UNDERSTANDING AND ADAPTING TO CROWD BEHAVIOR: A STUDY OF WIRELESS NETWORKS AND ENTREPRENEURIAL CROWDFUNDING

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ABSTRACT

The advances of the future will demand scholars have a systemic vision to solve problems. Integration across disciplines is needed to study, explain, inquire and discover beyond the traditional borders of academic areas. In this research, we consider the effects of crowd behavior in wireless networks and funding. First, we seek to demonstrate how to improve the allocation of wireless network resources based on the use of aggregate data from crowds' mobile phones and dynamically improve the wireless network around them. The data is used to develop an optimization allowing a more efficient management of the network. Second, using tool sets from engineering and entrepreneurship, we study the interaction of herding and speed to goal towards success on the crowdfunding environment using the liability of newness as a theoretical lens. Finally, we advance entrepreneurial crowdfunding literature through developing a new framework to understand the different paths to success.

One of the challenges of deploying dense networks is unpredicted human mobility behavior. Today, the static allocation of carriers results in a suboptimal use of spectrum resources. In this essay, we introduce the concept of Dynamic Carrier Allocation as the ability of dynamically move carriers from one cell to another based on the demand. Simulation results demonstrate on average 25% higher efficiency when compared with the previous static allocation schemes.

Crowdfunding has become a popular substitute for traditional sources of funding for new ventures. While some research has been done to explain the reasons an entrepreneur is successful in this environment, the understanding of the interaction between the early and late stages of the campaign still cloudy. In this essay, we use the liability of newness theory and over 2,400 crowdfunding projects to discuss the connection between the timing of the herding effect and the speed in which the campaign is funded. We also look how the size of the goal moderates this effect. Then, we propose a taxonomy for the different paths towards crowdfunding success. The conceptual and empirical findings of this work extend our understanding of entrepreneurial legitimacy and the roles played by early stage funding strategies in overcoming internal and external liabilities of newness.

APPROVAL PAGE

The faculty listed below, appointed by the Dean of the School of Graduate Studies, have examined a dissertation titled “Understanding and Adapting to Crowd Behavior: A Study of Wireless Networks and Entrepreneurial Crowdfunding,” presented by Pedro Tonhozi de Oliveira, candidate for the Doctor of Philosophy degree, and hereby certify that in their opinion it is worthy of acceptance.

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CHAPTER 1

INTRODUCTION

As an interdisciplinary student in Telecommunication & Computer Networking and Entrepreneurship & Innovation, my goal is to demonstrate I am able to not only work just efficiently as an Entrepreneurship Scholar and as an Engineering Scholar but also overcome research challenges by looking from an interdisciplinary lens. This dissertation explores the use of those perspectives to study crowd and effects. Using the interdisciplinary approach, it addresses each area of knowledge individually, both from the standpoint of future mobile networks and from the viewpoint of entrepreneurial success and failure in the crowdfunding environment.

The first essay addresses the concept of Dynamic Carrier Allocation (DCA). One of the challenges of deploying dense networks is unpredicted human mobility behavior. If resources must be allocated statically, carriers are allocated to cope with peak demands, but this results in a suboptimal use of spectrum resources. However, with the traffic demand needs of a smart city, innovative solutions are needed. In this essay, we introduce the concept of Dynamic Carrier Allocation as the ability of dynamically move carriers from one cell to another based on the demand. We revisit different approaches of allocation of frequencies to base stations and offer a new dynamic optimization perspective to serve the different demand needs in different times of the day. This solution is used to enable high-efficiency carrier aggregation on the top of the scheduling layer. Simulation results demonstrate on average 25% higher efficiency when compared with the previous static allocation schemes.

The second essay explores the exponential rise in the crowdfunding of entrepreneurial projects. Crowdfunding campaigns can be an integral part of the process used by founders to gain exposure for their products and acquire financial or social capital for their new ventures. In this essay, we investigate the relationship between the stages of a crowdfunding campaign and success and overfunding in the reward-based community–Kickstarter.

