the relationship between experience and performance once these indirect effects and other factors like social capital are controlled for.

As argued earlier, other than the mechanisms of social capital, campaign design, and goal level adjustment, multiple other ways exist in which experience may have a positive or negative impact on performance in crowdfunding. While I suggested that some of the hypothesized negative mechanisms in the serial entrepreneurship literature do not readily apply to the crowdfunding context, other mechanisms such as fatigue, loss of novelty appeal, and biased judgment may still be at play.

However, the ways in which experience could positively impact performance through learning-by-doing and improving the quality of offering are very powerful. In line with the serial entrepreneurship literature which seems to have found in general more evidence in support of positive effects than negative effects of experience, here we hypothesize that after controlling for indirect effects of campaign design, goal level, and social capital, the positive effects of experience still outweigh the negative ones. Thus, we predict that in the model of Figure 4, the direct effect of experience on performance will be positive:

Hypothesis 6: After controlling for the indirect effects of crowdfunding experience on performance through campaign design and goal level, experience still has a positive direct effect on performance.

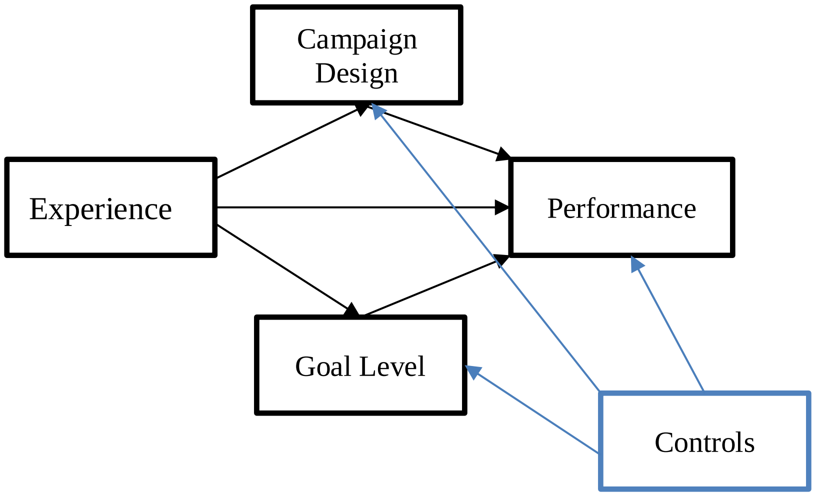

Figure 4. Direct and indirect effects of crowdfunding experience on performance

Chapter 3: Data and Variables

I selected the Kickstarter crowdfunding platform (www.Kickstarter.com) as the focus of study because it is the market leader in the crowdfunding industry, with more users and projects than any other platform. It is considered mainly a reward-based platform, to be distinguished from donation-based platforms like GoFundMe.com where backers do not expect to receive anything in return for their pledges, or more recently available equity-based platforms like Fundable.com where backers receive ownership shares in the companies they fund.

Kickstarter was launched in the United States in 2009, and by the time of writing in October 2018, more than 422,000 campaigns have been launched on this platform, among which 36% have successfully raised funds summing up to more than $3.5 Billion USD[1]. Each campaign has publicly available webpage that remains online even after the campaign is over, regardless of the outcome. Since Kickstarter refers to these campaigns as “projects” in this section we use the terms “project” and “campaign” interchangeably.

Not all of the collected data is used in this thesis, but a goal of this research has been to create a database that is useful for a series of future research projects. In this section I describe the overall data collection process and software components, but also describe the particular subset of the data used for the analysis in subsequent chapters.

---

[1] https://www.kickstarter.com/help/stats

Data Collection Software Architecture and Data Structure

A comprehensive software architecture was devised to collect data from the Kickstarter platform, similar to that of the CrowdBerkley project reported in Yu et al. (2017). An overall schematic of the data collection software architecture can be seen in Figure 5.

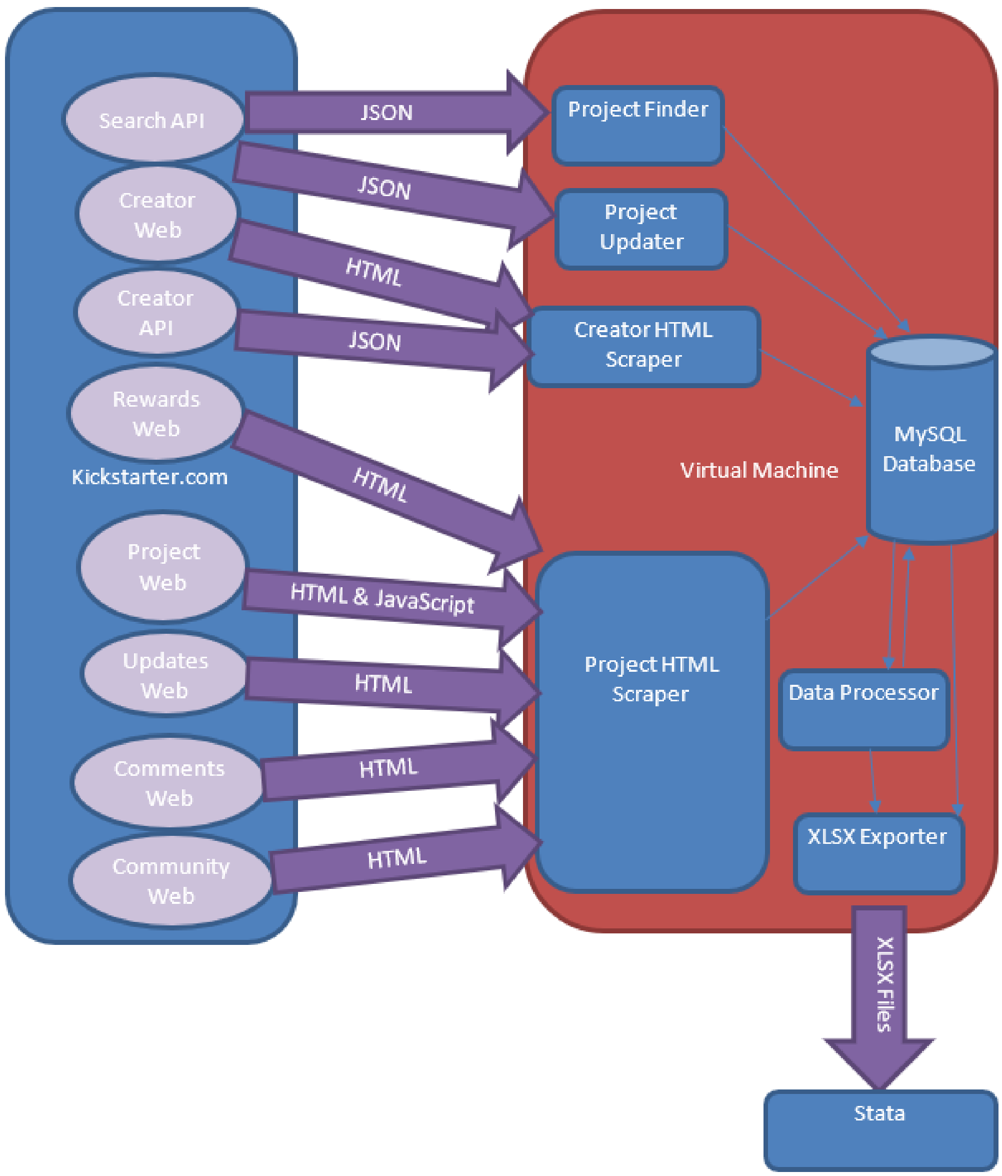

Figure 5. Data Collection Software Architecture

We collected various attributes of Kickstarter projects, creators, categories and locations from its website (web pages and ReST endpoints). In total, we have created seven tables in our MySQL database: locations, creators, projects, categories, comments, posts (updates) and rewards. Table 1 shows the list of all tables and their current number of columns and rows. The data was last updated in August 2018.

Table 1. List of MySQL tables to store Kickstarter data

Table Name	**Rows Count**	**Columns Count**
Categories	169	6
Comments	2,117,236	6
Creators	325,882	20
Locations	23,006	11
Posts	1,813,810	9
Projects	395515	126
Rewards	3,075,370	11

There is a parent-child relationship between the tables. The schema of the data can be illustrated by an Enhanced Entity-Relationship diagram EERD displayed in Figure 6.

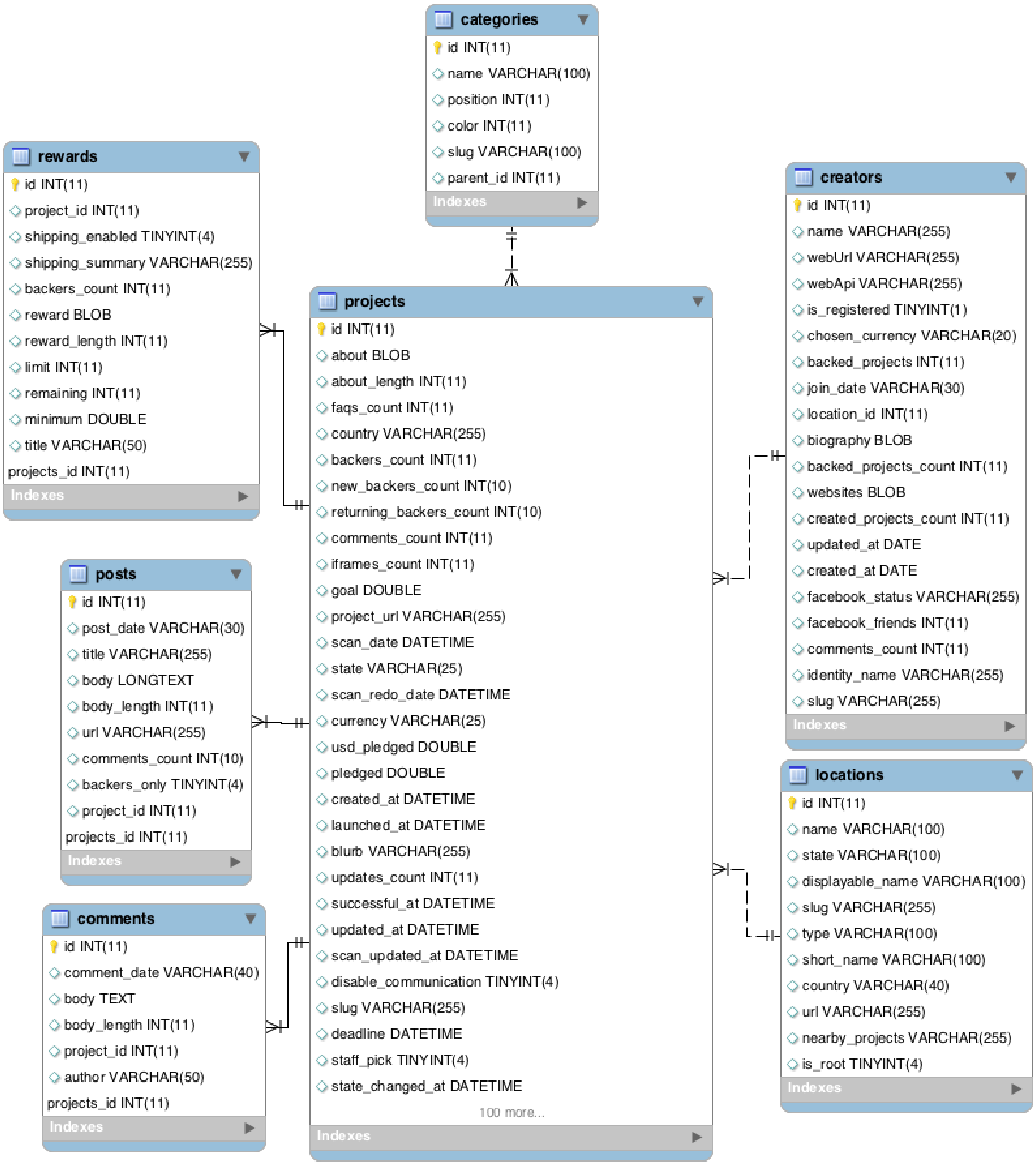

Figure 6. Enhanced entity-relationship diagram (EERD) of the Kickstarter database

Data Collection Software Components

A number of distinct software applications such as Project Finder, Project Updater, Project HTML Scraper, and Creator HTML Scraper were developed for the purpose of this project. This breakdown of components evolved over time, in order to solve various challenges and handle several constraints in the automated data collection process. Some of those limits are as below:

1. There is no complete list or directory of all URLs of campaign pages available, but the Kickstarter platform has some searching capabilities as well as an undocumented Application Programming Interface (API) that can be used to access these URLs and the data contained in them. However, each search query returns a limited number of results, so a distinct component was developed to systematically try different search queries such that the combined list of results covers as much of the Kickstarter platform as possible.
2. The number of remote calls to HTML pages allowed by Kickstarter is limited. As a standard security measure, Kickstarter blocks IPs that make many requests to their host(s) to avoid any possibility of DDOS (Denial of Service) attacks. So, I had to create a separate package for Projects HTML Scraper as well as Creators HTML Scraper to run according to certain schedules with idle times incorporated in between scraping processes.
3. In some cases the Kickstarter API has a random signature and token that expires in few hours. This forces the web crawler to act quickly to collect the data from the API before it expires, but it cannot be too quick as to flag our IP for blocking. To overcome this challenge, we had to develop another component to renew these tokens when needed.

Project Finder

This component basically calls the main search API to find a list of projects in every country, category, location, etc. depending on the particular search parameters of each query. For each search criteria, the search API returns up to 2,400 projects so we had to develop an algorithm to narrow down the cases with over 2,400 results, by adding more search parameters. For example, searching for all projects launched in Dallas returns more than 2,400 projects (as of the time of writing, 3080 projects) so we have to consider more search parameters (e.g. category) to narrow down the list. We can do this by searching for all projects launched in Dallas in the Art category, or the Comics category, etc. We tweaked the ordering of the narrow-down variables to achieve the best coverage and performance among all possible combinations.

The output of the API is a JSON object with 7 attributes as shown in Figure 7.


```
{
    "projects": [⟺],
    "total_hits": 3,
    "live_projects_count": 0,
    "past_projects_count": 3,
    "seed": 2545328,
    "search_url": "/discover/advanced?sort=most_funded",
    "has_more": false
}
```


Figure 7. Main JSON object of Kickstarter search API

The “projects” field is a JSON array of the found projects. The Project Finder component collects and stores all the found projects with their attributes listed in the JSON output. An example of project JSON is displayed in Figure 8.

```
{
    "projects": [
        {
            "id": 1226831187,
            "photo": {↔},
            "name": "Technical Weatherproof Outerwear with Style",
            "blurb": "One Man Outerwear and Mia Melon, leaders in technical outerwear with style and
                on trend designs, using special developed fabrics",
            "goal": 40000,
            "pledged": 44780,
            "state": "successful",
            "slug": "technical-weatherproof-outerwear-with-style",
            "disable_communication": false,
            "country": "CA",
            "currency": "CAD",
            "currency_symbol": "$",
            "currency_trailing_code": true,
            "deadline": 1436810572,
            "state_changed_at": 1436810572,
            "created_at": 1432845643,
            "launched_at": 1433786572,
            "staff_pick": true,
            "is_starrable": false,
            "backers_count": 279,
            "static_usd_rate": 0.80381071,
            "usd_pledged": "35994.6435938",
            "converted_pledged_amount": 44780,
            "fx_rate": 1,
            "current_currency": "CAD",
            "usd_type": null,
            "creator": {
                "id": 479095109,
                "name": "Todd Listwin",
                "is_registered": true,
                "chosen_currency": null,
                "avatar": {↔},
                "urls": {↔}
            },
            "location": {
                "id": 9807,
                "name": "Vancouver",
                "slug": "vancouver-ca",
                "short_name": "Vancouver, Canada",
                "displayable_name": "Vancouver, Canada",
                "localized_name": "Vancouver",
                "country": "CA",
                "state": "BC",
                "type": "Town",
                "is_root": false,
                "urls": {↔}
            },
            "category": {
                "id": 7,
                "name": "Design",
                "slug": "design",
                "position": 5,
                "color": 2577151,
                "urls": {
                    "web": {↔}
                }
            },
            "profile": {↔},
            "spotlight": true,
            "urls": {↔}
        },
```


Figure 8. A project, a JSON output of Kickstarter search API

Project Updater

At any given time, some projects are live so their attributes such as backers_count, pledged, faqs_count keep changing. Even past projects have some changing attributes such as comments_count and updates_count. In order to keep our databases up-to-date, we have developed another software component to redo the search and update the changing attributes of the existing projects. The component is called Project Updater.

Project HTML Scraper

Not every project attribute of interest for study (e.g. project description) is listed in the JSON output so we have developed another software component that scrapes the HTML pages and stores the HTML elements as auxiliary variables in our databases. This is the most time-consuming component because 1) it loads, reads, parses and stores heavy web pages, and 2) Kickstarter blocks repetitive calls so the application needs to work with a schedule of time intervals between runs.

Creator HTML Scraper

Similar to the Project HTML Scraper, not every piece of data we need on the project's creator is listed in the JSON output. This component is in charge of scraping creator related HTML elements, which are two different kinds of profile pages on the Kickstarter platform.

Data Processor

Many useful new variables can be generated through computations on existing data points. While many of these computer variables are generated later in Stata, some of them are easier to create when the data is structured in a relational database rather than a flat spreadsheet. These variables are created within the MySQL database by the Data Processor component. They include variables such as creator success rate, project order, previous project backers count, previous project location, days since first launch and much more.

Merged Dataset

Data from various MySQL tables along with calculated variables were merged to create a combined data table that could be converted to the format of a flat spreadsheet (rather than a relational database) so that it could be handled in statistical software applications like Stata for econometric analysis and data visualization software like Tableau for descriptive analysis.

In total, our data collection software was able to find 395,515 campaigns (number of rows in the Stata data file) out of the 398,966 campaigns that were searchable[2] at the time of data collection. The projects or campaigns span launched dates from April 2009 to April 2018 in 169 categories and subcategories and in 22,865 distinct locations. Kickstarter allows projects to be created in only 22 countries legally, but about 4% of campaign locations reported on the campaign pages are outside of those 22 countries, in total spanning 167 countries. More than 80% of all campaigns are located in the United States.

The total number of columns or data points for each campaign that have been either collected or calculated is about 200 (new variables are created regularly depending on the requirements of every new research project). A full Stata-generated codebook with clear labels and variable descriptions has been created for researchers interested in working with the dataset.

[2] Not every project is searchable. Total number of searchable projects is always smaller than the total number of projects mentioned on the website. Calling the search API (https://www.kickstarter.com/projects/search.json) with no parameters returns a JSON object with an attribute namely "total_hits" that is the number of total searchable projects. As of writing (Aug 15, 2018), total searchable projects are 410,493 while the website states 413,586.

Serial Crowdfunding Subset

I picked a subset of the main database for the purposes of this thesis. The subset includes only serial crowdfunders located in the US. In order to create the new subset, we dropped the following from the main database:

1. If the creator variable is missing or the creator of the project is not known in our data (thus we cannot track if it was a serial crowdfunder or not).
2. If the project was still live at the time of data collection.
3. If the project has an anomalous launch date (before Kickstarter even launched as a platform).
4. If the country displayed on the project page does not match the country legally reported to Kickstarter (about 4% of all projects).
5. If the country of the project is not USA.
6. If the goal set for the project is less than 10 (284 observations dropped) or more than 1 million (185 observations dropped).
7. Non-serials: we dropped projects if in the remaining sample they were the only project of their creator, so that the sample only contains projects of serial crowdfunders who have more than one project (about two thirds of all observations dropped).
8. Lastly, we dropped all projects of any creator who did not have all of their projects in the remaining sample (for example because one of them was outside the USA), in order to have a sample that includes the full track record of the serial crowdfunders included (3,650 observations dropped).

The final sample size is 81,458 projects created by 31,003 unique serial creators (creators with at least 2 projects) in the US only. In some regressions, the sample size is further reduced because of missing values in some variables. For example, many of the creators did not link their accounts to their Facebook pages or their accounts do not report the number of friends. So when we add the "Facebook Friends" variable to a regression, rows that do not have this data are dropped from the regression sample (the sample size is reduced from 81,458 to 47,878 campaigns).

Variables Used in this Study

The name and description of the measures used in this study are provided in Table 2, Table 3 and Table 4. Some of the variables do not appear in the main analysis and are used mainly for robustness checks.

The choice of control variables for regressions where the dependent variable is "Goal Level" such as mediator models is tricky. Some variables that are not known at the time of goal setting so would not be conceptually appropriate as control variables in these models. Some of Stata's commands for mediation models force the list of control variables for the mediator and dependent variable to be the same list. In such cases, we use the shorter list and remove the control variables that are not known at the time of goal-setting.

In our regression analyses, we use Amount Pledged as the main performance variable, but use Amount Raised and Success for robustness checks. We use Visuals Count as our main proxy for campaign design, but use Description Length, Rewards Count, FAQs Count, and Updates Count for robustness checks.

Table 2. Performance Variables

Name	Definition & Notes
Amount Pledged	Sum total of pledged amount by all backers of the campaign
Amount Raised	Equal to pledged amount if the project was successful (reached target), zero if the project was unsuccessful (did not reach target, was canceled or suspended).
Success	Equal to 1 if the project reached target, and 0 if the project did not reach target, or was cancelled or suspended.

Table 3. Mediator and Independent Variables

Name	Definition & Notes
Goal Level	Target set by the creator for the project at the outset (not changeable).
Experience	Order of the project in the creator's history: 1 plus the number of projects previously created by the creator of this project
Description Length	Length of text in the description of the project (measured in units of 100 characters, which approximates an English sentence).
Visuals Count	Number of visual elements (pictures and videos) used in the project description

Table 4. Control Variables

Name	**Definition & Notes**
Category	Dummies for top-level categories / industries
Rewards Count	Number of reward tiers set by the project creator
FAQs Count	Number of FAQs listed and answered by the creator
Updates Count	Number of update posts written by the creator
Staff Pick	Whether or not the project was highlighted as a “Staff Pick” by Kickstarter staff
Facebook Friends	Number of Facebook friends of the creator (only collected once)

Chapter 4: Descriptive Analysis

Summary Statistics

Table 5 provides summary statistics for the variables listed in the previous section. Because many of the variables have skewed distributions, both means and medians are provided.

Table 5. Summary Statistics

	Mean	Median	Std. Dev.	Min	Max
Amount Pledged	14602.07	1170	153473.89	0	20338986
Amount Raised	13661.58	0	153374.21	0	20338986
Success	0.47	0	0.50	0	1
Experience	2.50	2	3.62	1	111
Goal Level	15864.36	5000	51480.02	10	1000000
Visuals Count	8.15	3	11.83	0	204
Updates Count	7.26	3	11.89	0	350
Rewards Count	8.66	7	6.36	0	179
FAQs Count	0.13	0	0.89	0	30
Description Length	3485.87	2408	3532.28	0	192102
Staff Pick	0.12	0	0.33	0	1
Facebook Friends	1145.47	688	1243.56	2	5291

The average pledge and raised amounts among the set of campaigns by serial crowdfunders are $14,602 and $13,661 whereas the median pledged is only $1,170. The average success rate is relatively high (%47) compared to the average success rate of all projects including those of non-serial creators (%36). The average goal level is $15,864 whereas the median goal level is $5,000. The median campaign has three visual elements in their project description, and the median number of Facebook friends for creators is 688, which is much higher than the average number of friends in the general US population[3]. Although it should be noted that only 17,952 of the 31,003 creators in our data had their number of Facebook friends listed on their Kickstarter profile, so this data may suffer from exclusion bias.

Correlation Matrix

The correlation matrix corresponding to the above variables is provided in Table 6. Almost all coefficients are statistically significant, but small. No two variables with a correlation above 0.3 are simultaneously included in any of our regression models. Variables that are highly correlated are typically different proxy measures for the same concept. For example, Amount Pledged correlates heavily with Amount Raised, and campaign design parameters such as Visuals Count, Updates Count, and Rewards Count correlate relatively strongly with each other.

Data Visualization: Bar Charts and Scatterplots

In order to gain deeper insights into the nature and patterns of our dataset, a number of visual graphs are reported next. Figure 9 shows the number of projects for each level of experience. Obviously, the number of projects with order 1 and the number of projects with order 2 are equal because we dropped all order 1 projects whose creators did not launch at least one other project. In this and other bar charts, we display data for up to 9th projects, but as can be seen from Table 5 the maximum project order we observe in our database is 111. However, Figure 9 shows that the number of third projects (8,560) is much less than the number of second projects (31,003), and the numbers continue to drop with experience level such that only 427 creators had at least 9 projects.

---

[3] According to a Pew Research Survey (http://www.pewresearch.org/wp-content/uploads/2014/01/Survey-Questions_Facebook.pdf), the average (mean) number of friends of a US adult Facebook user is 338, and the median (midpoint) number of friends is 200.

Table 6. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. Amount Pledged	1.000											
2. Amount Raised	0.999	1.000										
	(0.000)											
3. Success	0.089	0.095	1.000									
	(0.000)	(0.000)										
4. Experience	0.034	0.035	0.145	1.000								
	(0.000)	(0.000)	(0.000)									
5. Goal Level	0.116	0.108	-0.137	-0.038	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)								
6. Visuals Count	0.182	0.176	0.203	0.124	0.073	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
7. Updates Count	0.174	0.174	0.458	0.055	0.010	0.383	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)						
8. Rewards Count	0.068	0.064	0.239	0.050	0.054	0.355	0.353	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
9. FAQs Count	0.047	0.046	0.056	-0.037	0.028	-0.023	0.144	0.062	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
10. Description Length	0.119	0.114	0.178	0.065	0.104	0.526	0.385	0.357	0.042	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
11. Staff Pick	0.124	0.122	0.273	0.024	0.028	0.184	0.265	0.201	0.056	0.205	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
12. Facebook Friends	0.009	0.009	0.160	0.023	-0.012	-0.033	0.057	0.132	0.011	-0.008	0.070	1.000
	(0.053)	(0.050)	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)	(0.012)	(0.064)	(0.000)	

p-values in parentheses

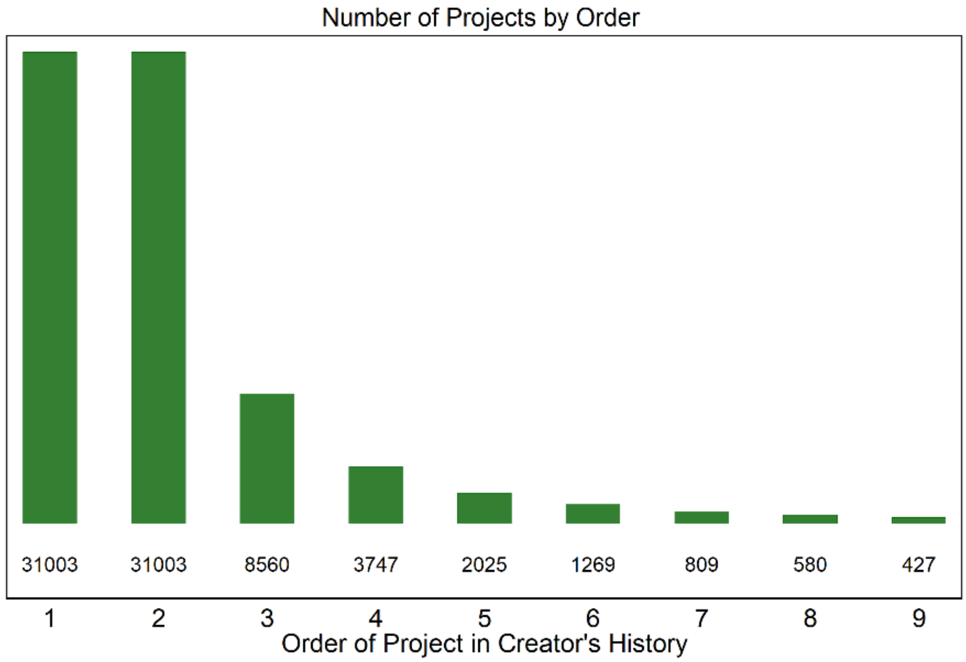

Figure 9. Number of projects by experience

Figure 10 illustrates a log-log scale scatter plot of pledged level plotted against goal level. The thickness of the plots just above the goal line illustrates that most successful projects do not raise much more money than their goal levels. The white space just below the goal line indicates a push phenomenon in the platform whereby the pledged levels are pushed or tipped over the line when they get close to the goal level.

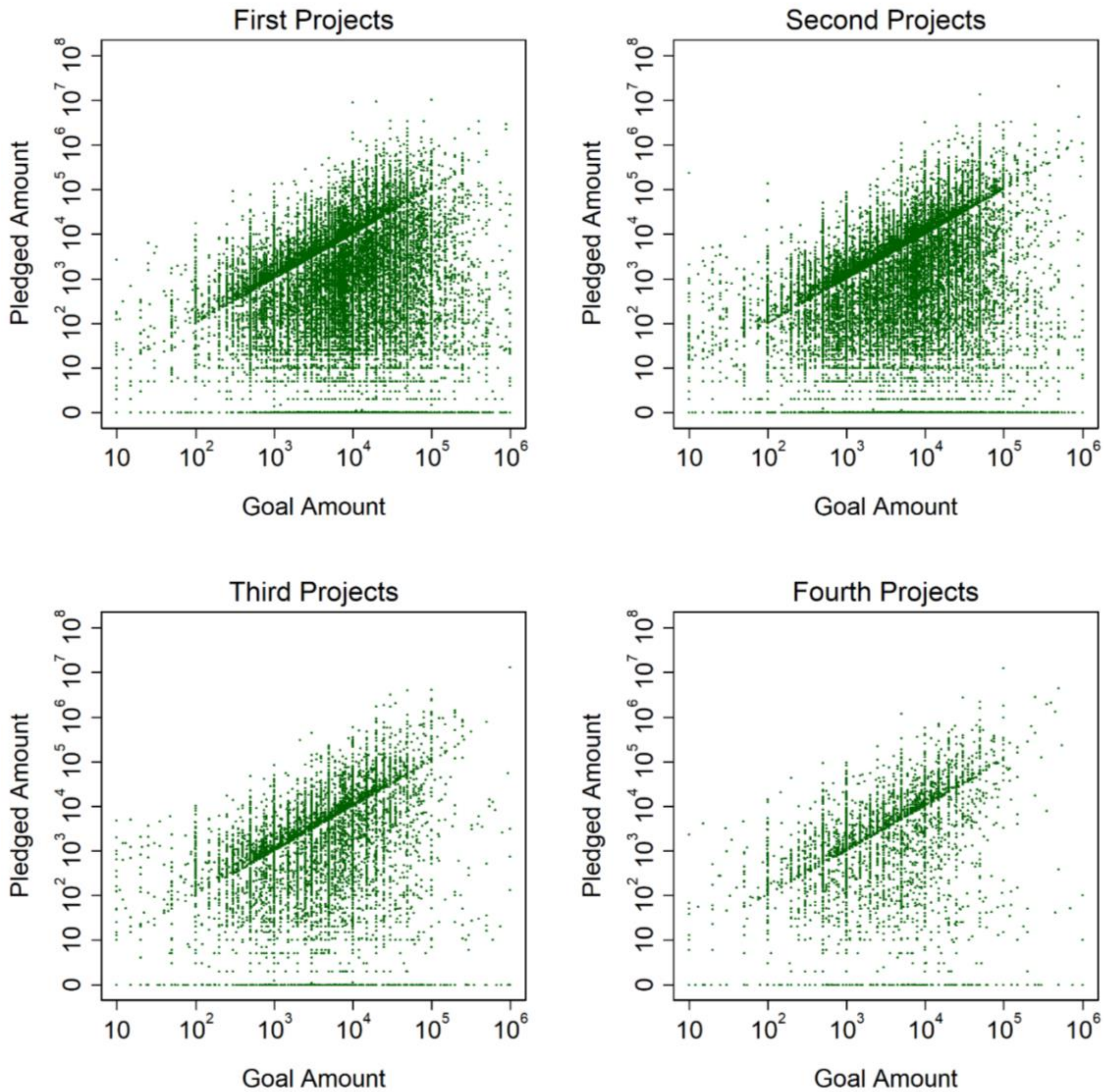

Figure 10. Scatterplots of goal vs. pledged amounts

Figure 11 and Figure 12 demonstrate that in general pledge levels increase by crowdfunding experience, although if measured by mean rather than median the effect seems to dissipate after the 6^{th} project. Figure 13 and Figure 14 demonstrate that in general goal levels are downwardly adjusted with increased crowdfunding experience. Figure 15 illustrates that success rates increase consistently with crowdfunding experience, with success becoming more likely than failure by the third campaign. These descriptive results are generally in line with our hypotheses.