Multiple factors contribute to entrepreneurs' success in crowdfunding campaigns, however, prior studies emphasize either only the speed at which the entrepreneurship achieves reward based goals or the concentration of backers (herding) at each campaign stage. Both have been shown to be predictors of crowdfunding success, however, we propose that the pathways to success are more varied. Factors such as the interaction of speed to goal and herding, as well as, the strategic orientation and responses of the entrepreneur founders may matter also.

To examine these questions, we use liability of newness as the theoretical lens. This framework allows us to ask questions about the role played by the legitimacy of the entrepreneurs, the products that are the foundation of their crowdfunding campaigns and the ventures themselves. In our first study, we use a unique database of over 2,400 crowdfunding projects to examine the herding behavior and speed to goal in the early and late stage of the campaign. This is possible because our panel data was collected every six hours, revealing intrinsic behavior not observed without this temporal detail. Then, we empirically demonstrate that there are alternative pathways to crowdfunding success.

This second study, drawing on emergent patterns, we develop a typology of alternate pathways that entrepreneurs can take to maximize the financial, human and social capital that support their crowdfunding campaigns. The conceptual and empirical findings of this work extend our understanding of entrepreneurial legitimacy and the roles played by early stage funding strategies in overcoming internal and external liabilities of newness. We do that by highlighting actions the entrepreneur may take to increase the probability of success in a crowdfunding campaign, not only raising extra funds but also creating an initial market value and proof of concept.

1.1 A Background to Dynamic Carrier Allocation

The 3GPP has released a Study on Scenarios and Requirements for Next Generation Access Technologies which predicts beyond the 5th Generation, and it lays out a pathway toward 2030 for the Wireless Industry [1]. It expects a fully connected and mobile society, using the technology in unimaginable ways, with a steep increase in the traffic, in the number of devices, and in the ways of using them. IMT-2020 set a metric for traffic increase of 200 times between 2010 to 2020, achieving the so-called 5G technology [59]. However, IMT-2030 foresees a further increase on the order of 100 times between 2020 to 2030 [60]. This increase creates a challenge for the industry and academia that must find ways to make this growth viable. In this sense, the improvement needs not only to address the telecommunication market but also allow the sustainable development of the eco-system, energy, operational and cost efficiencies.

Beck and Panzer in 1989 said that ”the limited availability of radio frequency spectrum will require the future systems to use efficient methods to increase network capacity and to adapt to various traffic situations” [18]. Back then, the challenge was allocating channels to users inside a base station. Additionally, there was not available a fast and centralized control system able to know the allocation of all channels in each base station. However, they highlight that in an ideal scenario the automatic adaptation to instantaneous interference and traffic situations would be required. Unthinkable at the time, the fairly new technology development in Carrier Aggregation, Software Defined Wireless Networks (using for example Cloud Radio Access Networks) and Network Function Virtualization have enabled new methods to improve the efficiency of the network.

Today, companies like Sprint in the United States are already deploying carrier aggregation using three 20-megahertz carrier bands in the 2.5 GHz band [82]. T-Mobile is also deploying this technology [83]. Those wireless service providers and many others must cope with the task of assigning and administrating the carrier resources they allocate efficiently.

Exploring those technologies and solving for the traffic increase was the motivation to the work presented in this dissertation. The goal is to provide an intriguing and exciting avenue of research as we challenge the status quo and develop a new perspective for the future network.

1.2 A Background to Crowdfunding

It was not until 2009 that crowdfunding started to gain momentum. The United States was recovering from the financial crisis in 2008, and many traditional forms of acquiring funds were frozen. Not only artisans, entrepreneurs, and early-stage enterprises were struggling to raise funds they needed, but also people had just lost their jobs and opening new ventures seemed right. Maybe they perceived it as the right moment because of the lack the courage to do so when they had a stable job, but now the table had changed, Perhaps they were able to perceive something that others have not. Regardless of the reason, traditional banks were less willing to lend, which made entrepreneurs start looking elsewhere for capital.