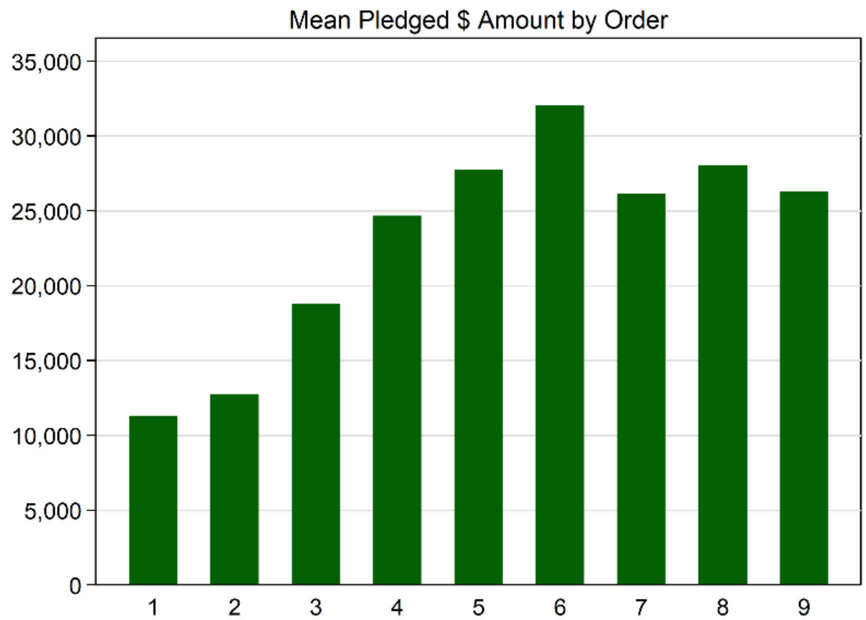

Figure 11. Mean pledged amount by experience (order in creator’s track record)

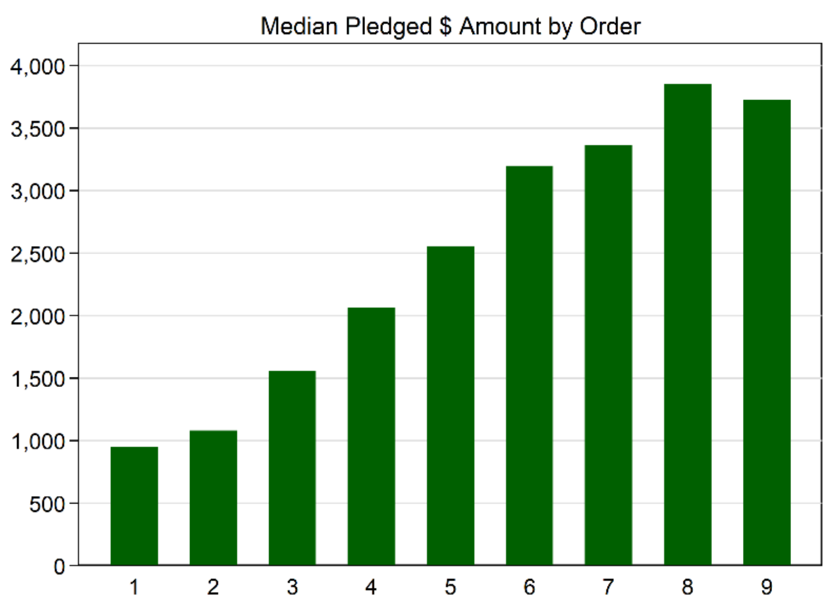

Figure 12. Median pledged amount by experience (order in creator’s track record)

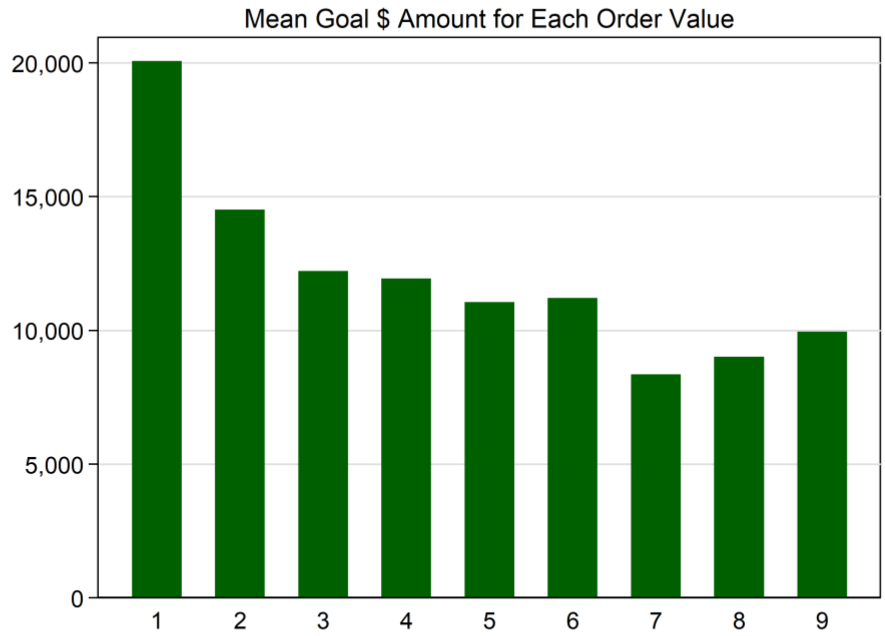

Figure 13. Mean goal level by experience

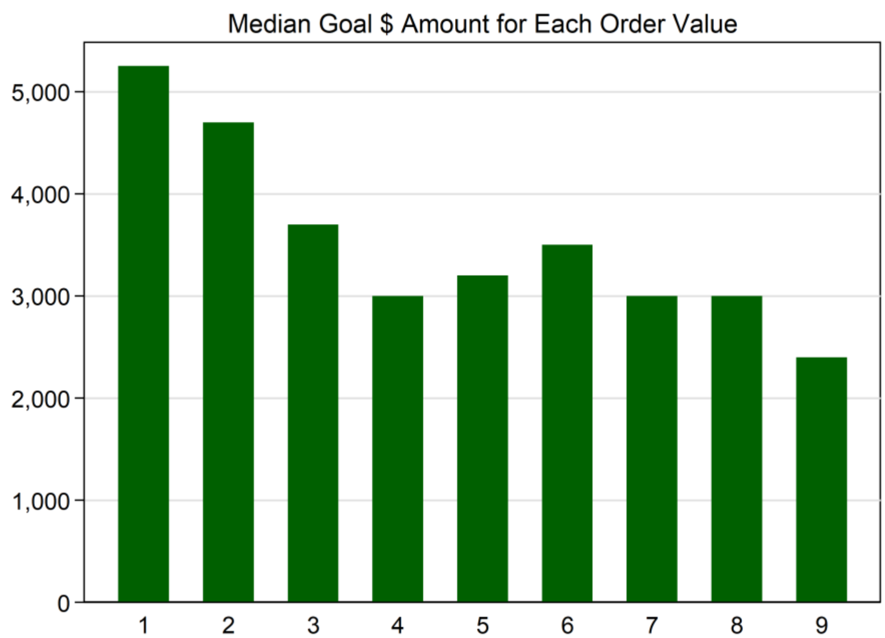

Figure 14. Median goal level by experience

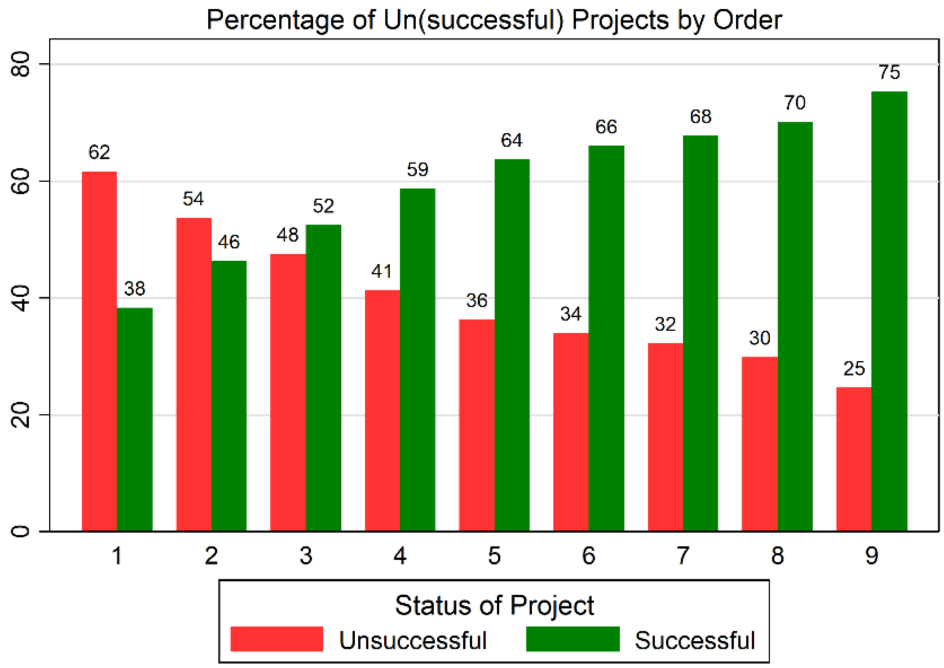

Figure 15. Chances of success increase by experience

Some Illustrative Cases

In this section, we bring the descriptive analysis down to a number of specific illustrative cases.

In our data, we have 13,696 serial crowdfunders in the US that never failed a project, and of those 40 have launched more than 12 projects. These exceptionally successful crowdfunders are listed in Table 7.

As shown in Table 7, Sasha Davies[4] (Cheese producer) and CoolMiniOrNot (Online retailer of tabletop games[5]) have launched the most projects and raised the most funds respectively. Table 8 and Table 9 show the details of their projects. It is interesting to point out that these serial

[4] https://www.kickstarter.com/profile/1287277253

[5] https://www.cmon.com/about

crowdfunders have launched consecutive campaigns around essentially the same type of product over time.

Another interesting case we have found in the database is the serial creators that never succeeded in any of their projects. Of 13,629 serial crowdfunders in the US that never succeeded a project, 12 have launched more than 10 projects. These are listed in Table 10.

Table 7. Serial Creators in the U.S. with no Project Failure

Avg.	Avg.	Total	Avg. Goal	Creator Name	Facebook	Creator's Location
527	15881.07	13	7269.23	Silence in the Library Publishing	1259	Salt Lake City, UT
909	131672.94	13	19038.46	Japanime Games	1436	Portland, OR
94	3606.15	13	969.23	M.C.A. Hogarth	0	Tampa, FL
146	6244.28	13	2884.62	Ruby Nile Games	NA	NA
102	3088.04	13	874.23	Shirley Jackson	0	Salt Lake City, UT
14	488.08	13	440	Benjamin Hennessey	975	Amsterdam, NY
771	18781.78	13	8769.23	Jason Kotarski	1698	Grand Rapids, MI
412	24327.56	13	15230.77	Lo-Fidelity Records	0	NA
273	11869.78	13	3869.23	Christopher West	1090	Lake City, PA
2185	125448.03	14	15857.14	Ryan Laukat	0	Sandy, UT
176	3035.36	14	1464.29	Venger Satanis	3325	Sun Prairie, WI
60	2337	14	803.57	Janet Willkomm	0	Kronenwetter, WI
326	8393.53	14	4964.29	unwoman	2275	El Cerrito, CA
547	16543.05	14	12357.14	Kel McDonald	416	Portland, OR
79	3448.88	15	2983.33	G. Todd Buker	726	Raleigh, NC
921	25180	15	9266.67	smallboxgames	0	Stockbridge, GA
68	8723.2	15	1045.53	Richard Parks	0	Carson City, NV
1766	69033.06	16	20704.38	IronSpike	1492	Chicago, IL
230	20677.5	16	5075	Boundless Comics	0	Rantoul, IL
1195	102697.27	16	8000	Shane Hensley	2918	Chandler, AZ
29	696.77	17	376.36	Jerry Paffendorf	2685	Detroit, MI
35	1638.36	18	322.22	Johnny Segura	NA	Lake Charles, LA
240	7746.05	18	897.33	Postworldgames Jim Pinto	0	NA
686	73727.38	19	31677.68	Frog God Games	NA	Poulsbo, WA
35	1478.05	19	355.26	Candlemark & Gleam	0	Cambridge, MA
70	753.41	19	144.74	Brian Garber	0	Cincinnati, OH
196	5912.04	19	3363.16	Robin Snyder	314	Bellingham, WA
1049	71643.26	21	10857.14	Goodman Games	0	San Jose, CA
200	28683.39	22	5181.82	Thornwillow	0	NA
122	6909.96	22	3527.27	Jeff Dee	4974	NA
138	3597.81	25	2784	Elly Blue	1155	Portland, OR
32	930.41	27	99	Incarna Comics	3813	Claremore, OK
2580	112920.88	28	12911.43	Travis	0	Oakland, CA
1936	195817.7	28	41785.71	Richard Thomas	474	Center Valley, PA
8835	1435093.03	30	90000	CoolMiniOrNot	0	NA
271	24592.04	30	7411.5	Thomas Negovan	2421	Los Angeles, CA
69	1052.52	32	262.5	Jose Pulido	NA	NA
51	4328.24	34	282.35	David Walsh	49	Dover, PA
31	504.22	37	277.86	John Rap	0	Staten Island, NY
46	1653.92	40	1236.22	Sasha Davies	489	Los Angeles, CA

Table 8. Projects launched by Sasha Davies

Project Order	Launched Date	Backers Count	Goal	Pledged	Location	Category Name	Project Status	Project Desc. Length	Visuals Count
1	2013-02-25	50	1500	1656	Portland,	Food	successful	2074	1
2	2013-01-30	31	960	1032	Portland,	Food	successful	1848	1
3	2013-04-02	39	1300	1350	Portland,	Food	successful	2437	1
4	2013-05-03	43	1350	1360	Portland,	Food	successful	2283	1
5	2013-05-31	40	1150	1350	Portland,	Food	successful	2188	1
6	2013-07-09	45	1260	1307	Portland,	Food	successful	2204	1
7	2013-07-31	49	1325	1700	Portland,	Food	successful	2469	1
8	2013-09-05	40	1480	1600	Portland,	Food	successful	2397	1
9	2013-10-04	43	1410	1426	Portland,	Food	successful	2623	1
10	2013-10-29	52	1050	1812	Portland,	Food	successful	2948	1
11	2013-12-02	40	1350	1956	Portland,	Food	successful	3406	1
12	2013-12-23	50	1860	2038	Portland,	Food	successful	3583	1
13	2014-01-24	37	1280	1369	Portland,	Food	successful	3066	1
14	2014-02-25	45	1075	1887	Portland,	Food	successful	4392	1
15	2014-03-28	37	1115	1691	Portland,	Food	successful	4694	1
16	2014-05-01	44	1110	1609	Portland,	Food	successful	3570	1
17	2014-05-30	55	945	1916	Portland,	Food	successful	3193	1
18	2014-07-10	39	778	1358	Portland,	Food	successful	3414	1
19	2014-08-09	37	970	1262	Portland,	Food	successful	2904	1
20	2014-09-05	36	1078	1329	Portland,	Food	successful	3270	1
21	2014-10-09	35	793	1211	Portland,	Food	successful	2594	1
22	2014-11-03	56	1530	2376	Portland,	Food	successful	2974	1
23	2014-12-05	39	1015	1368	Portland,	Food	successful	2742	1
24	2015-01-09	31	825	868	Portland,	Food	successful	2487	1
25	2015-02-10	36	1146	1269	Portland,	Food	successful	2944	1
26	2015-03-06	30	784	992	Portland,	Food	successful	2634	1
27	2015-04-08	30	915	1159	Portland,	Food	successful	2388	1
28	2015-05-06	52	1100	1573	Portland,	Food	successful	2891	1
29	2015-06-09	26	975	1090	Portland,	Food	successful	2674	1
30	2015-07-08	43	625	1487	Portland,	Food	successful	2474	1
31	2015-08-06	45	1045	1595	Portland,	Food	successful	2771	1

32	2015-09-10	40	775	985	Portland,	Food	successful	2519	1
33	2015-10-01	47	1060	1853	Portland,	Food	successful	2633	1
34	2015-11-09	50	1200	2205	Portland,	Food	successful	3135	1
35	2015-12-02	47	1400	1860	Portland,	Food	successful	3100	1
36	2016-01-07	34	915	1247	Portland,	Food	successful	2697	1
37	2016-02-03	50	1500	1899	Portland,	Food	successful	2704	1
38	2016-03-04	53	1100	1825	Portland,	Food	successful	2700	1
39	2016-04-05	42	700	1177	Portland,	Food	successful	2762	1
40	2018-02-27	195	5700	7110	Los Angeles, CA	Nonfiction	successful	6998	9

Table 9. Projects launched by CoolMiniOrNot, Serial Creator that Raised the Most Fund

Launched Date	Backers Count	Goal	Pledged	Category Name	Project Status	Project Desc. Length	Visuals Count
2012-04-06	5258	20000	781597.49	Tabletop Games	successful	15115	61
2012-05-25	4278	20000	951254.4	Tabletop Games	successful	15634	97
2012-08-07	3459	20000	909537.25	Tabletop Games	successful	16447	58
2012-12-05	2955	5000	116938	Tabletop Games	successful	3635	27
2013-01-04	2464	25000	582316	Tabletop Games	successful	17698	38
2013-03-02	8944	25000	2255018.04	Tabletop Games	successful	8080	50
2013-06-10	1896	25000	356752.92	Tabletop Games	successful	10539	49
2013-08-14	3756	50000	718152.5	Tabletop Games	successful	13509	62
2014-02-25	4885	50000	774222.04	Tabletop Games	successful	13683	80
2014-04-25	1139	25000	66703	Tabletop Games	successful	4601	29
2014-06-04	3367	25000	242832	Tabletop Games	successful	13863	62
2014-06-29	12011	100000	2849064.07	Tabletop Games	successful	7907	136
2014-09-19	1239	20000	88259	Tabletop Games	successful	8765	25
2016-01-12	4398	30000	383406.5	Tabletop Games	successful	7432	50
2014-10-30	1770	25000	101351	Tabletop Games	successful	5100	38
2014-12-02	4417	50000	739513	Tabletop Games	successful	10680	74
2015-03-02	9825	50000	905682	Tabletop Games	successful	5703	49
2015-04-28	4774	50000	567350	Tabletop Games	successful	8659	47
2015-06-08	20915	125000	4079204.52	Tabletop Games	successful	10437	63
2015-09-10	10136	100000	1464489.52	Tabletop Games	successful	11880	83
2015-11-16	9991	100000	1710713.62	Tabletop Games	successful	9270	103
2016-02-22	10862	60000	1010958.81	Tabletop Games	successful	9337	63
2016-04-11	5794	80000	917864.02	Tabletop Games	successful	11816	69
2016-06-07	22361	200000	3560642.66	Tabletop Games	successful	12239	93
2017-01-17	7892	70000	1174130.1	Tabletop Games	successful	13246	82
2017-03-07	31262	300000	4228060	Tabletop Games	successful	10630	78
2017-05-30	27236	300000	5004614.58	Tabletop Games	successful	11505	100
2017-07-25	9040	300000	1690466	Tabletop Games	successful	11844	92
2018-01-16	10227	200000	1469489.03	Tabletop Games	successful	13348	88
2018-04-10	18486	250000	3352208.89	Tabletop Games	successful	9915	82