This moment was when crowdfunding was born, an Internet-enabled way for individuals or organizations to raise funds in the form of either donation, pre-sale, loan or investment from multiple people. The initial idea was a community of friends and family that would pool resources to fund a promising business idea, however, this time using the Internet as a platform. Today, crowdfunding has not only became essential for funding in developed economies but also tapped into the developing economies with exceptional strength. When talking about developed economies, we find many platforms mediating crowdfunding campaigns in the United States, the United Kingdom, Australia, Germany, the Netherlands, Italy, and Canada. Within those, we have the big five platforms: Indiegogo (founded in 2008), Kickstarter (2008), Gofundme (2010), Teespring (2011) and Patreon (2013).

One of the reasons for the success of the crowdfunding concept is due to the wisdom of the crowd [111]. The notion is that the collective opinion is more accurate than a single expert. The caveat is that in this concept, there should be no irrational herding. Irrational herding occurs when someone else's decision affects the decision of the next. An example is when one decides to buy because everyone is buying, trusting in the judgment of others without executing any due diligence. The wisdom of the crowd acts as a decision-making tool, it enables projects and businesses that are relevant to be funded while defunding others.

Another player of this success is the creation of social capital. This is use of social interactions through social network platforms (e.g. Facebook, Twitter, LinkedIn, YouTube and Snapchat) to reach out to possible donors beyond one's close network. Many researchers are exploring this area.

However, some questions remain, what happens during a campaign that makes it successful? What can someone do to improve the quality of a campaign? How do the interactions happen? These questions were born in the second year of the Ph.D., and we decided to investigate the topic further.

1.3 Organization of the Work

This dissertation is structured as follow. Chapter 2 shows the work done on carrier aggregation. Chapter 3 discusses the different paths to crowdfunding success. Finally, Chapter 4 presents a summary of the topic discussed, conclusion and future research perspectives.

CHAPTER 2

OPTIMAL DYNAMIC CARRIER ALLOCATION FOR FUTURE WIRELESS NETWORKS

2.1 Abstract

One of the challenges of deploying dense networks is unpredicted human mobility behavior. If resources must be allocated statically, carriers are allocated to cope with peak demands, but this results in a suboptimal use of spectrum resources. However, with the traffic demand needs of a smart city, innovative solutions are needed. In this essay, we introduce the concept of Dynamic Carrier Allocation as the ability of dynamically move carriers from one cell to another based on the demand. We revisit different approaches of allocation of frequencies to base stations and offer a new dynamic optimization perspective to serve the different demand needs in different times of the day. This solution is used to enable a high-efficiency carrier aggregation on the top of the scheduling layer. Simulation results demonstrate on average 25% higher efficiency when compared with the previous and static allocation schemes.

2.2 Introduction

Today, the growing demand and ever-increasing volume of mobile data traffic create challenges for mobile operators and an increasing strain on cellular networks. Papers provide considerations on the road to the fifth generation (5G) and the challenges ahead [14, 49]. In the list of challenges, there is the threshold in the network capacity of macrocells, the constantly evolving concept of mobile performance and its metrics, and the growing number of devices and Radio Access Technologies (RATs). While many researchers have focused on many of those challenges, we have chosen to address the issue of limited radio bandwidth resources. As far as our knowledge we are the first to propose an innovative way to address the carriers in smart cities' dense network environment by providing a solution based on their dynamic allocation. This work then proposes an optimization scheme to enhance the use of carriers resources and compares it to the status quo. Our findings demonstrate improvement in efficiency on average of 25% over traditional methods of allocation.

In the network, one cell, regardless of the size, receives one carrier block (20 MHz) or partial sections of this resource. With the advance in the RAT, those carrier blocks started to be aggregated, and it is predicted, at least in theory, to have up to 32 aggregated carriers in the foreseen future [17, 89]. While this offers some improvement in the number of resources available, the management of the allocation of those resources become then highly complicated and easily susceptible to human error. One of the complications is the mismatch between a wireless service provider subscribers' traffic demand and its available capacity. Those users demands vary spatially and temporally resulting in resources being underutilized when there is a low user demand or in short supply in high demand locations. Wireless service providers and vendors have simplified the solution of this unpredicted human mobility behavior by addressing the average peak demand, which results in unhappy customers and wasted resources most of the time. To improve the management and efficiency of those carriers, we propose a new function to address demands instead of predicted peaks dynamically.

The goal is to adapt the network frequencies depending on the traffic, neighboring base stations, resource availability, and user demand. This concept of automatic adaptation offers a new view on how to increase the network capacity, reduce the need for frequency planning, and allow the introduction of new base stations without the need to re-plan the carrier allocation. One example would be bringing Cells On Wheels (COWs) to a particular area, activating them, having them borrow the resource from nearby cells, and returning those upon conclusion. Without automatic adaptation, the network is designed to cope with peak demands, resulting in a suboptimal use of carrier resources. Technologies like Software Defined Wireless Networks and Network Function Virtualization can be used as a platform in which such adaptation would run on top. In this essay, we present an optimization model for the allocation of carriers in base stations to serve the different demand needed for the daily operation.

The organization of the essay is as follows. In Section 2.3, we describe the current literature and directions proposed for the future technologies related to carrier allocation. Section 2.4 state the problem, the solution and presents the assumptions of the proposed carrier allocation optimization algorithm. Section 2.5 explains the algorithm, objective, constraints and provides the full equation. Section 2.6 calculates our mathematical expectation of the results. Next, in Section 2.7 we show the different simulations, followed in Section 2.8 by the discussion of the results found. In this, we were able to achieve on average 25% higher efficiency than the carrier aggregation methods available in the current state of the art solution. Finally, Section 2.9 explores the challenges and benefits of implementing the proposed method.

2.3 Literature Review

To assess the state of past research surrounding our proposed solution, we looked for relevant works in top networking and communications outlets. We included well-known articles on resource allocation then performed a systematic literature search. There are 15 publications pertinent to the carrier allocation issue. Specifically, we began our investigation by examining the set of peer-reviewed journals with an impact factor above two. This list included major communications journals, namely *IEEE Communications Surveys and Tutorials, ACM Computing Surveys, IEEE Communications Magazine, IEEE Wireless Communications, IEEE Journal on Selected Areas in Communications, Computer Physics Communications, Communications of the ACM, IEEE Transactions on Smart Grid, Internet Research, IEEE Transactions on Wireless Communications, IEEE Network, IEEE Transactions on Broadcasting, Journal of Network and Computer Applications, IEEE Transactions on Communications, IEEE Transactions on Vehicular Technology, IEEE/ACM Transactions on Networking and Computer Communications*.

We searched for all articles using one or more of the following terms in the title, abstract, or keywords: ”Dynamic Carrier Allocation,” ”Dynamic Spectrum Allocation,” ”Frequency Allocation,” ”Coloring Problem,” ”Resource Block Allocation,” ”Dynamic Subcarrier Allocation,” and ”Carrier Aggregation.” While many studies were concerned with carrier allocation for wireless cellular networks, others looked at different types of resource allocation in the network rather than carrier allocation. All resource allocation studies that did not directly address wireless cellular networks (e.g. resource allocation for virtual machines in cloud computing) were eliminated from the review sample. Based on this criteria, 15 original research pieces relevant to carrier allocation constitute previously published relevant work. Journals publishing this research included *IEEE Communications Surveys and Tutorials* (1), *IEEE Communications Magazine* (2), *IEEE Wireless Communications (1)*, *IEEE Journal on Selected Areas in Communications* (4), *IEEE Transactions on Wireless Communications* (4), and *IEEE Transactions on Vehicular Technology* (3). We offer a narrative on the literature below.