Table 10. Serial Creators that Never Succeeded

Avg. Backers	Avg. Pledged	Total Project	Avg. Goal	Creator Name	Facebook Friends	Creator's Location	Last Project Category
1	6.36	11	886.36	Andrew	129	Bensalem,	Classical
0	6.09	11	34454.55	Michael	0	Indianapolis,	Farmer's
1	8.27	11	61909.09	Joseph	403	NA	Festivals
3	81.27	11	14000	Jonathan	5	NA	Web
1	15.55	11	14863.64	J.d.	269	Pittsburgh,	Publishing
8	460.5	12	94916.67	Cypress	0	NA	Tabletop
8	494.58	12	9500	Konokopia	0	Seattle, WA	Mobile
2	251.75	12	17125	Richard Mansfield	102	Mars Hill, NC	Film & Video
34	1313.46	13	11342.38	Jason	0	Los Angeles,	Playing
4	146.67	14	5557.14	ERIC	1910	Los Angeles,	Graphic
1	1.36	14	3089	Vince	862	San Diego,	Publishing
1	2.67	15	9000	Gregg	0	Los Angeles,	Festivals

Table 11. Bradly Golden, an example of perseverance, failed 10 projects and succeeded the very last one

Launched Date	Backers Count	Goal	Pledged	Location	Category Name	Project Status	Project Desc. Length	Visuals Count
2013-09-10	8	5000	57	Pontotoc, MS	Comics	failed	1333	1
2014-03-14	12	600	186	Oxford, MS	Comics	failed	217	1
2014-05-27	6	600	45	Pontotoc, MS	Comics	failed	256	0
2014-12-15	7	600	79	Pontotoc, MS	Comics	failed	414	1
2015-03-23	11	4000	159	Pontotoc, MS	Comics	canceled	781	8
2015-04-17	4	400	56	Pontotoc, MS	Digital Art	canceled	351	17
2016-02-05	41	3200	532	Pontotoc, MS	Comic Books	failed	2708	22
2016-05-14	31	13000	839	Pontotoc, MS	Anthologies	failed	2171	22
2016-06-13	23	3200	861	Pontotoc, MS	Comics	canceled	2025	24
2016-07-19	8	500	174	Pontotoc, MS	Comic Books	failed	1544	18
2016-08-25	20	800	857	Pontotoc, MS	Comic Books	successful	1748	10

Table 12. Randomly Chosen Serial Creators Who Have Launched 2 Projects

Creator Name	Launched Date	Backers Count	Goal	Pledged	Location	Category Name	Project Status	Desc. Length
MagC	2017-10-19	105	1000	19443	Boston, MA	Hardware	suspended	169
MagC	2017-11-30	70	28000	6621	Boston, MA	Hardware	failed	191
Mackenzy Colton	2017-12-12	14	8613	720	Orlando, FL	Wearables	failed	187
Mackenzy Colton	2018-02-01	0	500	0	New York, NY	Product Design	failed	1405
Lance Hawvermale	2017-02-20	118	500	2666	Dallas, TX	Tabletop Games	successful	3949
Lance Hawvermale	2018-02-03	98	600	1613	Dallas, TX	Tabletop Games	successful	2086
Melanie Lee Pratt	2015-02-02	5	150000	785	Owosso, MI	Restaurants	canceled	4966
Melanie Lee Pratt	2015-03-02	9	30000	1011	Owosso, MI	Restaurants	failed	5192
Zachary Robert Craft	2011-10-03	51	3800	4295	Chicago, IL	Shorts	successful	1676
Zachary Robert Craft	2012-06-22	21	3500	1075	Chicago, IL	Narrative Film	canceled	7383
Dave Doering	2012-06-21	17	1800	1948	Bayfield, WI	Documentary	successful	1047
Dave Doering	2015-07-17	16	1000	1117	Washburn, WI	Shorts	successful	871

Table 13. Randomly Chosen Serial Creators Who Have Launched 3 Projects

Creator Name	Launched Date	Backers Count	Goal	Pledged	Location	Category Name	Project Status	Desc. Length
Remedy Drive	2013-01-19	152	10000	13843.36	Brentwood, TN	Rock	successful	779
Remedy Drive	2014-05-01	560	20000	27710.87	Lincoln, NE	Indie Rock	successful	2683
Remedy Drive	2017-09-26	515	20000	37361	Nashville, TN	Rock	successful	2157
Norman A Korpi	2013-09-29	441	23667	38972	San Francisco, CA	Hardware	successful	11155
Norman A Korpi	2016-12-08	636	5000	35600.8	Los Angeles, CA	Gadgets	successful	3934
Norman A Korpi	2017-06-16	60	4545	4934	San Francisco, CA	Gadgets	successful	157
Cedric Ingram	2014-04-09	1	15000	15	Los Angeles, CA	Fashion	failed	2204
Cedric Ingram	2014-06-17	1	15000	1	Los Angeles, CA	Apparel	canceled	1936
Cedric Ingram	2014-10-02	1	15000	26	Los Angeles, CA	Fashion	failed	2176
Eyes For Fire	2013-01-17	23	800	800	South Bend, IN	Rock	successful	156
Eyes For Fire	2014-04-21	21	1500	477.73	South Bend, IN	Music	failed	418
Eyes For Fire	2015-02-20	33	800	1436	South Bend, IN	Rock	successful	1063

Table 14. Randomly Chosen Serial Creators Who Have Launched 4 Projects

Creator Name	Launched Date	Backers Count	Goal	Pledged	Location	Category Name	Project Status	Desc. Length
Nicholas Vitek	2010-11-14	148	7500	9202	Houston, TX	Tabletop Games	successful	3755
Nicholas Vitek	2011-11-07	1111	25000	82056.72	Houston, TX	Tabletop Games	successful	7241
Nicholas Vitek	2012-11-07	96	20000	2789	Houston, TX	Tabletop Games	canceled	5044
Nicholas Vitek	2016-04-26	48	8500	973	Houston, TX	Tabletop Games	canceled	8586
Trevor Cram	2011-04-18	56	12000	2702	Salt Lake City, UT	Tabletop Games	failed	2104
Trevor Cram	2011-09-17	402	500	8624	Salt Lake City, UT	Tabletop Games	successful	261
Trevor Cram	2011-11-29	13	15000	395	Salt Lake City, UT	Tabletop Games	failed	1749
Trevor Cram	2012-02-16	307	1000	5940	Salt Lake City, UT	Tabletop Games	successful	4194
Tommy Tallarico	2013-08-14	5679	250000	285081.44	Los Angeles, CA	Video Games	successful	23384
Tommy Tallarico	2014-10-20	3712	150000	187646.27	Los Angeles, CA	Video Games	successful	22793
Tommy Tallarico	2016-02-18	3658	150000	263931.54	Los Angeles, CA	Video Games	successful	26356
Tommy Tallarico	2018-02-20	3144	150000	208711.14	San Juan Capistrano, CA	Video Games	successful	27943

An interesting example of perseverance is Bradley Golden who has launched 11 projects, and only the last one was successfully funded. He is the only example of a serial crowdfunder that succeeded after failing 10 previous campaigns. He had 4,291 Facebook friends when we collected the data in April 2018[6]. The detail of his 11 Kickstarter projects is displayed in Table 11.

To give more insights into what the track record of serial crowdfunders looks like, we report data on the trajectory of a random selection of creators with 2, 3, and 4 projects in their history in Table 12, Table 13, and Table 14 respectively.

[6] Refer to https://www.kickstarter.com/profile/95864769 for more details.

Chapter 5: Regression Analysis

We use Ordinary Least Squares (OLS) linear regression to test hypotheses involving one independent and one dependent variable (H1, H2 and H4). For mediation analyses (H3, H5, and H6), we employ the Sobel-Goodman test (Sobel, 1982) using the interaction of coefficients from a series of OLS regressions (Baron & Kenny, 1986). For H6 specifically, we use Zellner's method of seemingly unrelated regressions (Zellner, 1962) to test a multiple mediator model.

OLS Regressions

H1 posits that crowdfunding experience has a total positive effect on performance. Table 15 reports OLS regression results where the dependent variable is Amount Pledged as a proxy for campaign performance. Model 1 only includes control variables, and Model 2 adds the main independent variable Experience. The coefficient of Experience in Model 2 is found to be positive and significant ($\beta = 614.3$, $p < 0.05$). Thus, H1 is supported.

H2 suggests that crowdfunding experience is negatively associated with goal level, and H4 suggests that it is positive associated with campaign design. Table 16 reports on OLS regressions that test these hypotheses. In Model 7 where the dependent variable is goal level, the coefficient for experience is negative and significant ($\beta = -782.5$ $p < 0.001$), and in Model 9 where the dependent variable is visuals count, the coefficient for experience is positive and significant ($\beta = 0.391$, $p < 0.001$). Thus, both hypotheses H2 and H4 are supported.

Table 15. OLS regression results for Amount Pledged as the dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent Variable:	Amnt Pledged	Amnt Pledged	Amnt Pledged	Amnt Pledged	Amnt Pledged
Category	0	0	0	0	0
(Base Level: Design)	(.)	(.)	(.)	(.)	(.)
Art	-44765.5***	-44690.4***	-40390.3***	-30078.1***	-26819.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fashion	-33279.4***	-33121.4***	-29664.6***	-25899.9***	-23023.5***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Film & Video	-42492.1***	-42115.0***	-42898.4***	-24232.4***	-25988.3***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Publishing	-45936.8***	-45722.6***	-41110.2***	-28407.4***	-25002.8***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Music	-44875.0***	-44354.6***	-39541.2***	-23169.4***	-19793.0***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology	-18670.5***	-18408.9***	-24864.7***	-9786.6*	-16379.0***
	(0.000)	(0.000)	(0.000)	(0.028)	(0.000)
Games	-19604.4***	-20427.2***	-19587.1***	-22429.9***	-21518.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Photography	-46131.3***	-45862.4***	-40791.0***	-29397.0***	-25508.9***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food	-42427.4***	-42247.3***	-43376.8***	-24778.9***	-26840.5***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dance	-52060.4***	-51755.0***	-46798.2***	-28513.9***	-25117.5***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Journalism	-46330.5***	-45882.8***	-45625.7***	-25233.5**	-26157.0**
	(0.000)	(0.000)	(0.000)	(0.009)	(0.006)
Theater	-46481.1***	-46097.2***	-42406.9***	-24150.2***	-21884.6***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Crafts	-44454.0***	-44676.1***	-39353.1***	-33836.7***	-29391.6***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Comics	-48032.3***	-48282.9***	-43109.9***	-42306.1***	-37727.9***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Staff Pick	50930.1***	50786.6***	49406.0***	41484.6***	40697.4***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Facebook Friends	2.407***	2.315***	2.145***	1.622*	1.500*
	(0.000)	(0.001)	(0.001)	(0.015)	(0.023)
Experience		614.3*	903.0***	-43.88	267.7
		(0.027)	(0.001)	(0.875)	(0.335)
Goal Level			0.369***		0.351***
			(0.000)		(0.000)
Visuals Count				1681.4***	1586.2***
				(0.000)	(0.000)
_cons	40394.3***	38907.3***	30999.0***	16645.9***	10390.5***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
N	47878	47878	47878	47874	47874

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

Table 16. OLS regression results for Goal Level and Visuals Count as dependent variables

	Model 6	Model 7	Model 8	Model 9
Dependent Variable:	Goal Level	Goal Level	Visuals Count	Visuals Count
Category	0	0	0	0
(Base Level: Design)	(.)	(.)	(.)	(.)
Art	-11562.0^{***}	-11657.8^{***}	-8.739^{***}	-8.691^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Fashion	-9170.2^{***}	-9371.5^{***}	-4.396^{***}	-4.295^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Film & Video	2604.4^{**}	2124.0^{*}	-10.88^{***}	-10.64^{***}
	(0.008)	(0.030)	(0.000)	(0.000)
Publishing	-12231.7^{***}	-12504.6^{***}	-10.44^{***}	-10.30^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Music	-12386.8^{***}	-13049.6^{***}	-12.93^{***}	-12.60^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Technology	17835.0^{***}	17501.9^{***}	-5.284^{***}	-5.117^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Games	-3326.0^{***}	-2277.8^{*}	1.715^{***}	1.191^{***}
	(0.001)	(0.024)	(0.000)	(0.000)
Photography	-13406.4^{***}	-13748.9^{***}	-9.964^{***}	-9.793^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Food	3291.5^{*}	3062.0^{*}	-10.50^{***}	-10.39^{***}
	(0.015)	(0.023)	(0.000)	(0.000)
Dance	-13049.3^{***}	-13438.3^{***}	-14.02^{***}	-13.82^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Journalism	-126.9	-697.2	-12.57^{***}	-12.28^{***}
	(0.963)	(0.800)	(0.000)	(0.000)
Theater	-9515.6^{***}	-10004.6^{***}	-13.30^{***}	-13.05^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Crafts	-14713.7^{***}	-14430.8^{***}	-6.305^{***}	-6.447^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Comics	-14343.5^{***}	-14024.4^{***}	-3.395^{***}	-3.555^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Staff Pick	3560.0^{***}	3742.8^{***}	5.623^{***}	5.532^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Facebook Friends	0.343^{+}	0.460^{*}	0.000470^{***}	0.000412^{***}
	(0.072)	(0.016)	(0.000)	(0.000)
Experience		-782.5^{***}		0.391^{***}
		(0.000)		(0.000)
_cons	19545.9^{***}	21440.0^{***}	14.19^{***}	13.24^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
N	47878	47878	47874	47874

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

Mediation Tests

H3 predicted that goal level partially and negatively mediates the relationship between crowdfunding experience and performance, while H5 predicted that campaign design partially and positively mediates this relationship. In order to test H3 and H5, we ran partial mediation models using the Sobel-Goodman method (Baron & Kenny, 1986; Sobel, 1982), where the mediator was goal level for H3 and visuals count for H5. H6 predicted that after controlling for both mediation effects, the direct effect of experience on performance will be positive. To test H6, we ran a dual mediator model using Zellner's seemingly unrelated regressions method (Zellner, 1962). The results of these three models are reported in Table 17.

Given that both indirect effects are significant and in the predicted direction, hypotheses H3 and H5 are supported. However, in the single mediator model where the mediator is visuals count and also when testing both mediators simultaneously, the direct effect of experience disappears. These results do not provide support for H6.

Table 17. Results of main mediation tests

Model:	Model 10 Single Mediator (Goal Level)	Model 11 Single Mediator (Visuals Count)	Model 12 Dual Mediator (Goal Level & Visuals Count)
Indirect Effect through Goal Level	-288.64*** (0.000)		-274.31*** (0.000)
Indirect Effect through Campaign Design		568.22*** (0.000)	620.98*** (0.000)
Direct Effect of Experience	902.968*** (0.001)	-43.88 (0.875)	267.66 (0.335)
Total Effect of Experience	614.3* (0.027)	614.3* (0.027)	614.3* (0.027)

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

Robustness Checks

First, we ran tests to see if the results are sensitive to our choice of dependent variable. Table 18 reports the results of retesting Models 2 and 5, but this time with alternative measures of performance. In Models 13 and 14 the performance measure is Amount Raised (which unlike amount pledged, is zero unless the campaign reached its goal level), and in Models 15 and 16, the performance measure is Success (whether or not the campaign reached its goal level). Models 13 and 14 use OLS regression while models 15 and 16 use logistic regression (a.k.a. logit) due to the binary nature of the dependent variable. The results for Amount Raised are completely in line with previous results for Amount Pledged, but results for Success indicate that the direct effect for crowdfunding experience does not vanish once both mediators are controlled for (Model 16: Odds Ratio = 1.135, $p < 0.001$). These results lend some support to H6.

Second, we ran tests to see if the results are sensitive to our choice of proxy measure for campaign design. Table 19 reports the results of retesting Model 5 with four alternative measures of campaign design in place of Visuals Count. These alternative measures are Description Length, Updates Count, Rewards Count, and FAQs Count. In all four models (Models 17-20), it seems that the direct effect of crowdfunding experience no longer disappears. These results lend additional support to H6.

To fully check the sensitivity of results for H6 to the choice of proxy measure for campaign design, we re-ran the dual mediator model four additional times, each time replacing the mediator with one of the four alternative measures. These results are reported in Table 20 alongside the results for Visuals Count (Model 21).