2.3.1 Coloring Problem

The fundamental problem of spectrum assignment in a cellular network used to be the assignment of carriers to cells in a manner that every client was served. The concept of coloring is to assign different colors for each frequency allocated and then minimize the number of colors used. It is used to reduce the effects caused by the mutual interference of two or more base stations that are assigned the same frequency. Many researchers have studied this problem and present solutions, Even et al. [43] has demonstrated that it is not as easier as the classic graph coloring problem, others have assume the static proprieties of the macrocell to propose optimization algorithms [62], or demonstrated that this to be NP-complete and propose an hybrid approach [23, 41]. However, the solution presented is intended for a static frequency assignment [88]. The solutions presented by themselves are not enough to address the need for higher efficiency in the use of those resources of the present and future. With the introduction of carrier aggregation, more spectrum as being allocated to service providers and thus requires a way to use them dynamically with the fast pace changing environment efficiently.

2.3.2 Dynamic Channel Allocation

Some studies focus on the individual level communication between the base station–user pair to provide more efficient access to the channel to the individual or group through competition or cooperation. The solution can be based on game theory [6], the use of synchronous or asynchronous techniques [32, 98], channel segregation [5] or channel partitioning [30], with or without frequency hopping [69, 113]. The goal is to provide the best dynamic channel allocation strategy to reduce delay and attain better performance [57, 94]. A good summary of this topic can be found in [53].

A fundamental problem of dynamic channel allocation strategies with distributed control concerns the coordination among base stations to avoid conflicting acquisitions of the same carrier from two base stations located at a distance lower than the reuse distance. While our proposed solution differs from dynamic channel allocation, we still rely on it to avoid interference between carriers. We address the coordination problem by reducing the update time in the optimization.

2.3.3 Dynamic Subcarrier Assignment

Dynamic subcarrier assignment is utilized in an orthogonal frequency-division multiple access (OFDMA) system to improve the system data rate when multiple users are present [107]. This works under the assumption that while one user might be under a deep fade, others might not. Therefore, assign subcarriers dynamically to adjust to the fading situation. This results in a better channel response and better response to the users. However, our proposed algorithm works before the dynamic subcarrier assignment, and its goal is to define the number of carriers needed in an area based on demand before the allocation of actual resources. The prior research looked at dynamic subcarrier assignment from the perspective of fractional frequency reuse which divides the coverage of the cell into two geographical areas close and far from the base station [8]. Our solution complements [8] by pre-determining the best amount of resources to be made available for each base station. A practical example of this integration would be our solution for first intelligently distributing and allocating the number of carriers needed at each base station, then second, allocating actual subcarriers among the geographical locations of cells and finally, allocating within a cell, among users.

2.3.4 Carrier Aggregation

Carrier Aggregation is one of the key features for LTE-Advanced. One of the main reasons behind this work is to provide a more efficient and fair distribution of carrier blocks, enabled by both contiguous and non-contiguous aggregation of bandwidths. The larger bandwidth obviously results in improved user data rates. However, equally important, our solution would allow a more flexible and optimally efficiently utilization of frequency assets. We assume that Carrier Aggregation is known by readers, who may otherwise refer to [93] for additional information.

An important point from [93] is that it is of particular importance for heterogeneous networks to have time-variant carrier allocation instead of all cells having access to all carriers. This would enable interference coordination based on factors e.g. time-variant traffic demands and cell locations. Scheduling alone is too complex; small cells need to be separated by having different carriers.

2.3.5 Dynamic Access to Unlicensed Bands

Another set of research works looks at the resource allocation protocol for distributed dynamic spectrum allocation systems, where a secondary user can utilize multiple protocols to sense and exploit the spectrum bands efficiently when the resource is not being used by the primary users [50]. Some more advanced solutions make use of cognitive radios to operate over an exceedingly wide spectrum, developing maximum likelihood detection models to detect the presence and locations of licensed users' signals in the frequency domain and avoid interfering with them [79]. Others use a game-theoretic learning perspective; a secondary user can copy the behavior of another secondary user from locally available information, generating a globally optimal solution [40].

2.3.6 Wireless Service Providers and Network Management

A different solution for the mismatch between a wireless service provider subscribers' traffic demand and its available capacity is to share carrier bands owned by different wireless service providers when the primary owner is not using it [75]. However, this requires extreme cooperation among service providers that are usually competitors. Our solution addresses this issue by keeping resources within the wireless service provider own network.