Table 18. Robustness checks for sensitivity to choice of performance measure

Dependent Variable:	Model 13: OLS Amnt Raised	Model 14: OLS Amnt Raised	Model 15: Logit Success	Model 16: Logit Success
Category	0	0	1	1
(Base Level: Design)	(.)	(.)	(.)	(.)
Art	-43054.0***	-26091.7***	1.185***	1.305***
	(0.000)	(0.000)	(0.001)	(0.000)
Fashion	-31963.9***	-22393.1***	0.653***	0.619***
	(0.000)	(0.000)	(0.000)	(0.000)
Film & Video	-41054.8***	-25686.4***	0.726***	1.142***
	(0.000)	(0.000)	(0.000)	(0.005)
Publishing	-44133.4***	-24462.4***	0.758***	0.916+
	(0.000)	(0.000)	(0.000)	(0.076)
Music	-42660.7***	-19333.6***	1.494***	2.016***
	(0.000)	(0.000)	(0.000)	(0.000)
Technology	-19933.0***	-17916.5***	0.494***	0.757***
	(0.000)	(0.000)	(0.000)	(0.000)
Games	-20126.5***	-21176.5***	1.099*	0.976
	(0.000)	(0.000)	(0.031)	(0.613)
Photography	-44329.5***	-25013.4***	0.600***	0.686***
	(0.000)	(0.000)	(0.000)	(0.000)
Food	-41140.4***	-26452.9***	0.483***	0.733***
	(0.000)	(0.000)	(0.000)	(0.000)
Dance	-49871.2***	-24569.0***	3.373***	4.604***
	(0.000)	(0.001)	(0.000)	(0.000)
Journalism	-44595.2***	-25813.0**	0.357***	0.534***
	(0.000)	(0.007)	(0.000)	(0.000)
Theater	-44399.8***	-21390.2***	1.869***	2.675***
	(0.000)	(0.000)	(0.000)	(0.000)
Crafts	-43042.0***	-28556.6***	0.652***	0.633***
	(0.000)	(0.000)	(0.000)	(0.000)
Comics	-46678.1***	-36694.8***	1.594***	1.342***
	(0.000)	(0.000)	(0.000)	(0.000)
Staff Pick	50067.3***	40477.5***	6.612***	7.590***
	(0.000)	(0.000)	(0.000)	(0.000)
Facebook Friends	2.219***	1.445*	1.000***	1.000***
	(0.001)	(0.029)	(0.000)	(0.000)
Experience	666.6*	332.6	1.183***	1.135***
	(0.017)	(0.231)	(0.000)	(0.000)
Goal Level		0.329***		1.000***
		(0.000)		(0.000)
Visuals Count		1510.6***		1.057***
		(0.000)		(0.000)
_cons	37022.2***	9969.4***		
	(0.000)	(0.001)		
N	47878	47874	47878	47874

p-values in parentheses, coefficient for logistic regression (logit) models are reported as odds ratios

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

Table 19. OLS regressions testing for sensitivity to choice of campaign design measure

Dependent Variable:	Model 17 Amnt Pledged	Model 18 Amnt Pledged	Model 19 Amnt Pledged	Model 20 Amnt Pledged
Category	0	0	0	0
(Base Level: Design)	(.)	(.)	(.)	(.)
Art	-36932.4^{***}	-36161.6^{***}	-40223.0^{***}	-39840.9^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Fashion	-26320.4^{***}	-25401.7^{***}	-29329.0^{***}	-29010.0^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Film & Video	-40455.7^{***}	-39134.7^{***}	-42860.9^{***}	-42455.7^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Publishing	-40079.3^{***}	-37909.6^{***}	-40620.4^{***}	-40706.1^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Music	-34771.5^{***}	-34389.3^{***}	-39470.3^{***}	-39063.9^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Technology	-25211.2^{***}	-22352.1^{***}	-23896.0^{***}	-24532.4^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Games	-23919.2^{***}	-29550.0^{***}	-19667.0^{***}	-19580.6^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Photography	-37501.3^{***}	-35451.0^{***}	-40254.5^{***}	-40130.0^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Food	-40116.9^{***}	-37799.3^{***}	-42799.5^{***}	-42741.5^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Dance	-42221.5^{***}	-38063.5^{***}	-45070.0^{***}	-45908.2^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Journalism	-42267.5^{***}	-37726.4^{***}	-43686.8^{***}	-44839.7^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Theater	-38178.8^{***}	-34987.9^{***}	-41128.0^{***}	-41888.3^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Crafts	-36362.9^{***}	-35278.6^{***}	-39948.9^{***}	-38574.0^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Comics	-41857.0^{***}	-48810.2^{***}	-45396.2^{***}	-42675.9^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Staff Pick	43818.2^{***}	37145.8^{***}	47119.3^{***}	48797.4^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Facebook Friends	1.861^{**}	1.015	1.742^{**}	2.091^{***}
	(0.005)	(0.126)	(0.009)	(0.002)
Experience	731.7^{**}	896.7^{***}	816.4^{***}	983.1^{***}
	(0.008)	(0.001)	(0.003)	(0.000)
Goal Level	0.354^{***}	0.373^{***}	0.364^{***}	0.368^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Description Length	291.5^{***}			
	(0.000)			
Updates Count		1458.5^{***}		
		(0.000)		
Rewards Count			665.8^{***}	
			(0.000)	
FAQs Count				4582.4^{***}
				(0.000)
_cons	20772.9^{***}	20948.3^{***}	25953.1^{***}	29969.6^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
N	47878	47878	47878	47878

p-values in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

Table 20. The direct and indirect effects of crowdfunding experience on performance measured as Amount Pledged, in dual mediator models with different proxies for campaign design

Campaign Design measure:	Model 21 Visuals Count	Model 22 Desc. Length	Model 23 Updates Count	Model 24 Rewards Count	Model 25 FAQs Count
Indirect Effect through Goal Level	-274.31*** (0.000)	-276.63*** (0.000)	-291.74*** (0.000)	-285.2*** (0.000)	-287.68*** (0.000)
Indirect Effect through Campaign Design	620.98*** (0.000)	159.22*** (0.000)	9.39 (0.719)	83.07*** (0.000)	-81.08*** (0.000)
Total Indirect Effect	346.67*** (0.000)	-117.41*** (0.002)	-282.35*** (0.000)	-202.12*** (0.000)	-368.76*** (0.000)
Direct Effect of Experience	267.66 (0.335)	731.74** (0.008)	896.67*** (0.001)	816.45*** (0.003)	983.08*** (0.000)
Total Effect of Experience	614.3* (0.027)	614.3* (0.027)	614.3* (0.027)	614.3* (0.027)	614.3* (0.027)

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

The results in Table 20 indicate that Updates Count is not a significant mediator of the relationship between crowdfunding experience and performance measured as Amount Pledged. Furthermore, contrary to expectations, FAQs Count mediates the experience-performance relationship negatively rather than positively, which also indicates that it may not be a good measure of high quality campaign design.

But the results for Description Length (Model 22) and Rewards Count (Model 24) confirm the mediation relationships hypothesized in this paper, and also do not show a vanishing of the direct effect of experience. Hence, Models 22 and 24 provide additional support for H6. Overall, we can conclude that H6 is generally supported, but that the particular proxy measure of Visuals Count has such a strong effect on performance that it dilutes other positive effects of crowdfunding experience on performance when included in the regression models.

Lastly, we tried removing the number of Facebook friends variable from the list of controls, because it significantly reduces the sample size. Without this variable, the sample size increases to 81,458. We find that in Model 5, if we remove the Facebook friends variable, the coefficient for experience becomes much larger and statistically significant ($\beta = 750.9$, $p < 0.001$, full regression results not reported here). This indicates that after controlling for mediators, there is a significant and positive effect of crowdfunding experience on performance. However, given that previous literature has shown that an important mechanism through which experience impacts performance is the development of social capital (Butticè et al., 2017; Skirnevskiy et al., 2017), this finding is not surprising. The reason we had included Facebook friends as a control in the first place, was to isolate the effect of mechanisms other than social capital.

Chapter 6 Discussion and Concluding Remarks

Summary of Results

In this thesis we found that crowdfunding experience impacts performance through multiple mechanisms. While the total effect is positive, there are also mechanisms at play in the negative direction. We found two particular indirect effects in opposing directions. First, we found that with experience, crowdfunders tend to adjust their goal levels downward, which results in lower pledge amounts for their campaigns (although it increases their chances of success). The negative effect of goal level on performance is not necessarily a bad thing: crowdfunders are deriving less pledged amounts because of lower goals, but those lower goals are increasing their probability of actually receiving the pledged amounts. Second, we found that with experience, crowdfunders learn to design better campaigns by including more visual elements, more reward tiers, and lengthier descriptions. These in turn were found to increase performance.

After controlling for these mechanisms, as well as for social capital, we predicted that the remaining direct effect of crowdfunding experience on performance would be positive and significant due to learning by doing effects and increased quality of offerings, despite potential negative effects such as fatigue and loss of novelty. We found support for this prediction in various ways, except for when Visuals Count was included in the regression models. It seems that the number of visual elements in a campaign page has such a strong effect on performance that it dilutes other positive effects of crowdfunding experience on performance.

In general, the various countervailing forces illustrate why conflicting results may be found on the experience-performance relationship if all effects are not accounted for. While the serial crowdfunding context has unique characteristics that differentiate it from the general serial entrepreneurship context, the same reason identified here may be responsible for conflicting findings in the serial entrepreneurship literature.

Future Research

The extensive data collection software architecture implemented in this research project, provides ample opportunities for future research on crowdfunding. I have reported more details on the data collection effort and more data visualizations than those that were directly relevant to the research questions outlined in the introduction, because I wanted to illustrate the potential of this dataset for many future research directions.

Regarding the particular topic of serial crowdfunding, future studies may expand on the present research in multiple ways. We outline some of these possible directions below.

In this thesis, we tested a limited number of design elements as proxies for campaign design. Mitra and Gilbert (2014) find that computer-identifiable patterns in the text used in Kickstarter campaign descriptions is a substantial predictor of campaign success, accounting for 58.56% of the variance. Using text mining techniques, we can study ways in which serial crowdfunders improve or change their style of writing and linguistic design elements used. For example Anglin, Short, et al. (2018) have shown that the use of language associated with positive psychological capital significantly improves the performance of crowdfunding campaigns. It would be interesting to see if serial crowdfunders learn to improve their use of language with experience.

Augmenting the Kickstarter data with additional data from other sources, we may be able to identify the gender and education level of creators and examine the extent to which learning and performance patterns differ within these categories. There are already research findings that indicate women are more successful at crowdfunding than men, and it would be interesting to see if this pattern holds among serial crowdfunders or if men and women have different rates of learning from crowdfunding experience. Similarly, although we have controlled for industry / category, we have not looked at it more closely as a moderator. Future research may investigate the ways in which learning and performance patterns of serial crowdfunders differ over time in different categories and subcategories.

Lastly, our dataset included only one row for every Kickstarter campaign. Future studies can take a more dynamic and fine-grained approach and collect multiple data points on each campaign throughout its campaign period when its status is “live”. Such dynamic data can open up new opportunities for understanding the nature of crowdfunding campaigns.

References

Afuah, A., & Tucci, C. L. (2001). *Internet business models and strategies : text and cases*. Boston: Irwin/McGraw-Hill.

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy, 24*(2), 253-274.

Anglin, A. H., Short, J. C., Drover, W., Stevenson, R. M., McKenny, A. F., & Allison, T. H. (2018). The power of positivity? The influence of positive psychological capital language on crowdfunding performance. *Journal of Business Venturing*.

Anglin, A. H., Wolfe, M. T., Short, J. C., McKenny, A. F., & Pidduck, R. J. (2018). Narcissistic rhetoric and crowdfunding performance: A social role theory perspective. *Journal of Business Venturing*.

Audia, P. G., Locke, E. A., & Smith, K. G. (2000). The paradox of success: An archival and a laboratory study of strategic persistence following radical environmental change. *Academy of Management Journal, 43*(5), 837.

Bannerman, S. (2013). Crowdfunding culture. *Wi: Journal of Mobile Media, 7*(1).

Baron, R. M., & Kenny, D. A. (1986). The Moderator Mediator Variable Distinction in Social Psychological-Research - Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology, 51*(6), 1173-1182.

Best, J., & Neiss, S. (2014). Crowdfunding: A Historical Perspective. In S. Dresner (Ed.), *Crowdfunding: A Guide to Raising Capital on the Internet* (pp. 3-14). Hoboken, New Jersey: Wiley.

Busenitz, L. W., & Barney, J. B. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing, 12*(1), 9-30.

Butticè, V., Colombo, M. G., & Wright, M. (2017). Serial crowdfunding, social capital, and project success. *Entrepreneurship Theory and Practice, 41*(2), 183-207.

Butticè, V., Orsenigo, C., & Wright, M. (2018). The effect of information asymmetries on serial crowdfunding and campaign success. *Economia e Politica Industriale, 45*(2), 143-173.

Cardon, M. S., Stevens, C. E., & Potter, D. R. (2011). Misfortunes or mistakes?: Cultural sensemaking of entrepreneurial failure. *Journal of Business Venturing, 26*(1), 79-92.

Christensen, C. M. (1997). *The innovator's dilemma : when new technologies cause great firms to fail*. Boston, Mass.: Harvard Business School Press.

Coase, R. H. (1937). The Nature of the Firm. *Economica-New Series, 4*(16), 386-405.

Coke, T. (2017). Why the New Crowdfunding Rules are Important but Ultimately a Letdown. *Journal of Business & Securities Law, 17*(1), 217.

Cope, J. (2005). Toward a Dynamic Learning Perspective of Entrepreneurship. *Entrepreneurship Theory and Practice, 29*(4), 373-397.

Crosetto, P., & Regner, T. (2018). It's never too late: funding dynamics and self pledges in reward-based crowdfunding. *Research Policy, 47*(8), 1463-1477.

Cumming, D. J., Leboeuf, G., & Schwienbacher, A. (2014). *Crowdfunding models: Keep-it-all vs. all-or-nothing.* Paper presented at the Paris December 2014 finance meeting EUROFIDAI-AFFI paper.

Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, N.J.,: Prentice-Hall.

Du, Z., Li, M., & Wang, K. (2018). “The more options, the better?” Investigating the impact of the number of options on backers’ decisions in reward-based crowdfunding projects. *Information & Management*.

Eggers, J., & Song, L. (2015). Dealing with failure: Serial entrepreneurs and the costs of changing industries between ventures. *Academy of Management Journal, 58*(6), 1785-1803.

Etter, V., Grossglauser, M., & Thiran, P. (2013). Launch hard or go home: predicting the success of kickstarter campaigns (pp. 177-182).

Fan-Osuala, O. (2017). Essays on Crowdfunding: Exploring the Funding and Post-funding Phases and Outcomes. In W. Jank, B. Padmanabhan, T. Sincich, & H. Zhang (Eds.): ProQuest Dissertations Publishing.

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction (TOCHI), 20*(6), 34.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics, 96*(1), 18-32.

Gottschalk, S., Greene, F. J., & Müller, B. (2017). The impact of habitual entrepreneurial experience on new firm closure outcomes. *Small Business Economics, 48*(2), 303-321.

Greenberg, M., Pardo, B., Hariharan, K., & Gerber, E. (2013). Crowdfunding support tools: predicting success & failure (Vol. 2013-, pp. 1815-1820).

Hertwig, R., Pachur, T., & Kurzenhäuser, S. (2005). Judgments of Risk Frequencies: Tests of Possible Cognitive Mechanisms. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*(4), 621-642.

Hughes, L. M. (2013). Crowdfunding: Putting a Cap on the Risks for Unsophisticated Investors. *Charleston L. Rev., 8*, 483.

Kamath, R. S., & Kamat, R. K. (2018). Supervised Learning Model For Kickstarter Campaigns With R Mining. *International Journal of Information Technology, Modeling and Computing, 4*(1), 17-28.

Kim, J.-Y., Kim, J.-Y., & Miner, A. (2009). Organizational Learning from Extreme Performance Experience: The Impact of Success and Recovery Experience. *Organization Science, 20*(6), 958-978.

Lafontaine, F., & Shaw, K. (2016). Serial entrepreneurship: Learning by doing? *Journal of Labor Economics, 34*(S2), S217-S254.

Leboeuf, G. (2016). *Does the crowd forgive?*

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *Mis Quarterly*, 147-167.

Levinthal, D. A., & March, J. G. (1993). The Myopia of Learning. *Strategic Management Journal, 14*(S2), 95-112.

Li, S., Schulze, W., & Li, Z. (2009). Plunging into the sea, again? A study of serial entrepreneurship in China. *Asia Pacific Journal of Management, 26*(4), 667-680.

Macmillan, I. C. (1986). To really learn about entrepreneurship, let's study habitual entrepreneurs. *Journal of Business Venturing, 1*(3), 241-243.

Macmillan, I. C., & Katz, J. A. (1992). Idiosyncratic milieus of entrepreneurial research: The need for comprehensive theories. *Journal of Business Venturing, 7*(1), 1-8.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71-87.

Mitra, T., & Gilbert, E. (2014). The language that gets people to give: phrases that predict success on kickstarter (pp. 49-61).

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing, 29*(1), 1-16.

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6).

NCFA. (2016). *Alternative Finance Crowdfunding in Canada: Unlocking Real Value through Fintech and Crowd Innovation National Crowdfunding Association of Canada*. Retrieved from http://ncfacanada.org/2016-alternative-finance-crowdfunding-in-canada-industry-report/

Nelson, R. R., & Nelson, K. (2002). Technology, institutions, and innovation systems. *Research Policy, 31*(2), 265-272.