2.3.7 Similar Works

Previous work has emulated Dynamic Carrier Allocation. However, their focus was on the Global System for Mobile communications (GSM) technology [99], and the concept of carrier aggregation was not available nor implemented. Their goal was to create an allocation based on the minimum interference between a cell pair and not in the user demand, being more closed related to the solutions mentioned in Section 2.3.2.

The final consideration for carrier allocation in this work is its relation to the extensive literature on scheduling algorithms. Such works, such as [11], schedule individual frequencies and time slots. Since such approaches are NP-complete and impossible to perform optimally every few milliseconds, a variety of heuristics is suggested. We assume these works are implemented, but only after our work. We first determine the numbers of large blocks (carriers) of bandwidth that are needed. This occurs on the time scales of minutes or hours. We show that our optimal solution can be used on such time scales. As a matter of fact, a grid of 100 cells can be optimized on average in less than 30 milliseconds.

2.4 Dynamic Carrier Allocation

The use of the Dynamic Carrier Allocation offers a new way to design, deploy and manage networking services. This is not a heuristic approach but an actual optimization, allowing us to automate one challenging piece of network planning. Software Defined Wireless Networks provide the platform for such automation [76]. Our goal is to develop a new networking concept that adapts to the user need and creates great flexibility for the service provider. We define users as the aggregated demand of user equipment devices connected to a certain base station (e.g. macro-, micro-, femto-, nano-cell). Our contribution not only enables a much shorter cycle to upgrade but also further develops today's state-of-the-art mobile network functionalities.

2.4.1 The Problem

In Fig. 1 we present a three base station system, each with three single blocks (C_i) of 20 MHz spectrum allocated for each of them, and a random demand. Base Station A has a capacity greater than demand, D_i. Base Station B has the same demand as capacity, and Base Station C has a demand higher than its capacity. Network operators traditionally assign those spectrum resources based on the predicted user peak demand. Such static spectrum allocation is unlikely to change at the same pace as the demand requirements, although scheduling techniques will help address to a certain extent this demand requirements increase. However, we find that the combination of our work, coloring, and scheduling will offer best results. We determine proper amounts of bandwidth to be allocated per cell. Coloring and scheduling mitigate interference problems.

For now, let us focus on an example, a base station nearby a university might serve many users during the weekday, but it will use only a percentage of its capacity during nights, weekends and school breaks. Perhaps a neighbor base station is serving the area of a popular park where people go after work to hang out or spend time during the weekends with their children. In this case, it would make sense to redistribute the unused resources of the other base station to supply the demand. Moreover, it is unreasonable to

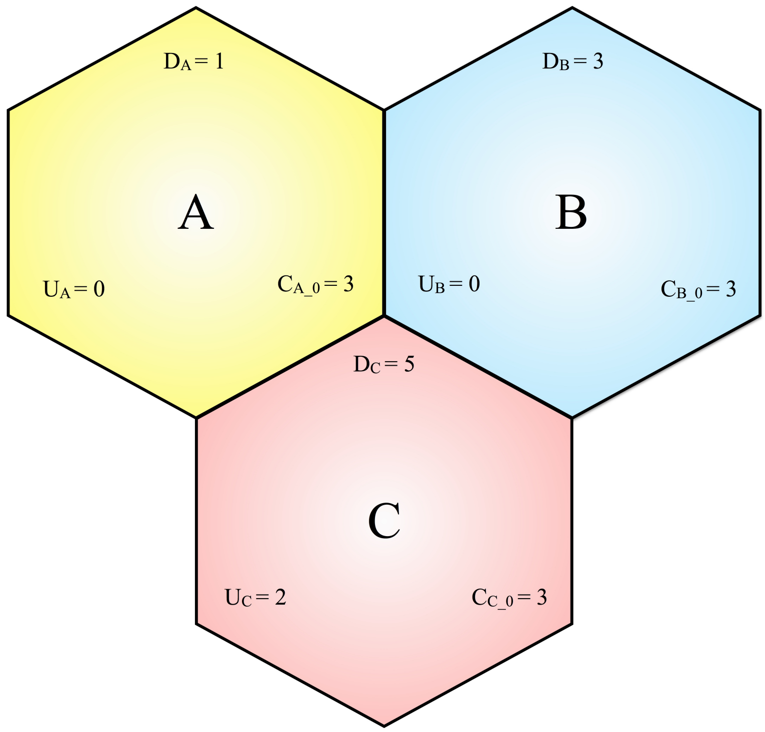

Figure 1: Simulation Results for the Network Prior Optimization

give enough capacity in all locations to handle all peak demands.