Oo, P. P., Allison, T. H., Sahaym, A., & Juasrikul, S. (2018). User entrepreneurs' multiple identities and crowdfunding performance: Effects through product innovativeness, perceived passion, and need similarity. *Journal of Business Venturing*.

Paik, Y. (2014). Serial entrepreneurs and venture survival: Evidence from US venture-capital-financed semiconductor firms. *Strategic Entrepreneurship Journal, 8*(3), 254-268.

Parker, S. C. (2013). Do serial entrepreneurs run successively better-performing businesses? *Journal of Business Venturing, 28*(5), 652-666.

Rerup, C. (2005). Learning from past experience: Footnotes on mindfulness and habitual entrepreneurship. *Scandinavian Journal of Management, 21*(4), 451-472.

Shepherd, D., & Griffin, D. (2006). A Hubris Theory of Entrepreneurship. *Management Science, 52*(2), 160-172.

Short, J. C., Ketchen, D. J., McKenny, A. F., Allison, T. H., & Ireland, R. D. (2017). Research on Crowdfunding: Reviewing the (Very Recent) Past and Celebrating the Present. *Entrepreneurship Theory and Practice, 41*(2), 149-160.

Skirnevskiy, V., Bendig, D., & Brettel, M. (2017). The influence of internal social capital on serial creators' success in crowdfunding. *Entrepreneurship Theory and Practice, 41*(2), 209-236.

Sobel, M. E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. *Sociological methodology, 13*, 290-312.

Starr, J. (1996). Resource parsimony, resource cooptation and habitual entrepreneurs: New concepts for entrepreneurship theory and research. In S. Venkataraman (Ed.): ProQuest Dissertations Publishing.

Stevenson, R. M., Ciuchta, M. P., Letwin, C., Dinger, J. M., & Vancouver, J. B. (2018). Out of control or right on the money? Funder self-efficacy and crowd bias in equity crowdfunding. *Journal of Business Venturing*.

Toft-Kehler, R., Wennberg, K., & Kim, P. H. (2014). Practice makes perfect: Entrepreneurial-experience curves and venture performance. *Journal of Business Venturing, 29*(4), 453-470.

Tversky, A., & Kahneman, D. (2004). Judgment under Uncertainty: Heuristics and Biases. In E. Shafir (Ed.), *Preference, Belief, and Similarity: Selected Writings by Amos Tversky* (pp. 203-220). Cambridge, MA: MIT Press.

Ucbasaran, D., Westhead, P., & Wright, M. (2009). The extent and nature of opportunity identification by experienced entrepreneurs. *Journal of Business Venturing, 24*(2), 99-115.

Ucbasaran, D., Westhead, P., Wright, M., & Flores, M. (2010). The nature of entrepreneurial experience, business failure and comparative optimism. *Journal of Business Venturing, 25*(6), 541-555.

Ucbasaran, D., Wright, M., & Westhead, P. (2003). A longitudinal study of habitual entrepreneurs: starters and acquirers. *Entrepreneurship & Regional Development, 15*(3), 207-228.

Varian, H. R. (2010). Computer mediated transactions. *The American Economic Review, 100*(2), 1-10.

Wells, N. (2013). The risks of crowdfunding. *Risk Management, 60*(2), 26.

Westhead, P., Ucbasaran, D., & Wright, M. (2009). Information search and opportunity identification: The importance of prior business ownership experience. *International Small Business Journal, 27*(6), 659-680.

Westhead, P., & Wright, M. (1998). Novice, portfolio, and serial founders: are they different? *Journal of Business Venturing, 13*(3), 173-204.

Wright, M., Robbie, K., & Ennew, C. (1997). Serial entrepreneurs. *British Journal of Management, 8*(3), 251-268.

Yang, L. (2017). The Dynamics of Crowdfunding: An Entrepreneurial Learning Perspective. In H. Jungpil (Ed.): ProQuest Dissertations Publishing.

Yang, L., & Hahn, J. (2015). Learning from Prior Experience: An Empirical Study of Serial Entrepreneurs in IT-enabled Crowdfunding.

Yu, S., Johnson, S., Lai, C., Cricelli, A., & Fleming, L. (2017). Crowdfunding and regional entrepreneurial investment: an application of the CrowdBerkeley database. *Research Policy*, *46*(10), 1723-1737.

Zellner, A. (1962). An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association*, *57*(298), 348-368.

Appendix

Data Visualization: Plots over Time

Time trends can provide valuable insight into the nature of any longitudinal dataset. Below, we provide a number of graphs that illustrate how the statistics of projects, their backers, pledged amounts, success to failure ratio, etc. changed year over year in the Kickstarter platform. In these graphs, we have eliminated the data of 2018 since we do not have complete data for the whole year. Figure 16 shows the time trends for the number of projects and number of backers during Kickstarter's lifetime. A descriptive analysis of backers, project, success/failure, and pledged can be found in Figure 17, Figure 18 and Figure 19. Figure 20 and Figure 21 breakdown the performance indicators of all projects and successful project by experience over time respectively. Another useful parameter to investigate is category. In Figure 22, we see the performance over time broken down by category.