2.4.2 The Solution

Given our original case in Fig.1, two of the frequency blocks located at Base Station A can be reallocated to Base Station C. Now, Base Stations A, B, and C can meet their demands. This ability of self-configure is an essential requirement of future wireless networks. It offers fair and optimal performance, as well as the best user experience possible. While this concept is logical, some issues need attention first. This is shown in Fig.2.

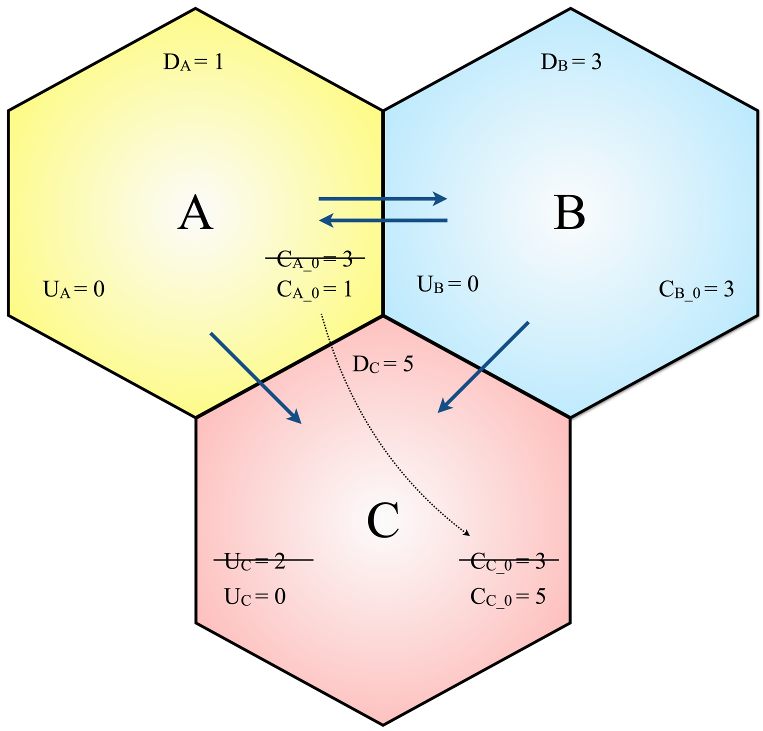

Figure 2: Simulation Results for the Network After Optimization

First, the optimization should have the minimal processing time, but the change of resources between base stations, while dynamic, might occur in a longer interval (e.g. every half hour) than the Transmission Time Interval of $1\ ms$. Second, since those updates are in a large interval, one base station shall not have zero resources as a user might enter its area after the optimization and be left without connection. For this we say that a base station cannot give all the resources it has been initially allocated; it will need to keep at least one block regardless if the demand is zero. However, there are exceptions with some types of cells, e.g. Cells on Wheels (COWs), femtocells and picocells, where the "at least one block" rule might not apply. Finally, different providers might have different network necessities. One might argue that being fair to all users is the best goal, while others might say that it is best to serve the maximum number of simultaneous users. We incorporate this in the study but found no significant improvement in doing so.

2.4.3 Assumptions

Now, we create an algorithm and optimization scheme to satisfy all three issues of minimal processing, protecting a minimum allocation and provide flexibility. To address the first, we have created two constraints. Resources cannot move beyond the neighboring cells where they were first allocated. Thus, allowing resources to go beyond the neighboring base stations would create problems with interference and exponentially complicate the model. We also assume that any interference will be controlled and mitigated by the scheduler. The processing of the optimization algorithm needs to be done in milliseconds, and for this reason, simplifying the equations should reduce the processing time.