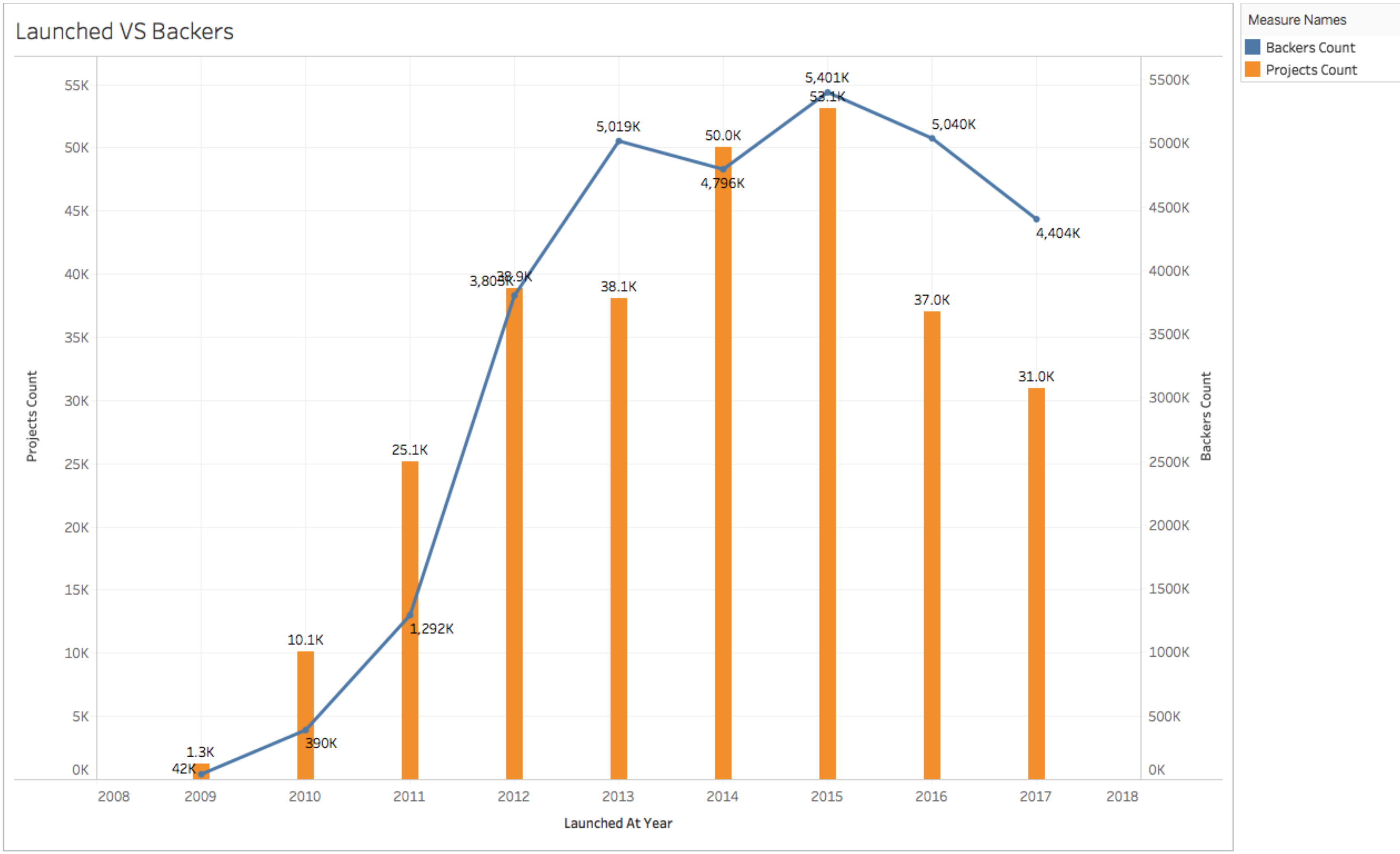

Figure 16. Backers and projects count over time

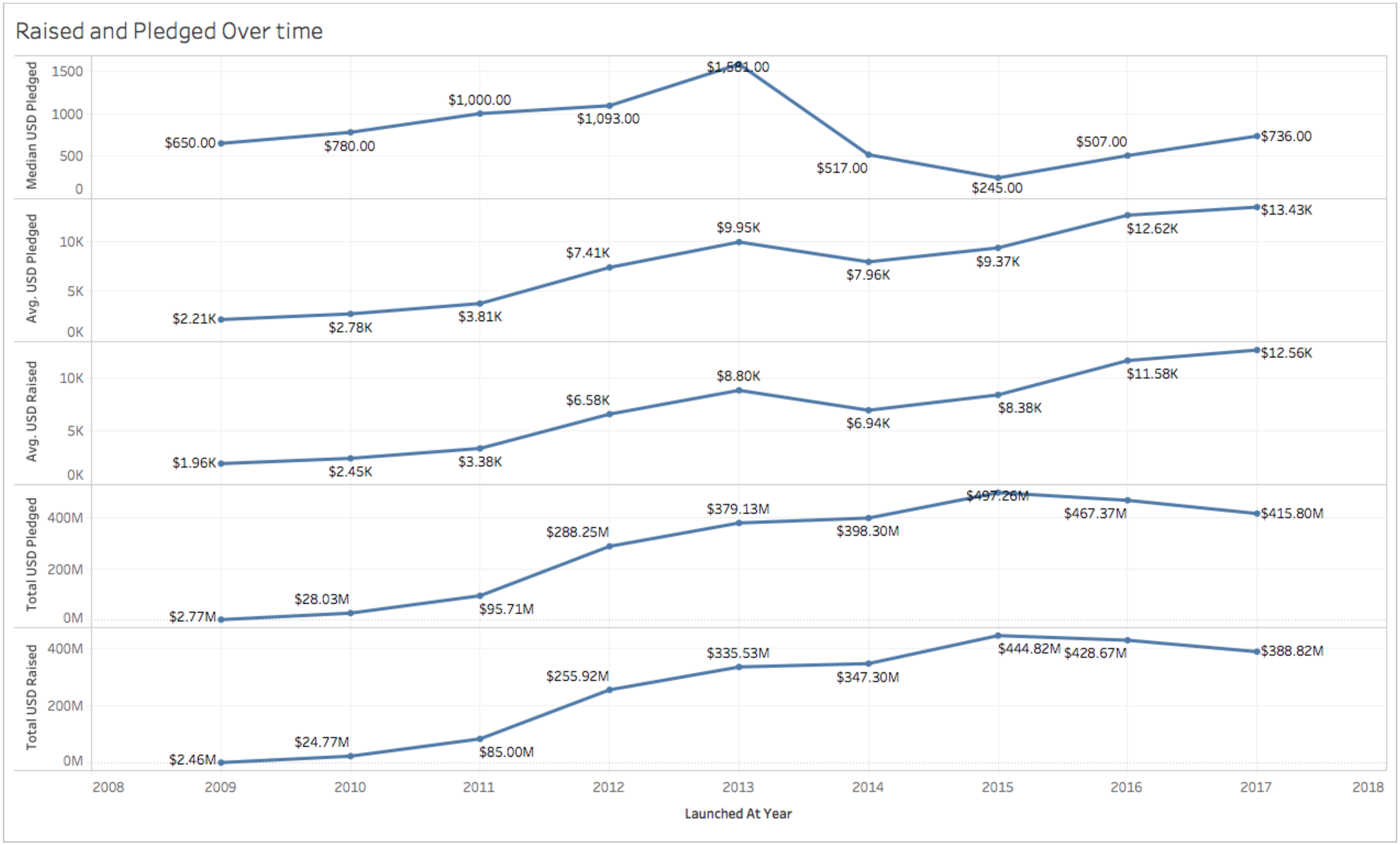

Figure 17. Pledged and raised amounts over time

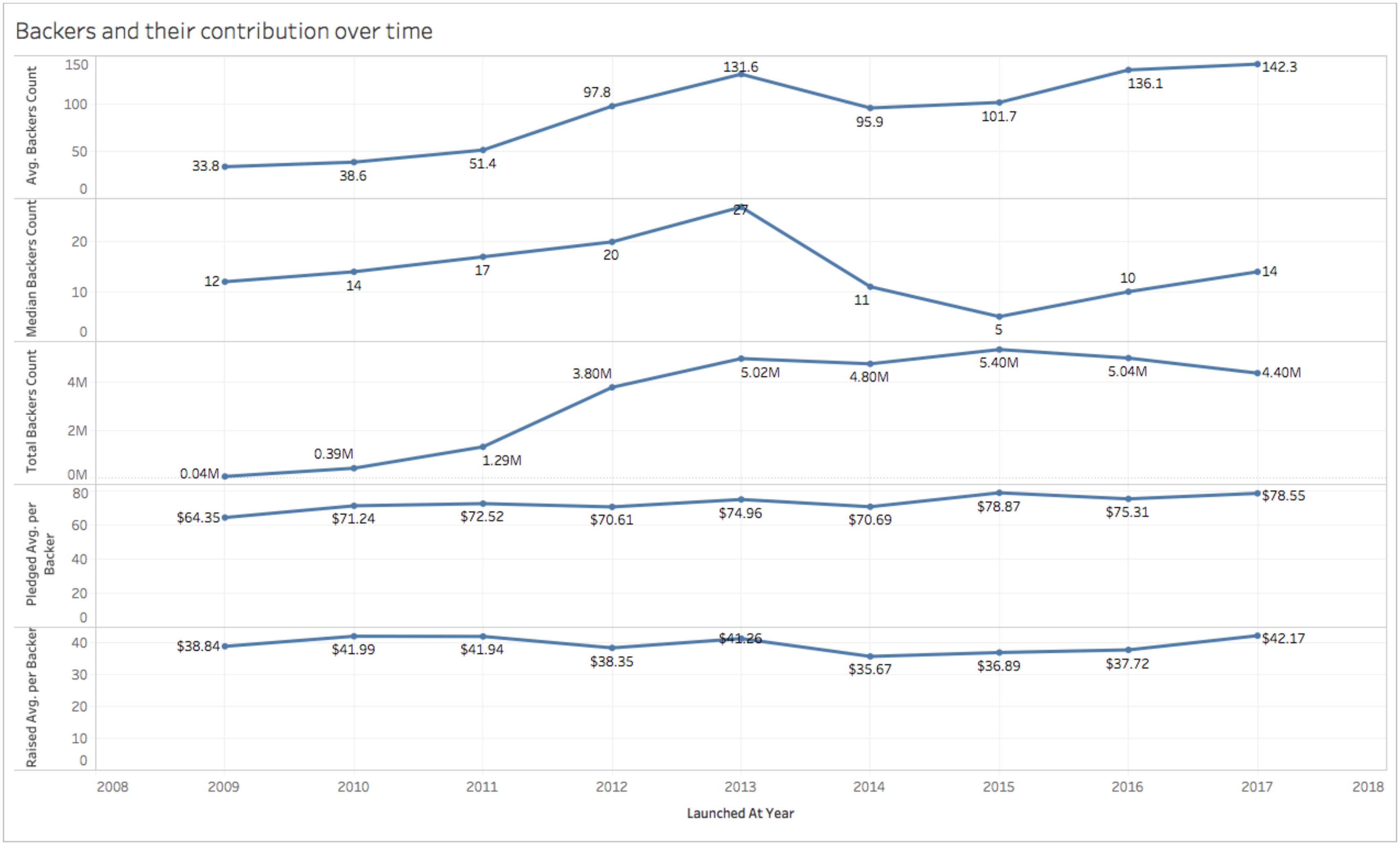

Figure 18. Backers and their contribution over time

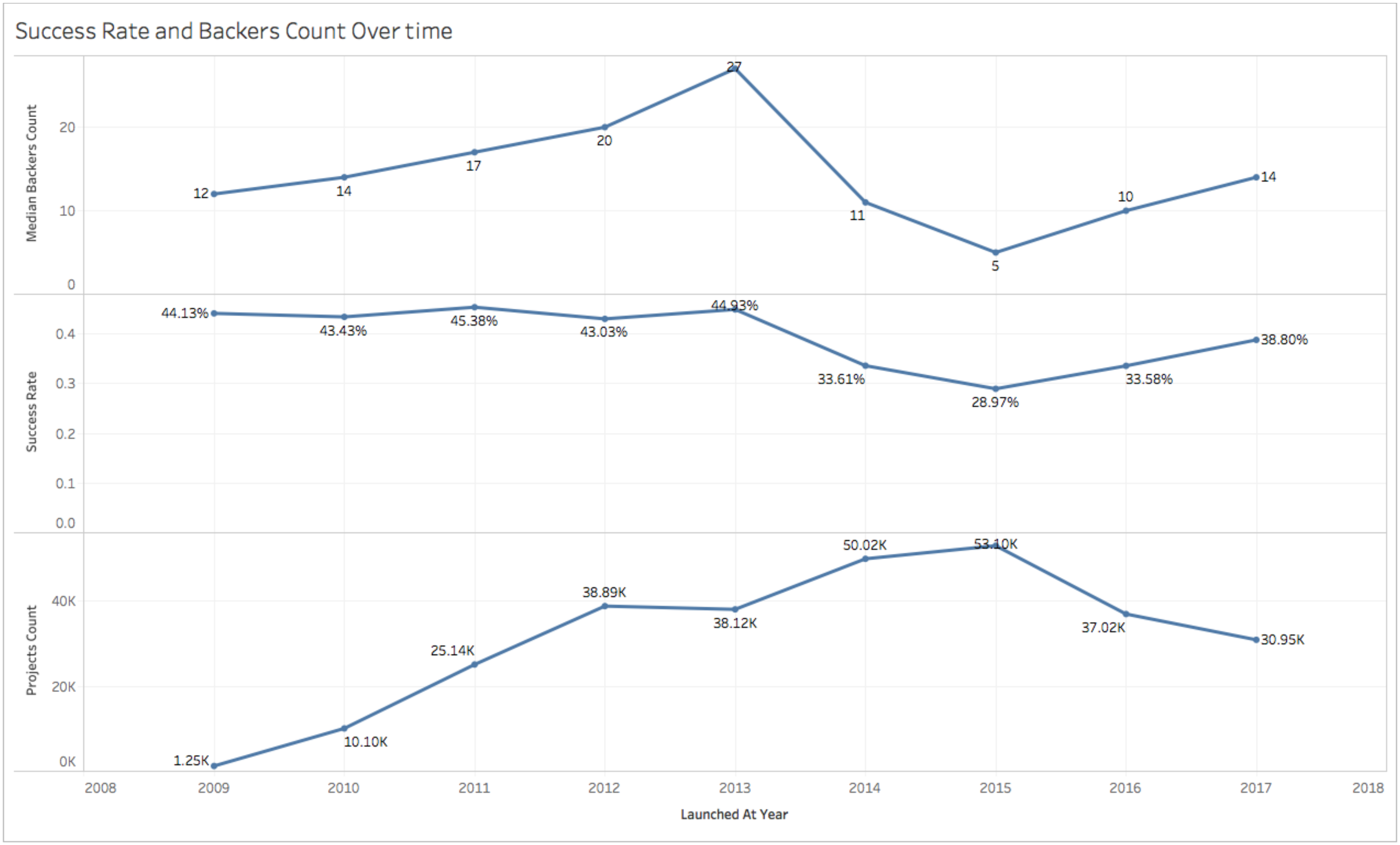

Figure 19. Success and backers count over time

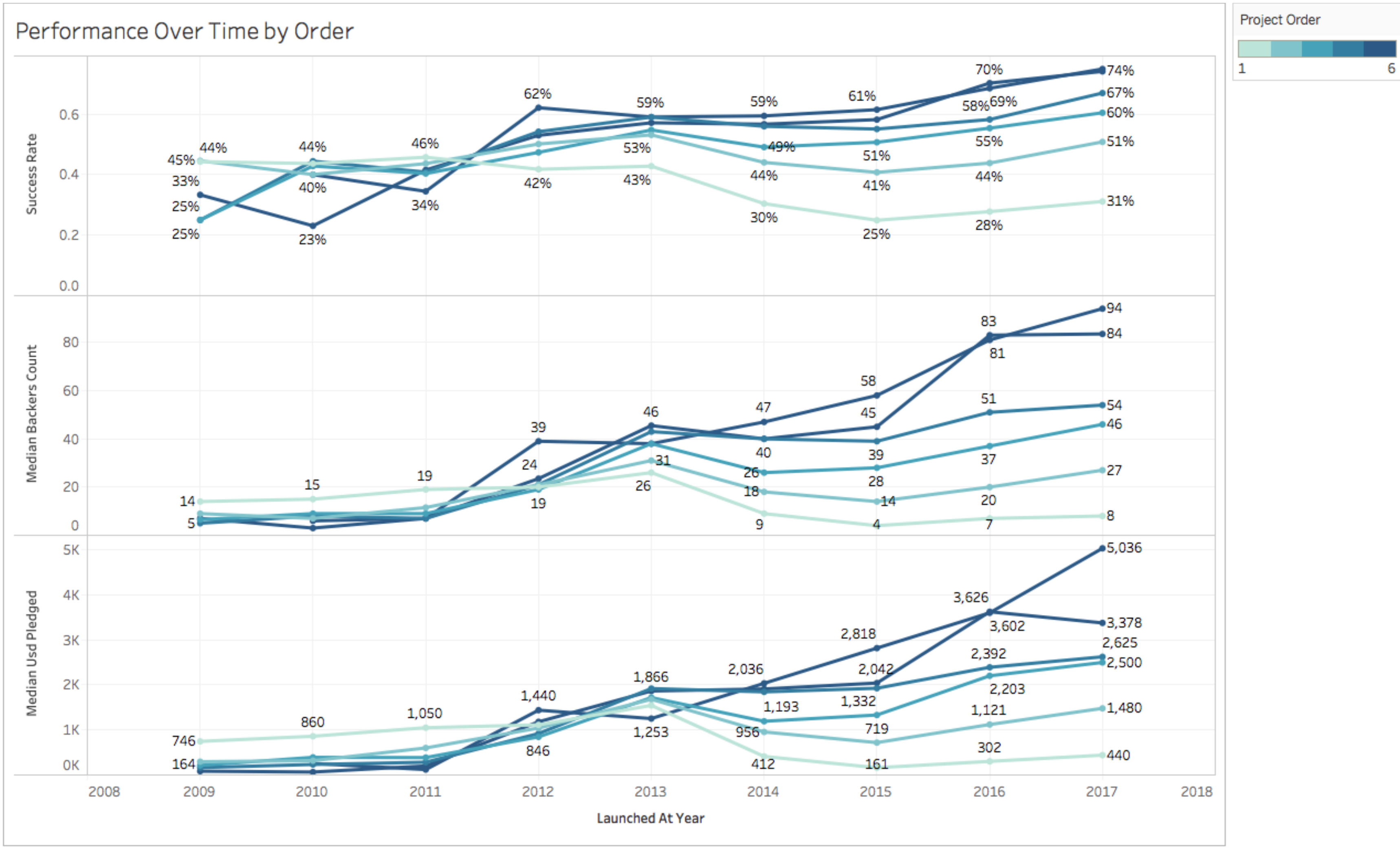

Figure 20. Performance over time by experience

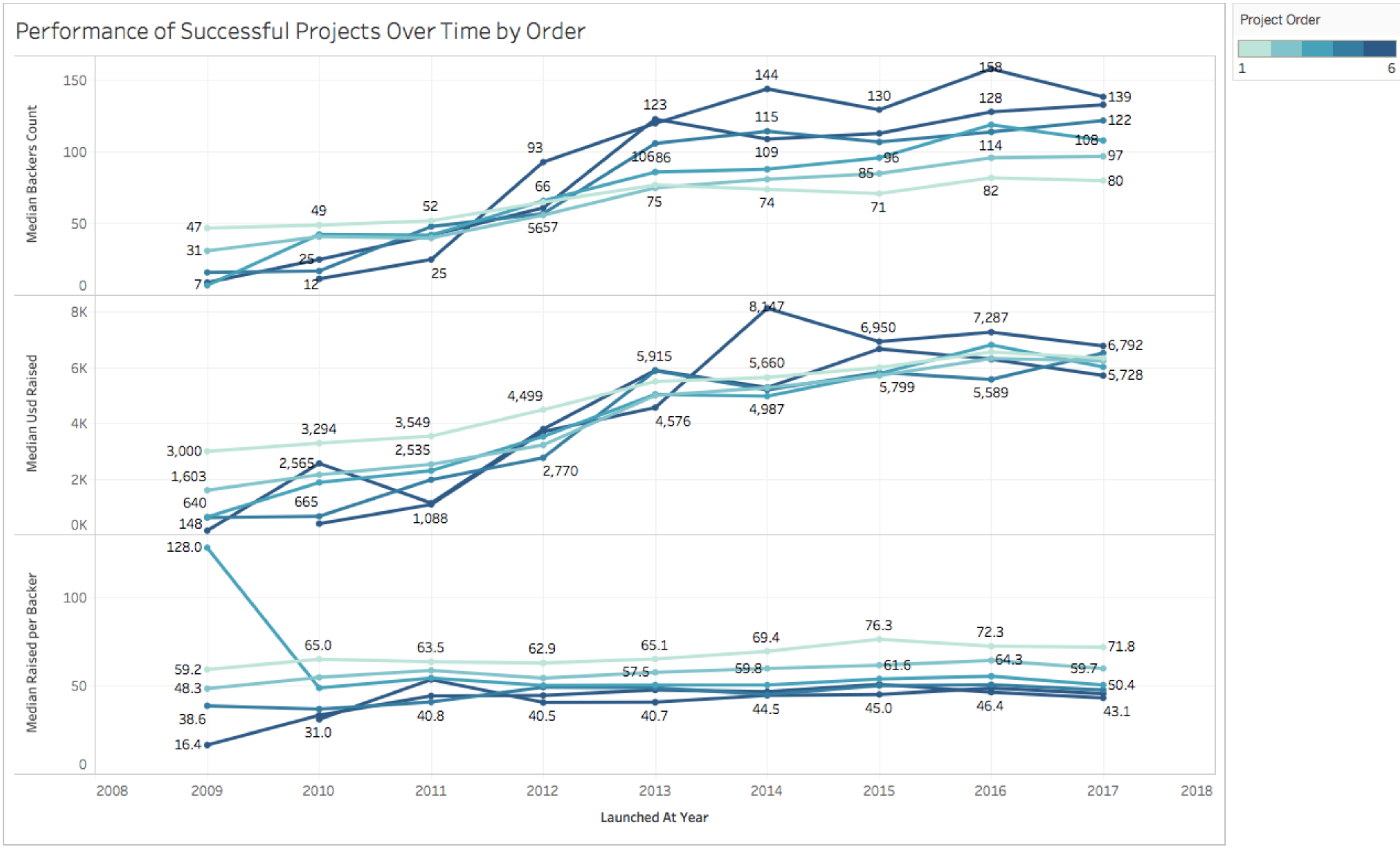

Figure 21. Performance of successful campaigns over time by experience

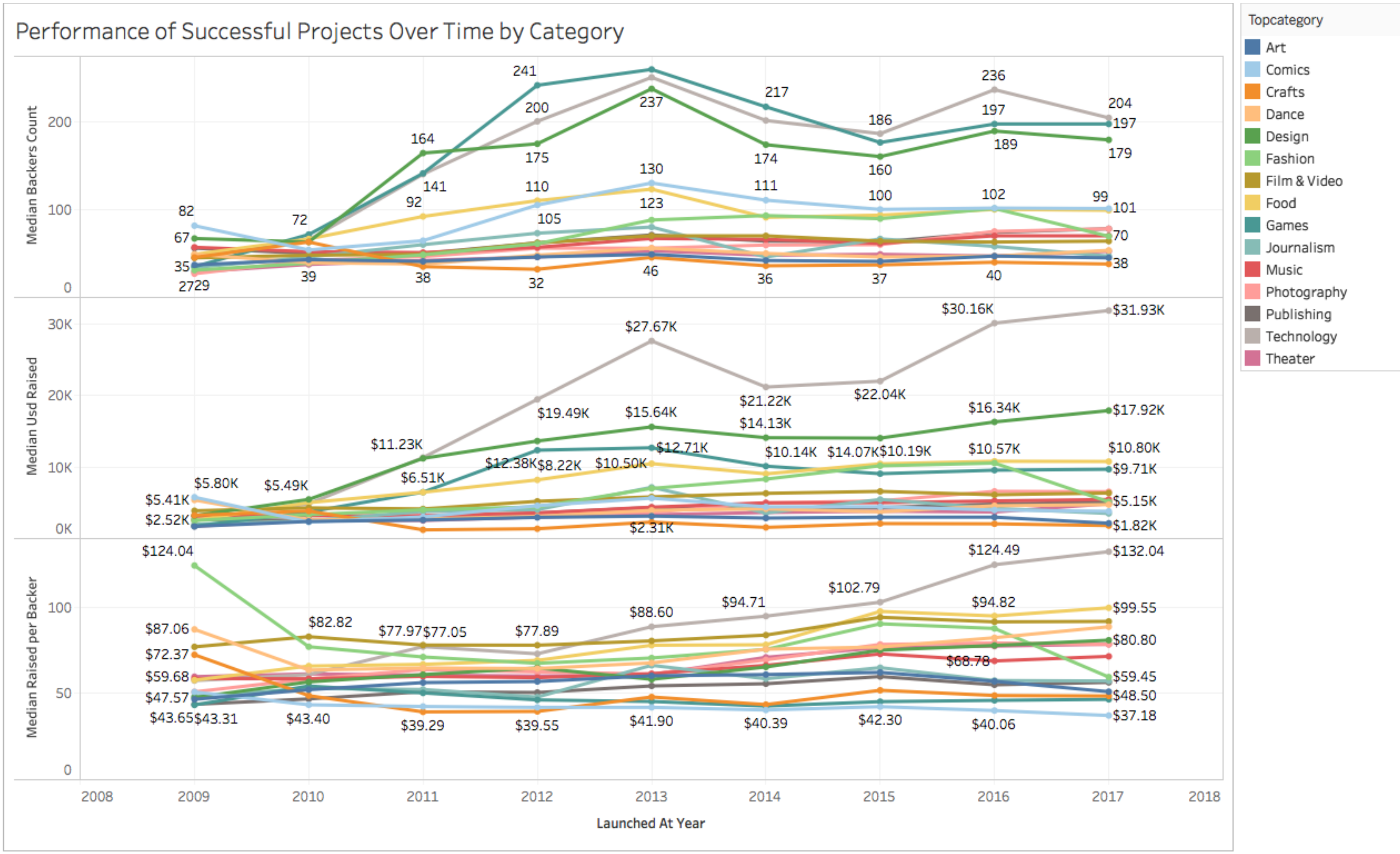

Figure 22. Performance of successful campaigns over time by category

Data Visualization: Maps and Geographic Distributions

Data visualization on geographic maps is another method of gaining deeper insight into the nature of a dataset. Here, we map different variables of our data of the US including Facebook friends, backers count, serial rate (the percentage of serial creators among all creators), success rate and projects count are shown in Figure 23, Figure 24, Figure 25, Figure 26 and Figure 27 respectively.

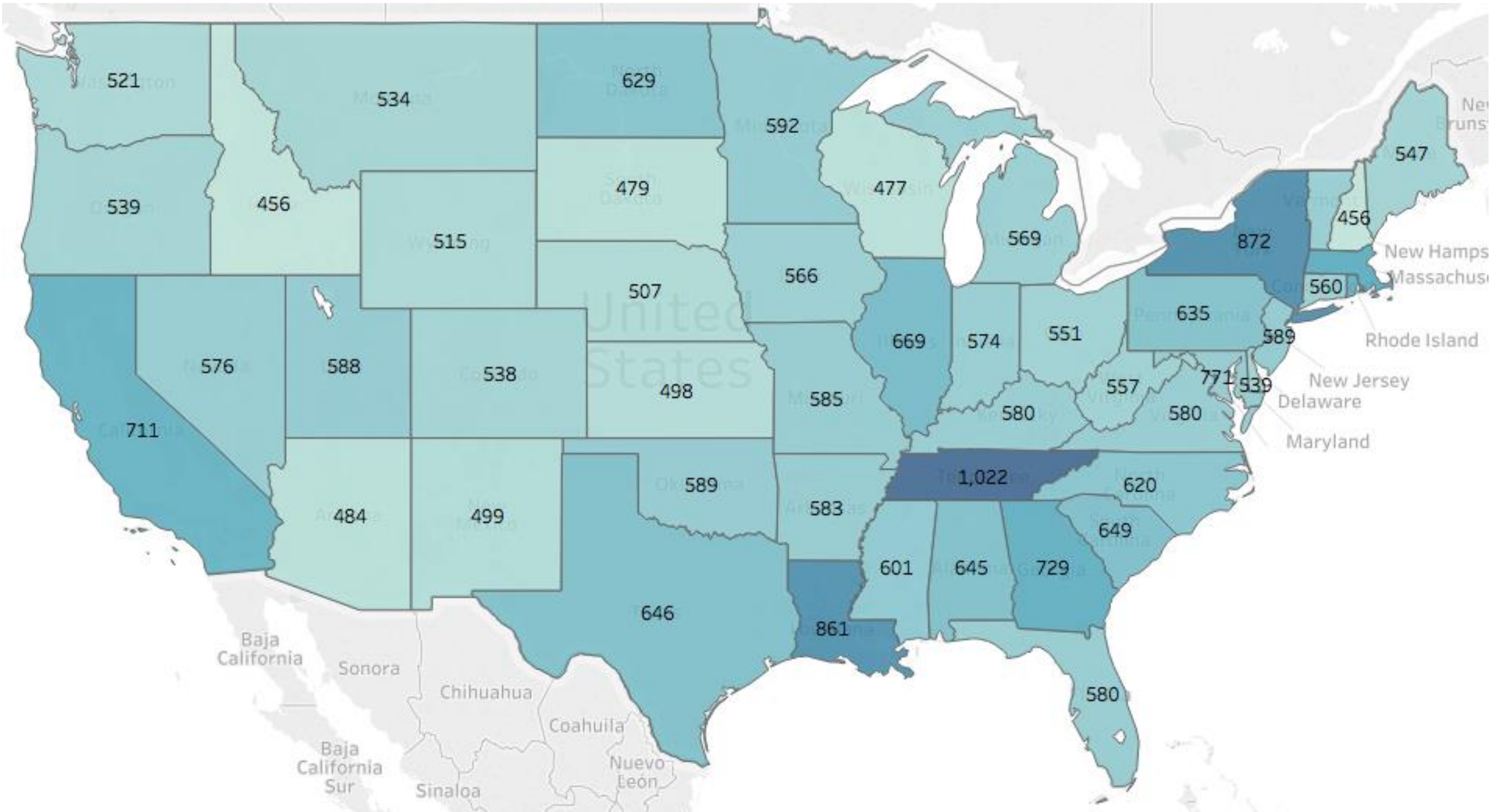

Figure 23. Median Facebook friends of all crowdfunders in the US States

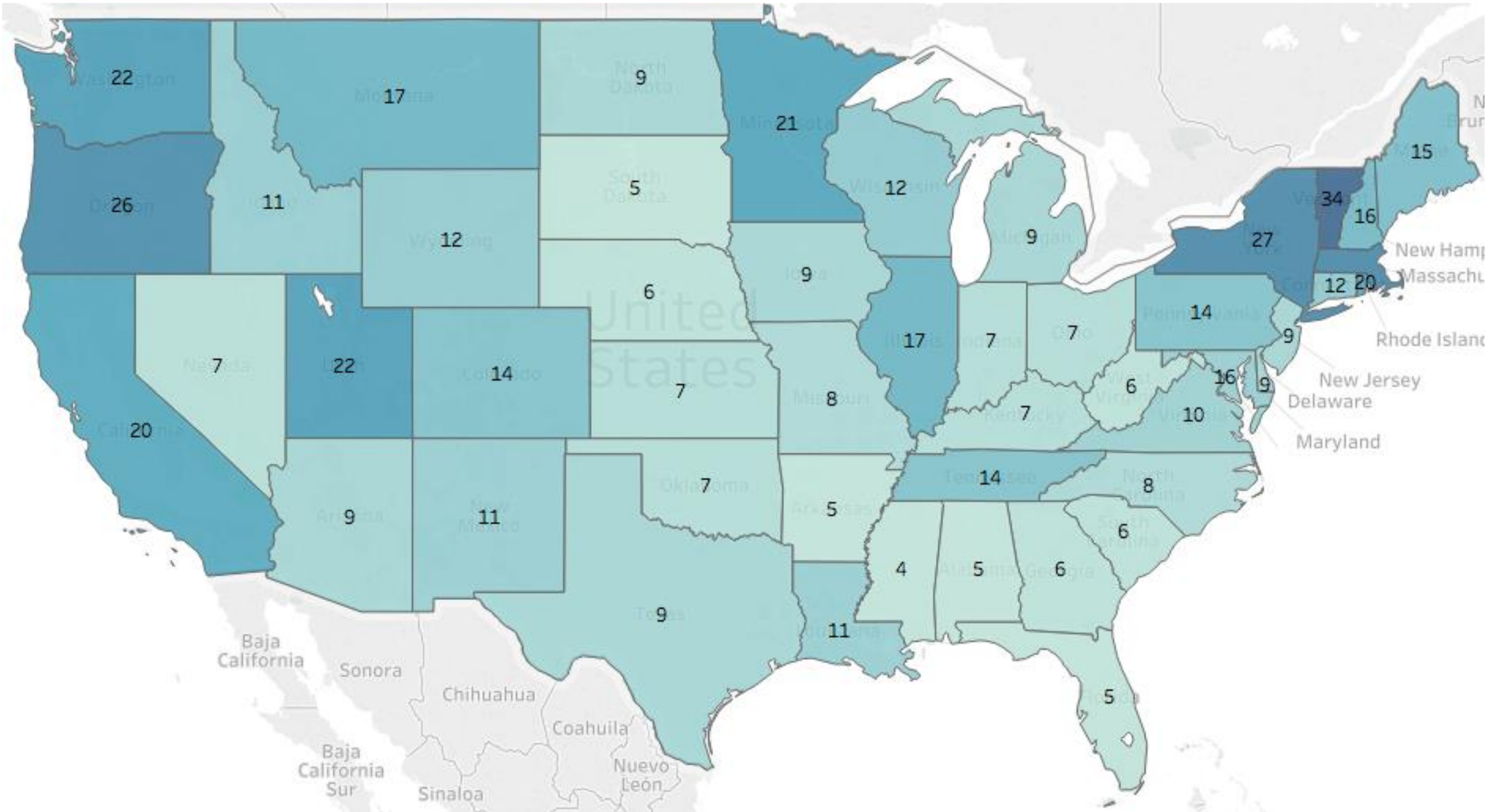

Figure 24. Median backers count in the US States

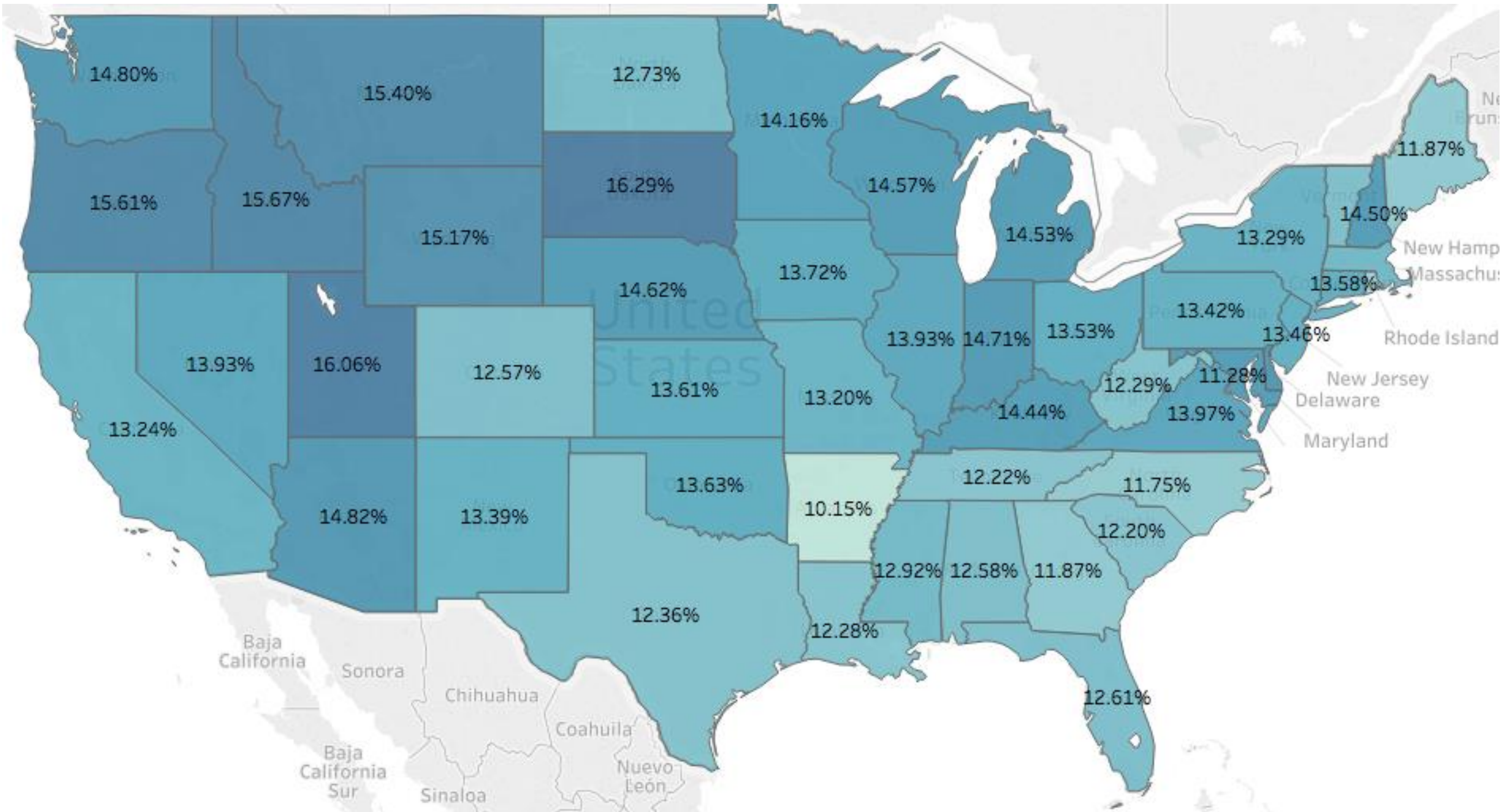

Figure 25. Serial creator rates (percentage of serial creators among all creators) in the US States

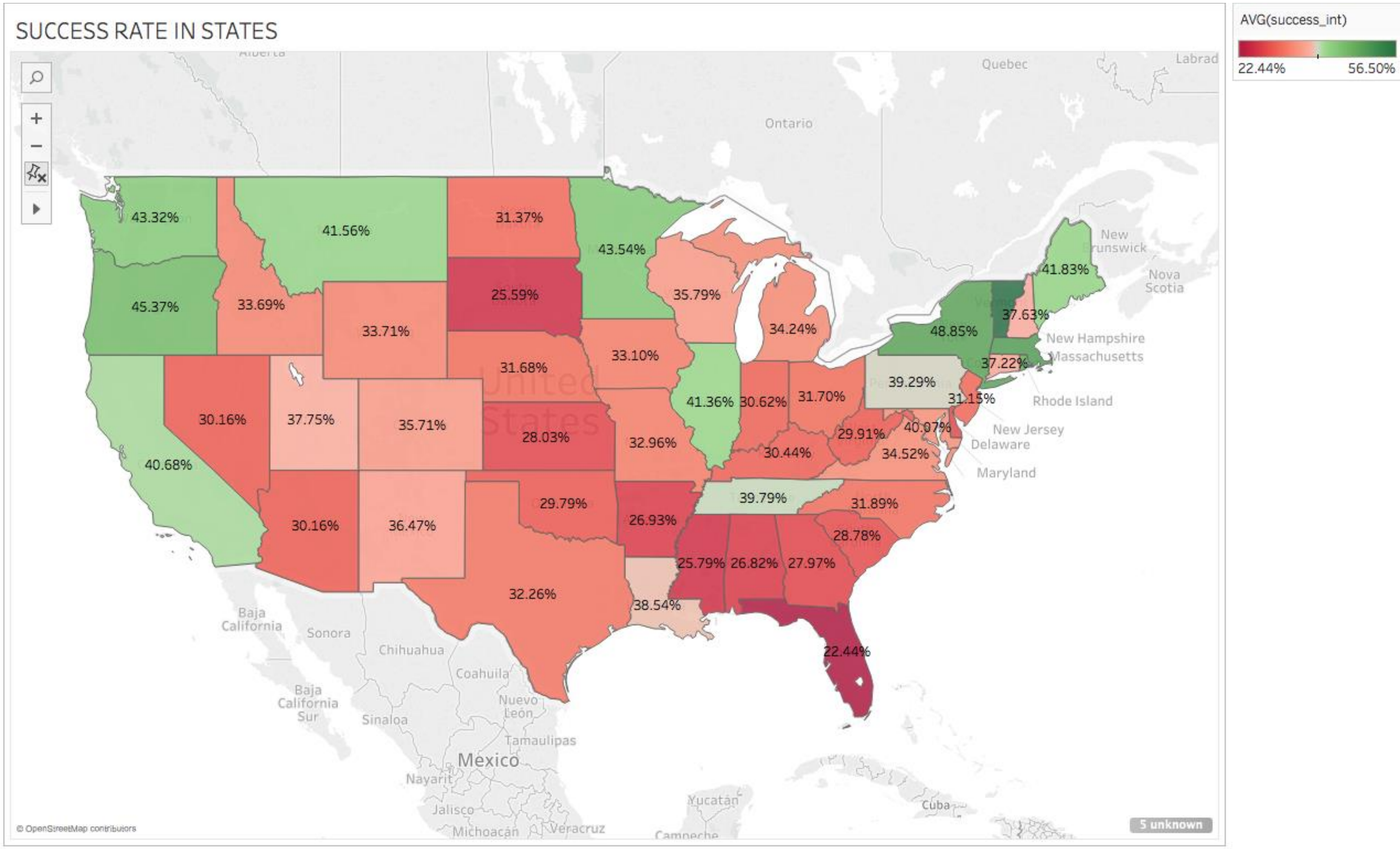

Figure 26. Success rate in the US States

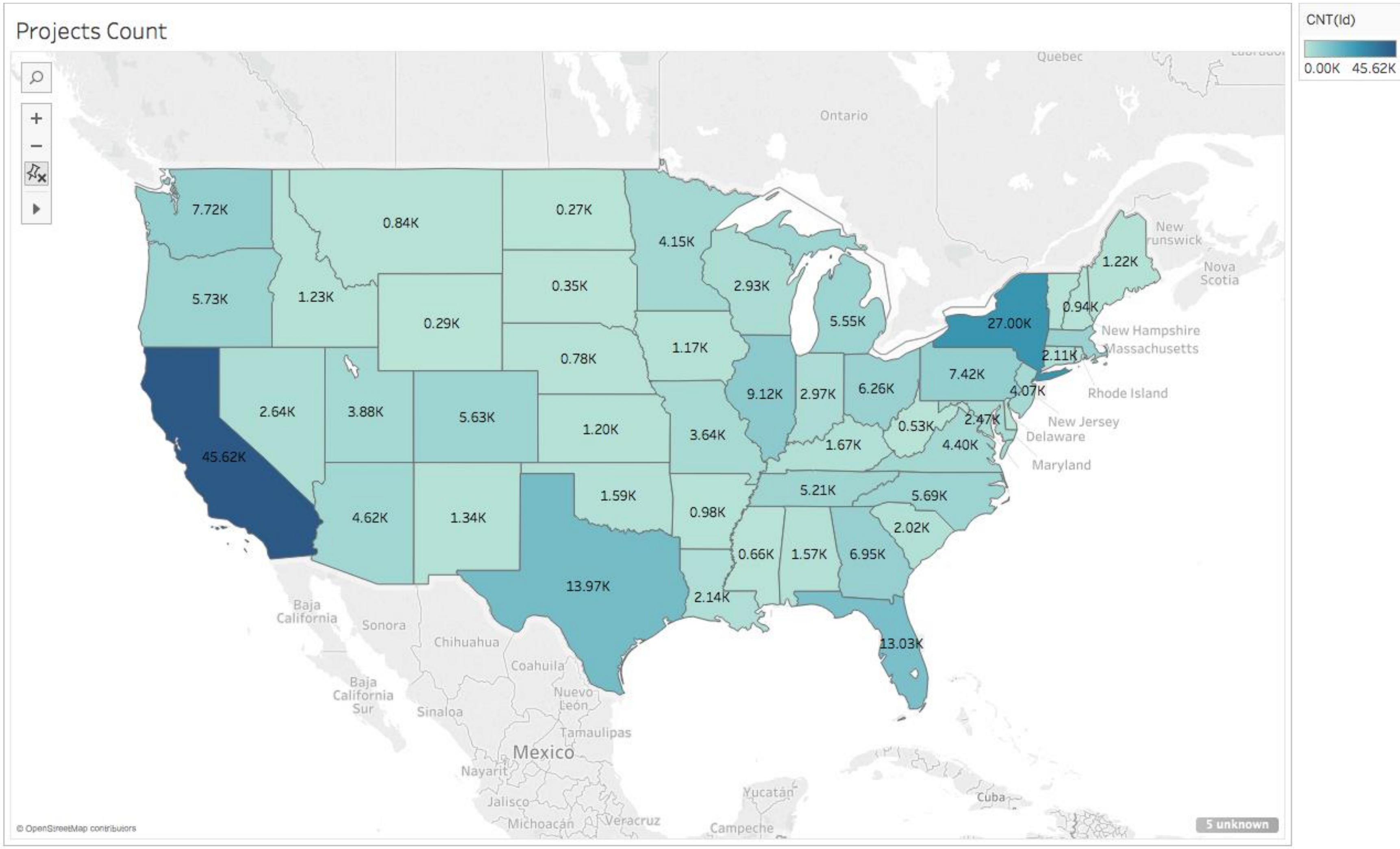

Figure 27. The number of all projects in the US State