To simplify the equations, we introduce our second constraint: the definition of the type of base station. Each one is allocated one of four schemes, the cells that are ”Type 0” can donate resources to all other types, ”Type 1” can donate to all but to ”Type 0”. ”Type 2” donates to its members and to ”Type 3”, which in turn donate to its own. The distribution of cell types is configurable and hypothesized as a key network design issue. One might think that this feature would simplify the set of equations and create priorities for the base stations with higher demand. Results from simulations demonstrated that introducing those constraints do indeed simplify the set of equations but with non-significant performance improvement or detrimental efficiency as explored later in Section 2.8.1.

For the second issue, we assume first that all base stations shall have at least one resource available all times. Later, we expand the concept allowing some base stations to start with no resources. These cells represent, for example, a service provider placing a temporary Cell on Wheels to help the coverage for one event. Once enabled, it would borrow full or partial resources of the nearby stations. For the last issue, whether providing the best resource availability or ensuring that no user is penalized in the system, we propose a compromise of both options. After exploring independently in simulation the first and latter options, and the combination of both, our results demonstrate that overall there is little difference between efficiency and fairness when looking at the entire system, but it does show effects at the individual level.

2.5 Optimization Algorithm

Next, we list information required to prepare the system for the optimization. First, the number of 20 MHz spectrum bands available. While earlier releases of LTE limited the Carrier Aggregation at five blocks, Release 16 enables up to 32 blocks to be aggregated [1, 17]. Second, the momentary demand at each base station is needed as well as the neighboring base stations. A base station will be considered a neighbor if it has an overlapping area with each other. Finally, each base station is assigned a type based on its load, the ratio between starting resources and demand.

2.5.1 Algorithm

Denote each base stations as i and the total number of base stations as I, and each of its neighbors as j and the total number of neighbors for each cell i, J_i, where $1 \leq J_i < I$. Each base station has an initial allocation that belongs to that location, C_i^0. It also has a demand, D_i, which can change during the day but not fast enough such as we can consider it as a constant. The primary resources allocated to a base station that can be donated to a neighbor called C_{ij} and is bounded between $0 \leq C_{ij} \leq (C_i^0 - 1)$. At least one resource must remain. The same way one can donate resources, it can also be a recipient, C_{ji}, with similar boundaries of donations $0 \leq C_{ji} \leq (C_j^0 - 1)$. It is not always possible to meet the demand; events like parades after an MLB World Series victory might attract hundreds of thousands of people that will disrupt the system. To be able to adapt and attend those demands, we introduce the unmet demand, U_i. Finally, there is also the case of excess capacity or unused resources, represented by X_i.

2.5.2 Objective

Our objective is not only to improve efficiency but also to provide a fair distribution of resources. First, we could minimize the sum of unmet demand using (2.1). We know that only minimizing the unused resources should result in an efficient result. However, while this improves efficiency, we also want it to be fair. Thus we introduce r. The r is defined as the maximum allowed number of resources for any given cell above demand. Then, we need to minimize the value of r. This part of our objective is responsible for spreading out the resources not being used instead of concentrating into clusters. We also add a normalizing constant $1/I$ representing the inverse of the number of cells in the system as shown in (2.2). This constant balances out the equation such as (2.1) and r have the same order of magnitude. Finally, we minimize also the number of unused resources X_i also normalized with $1/I$, (2.3) shows our final the objective. Note that we explore both results produced by (2.1) and (2.3) in Fig. 3 and Fig. 4, discussed fully later in the essay. It is worth noting here that as our capacity over demand tends toward unity or higher since we are exploring a dense network, setting our objective only to minimizing r would make the problem infeasible.

$$Minimize \quad \sum U_i \tag{2.1}$$

$$Minimize \quad r + \frac{1}{I}\sum U_i \tag{2.2}$$

$$Minimize \quad r + \frac{1}{I}\sum U_i + \frac{1}{I}\sum X_i \tag{2.3}$$

2.5.3 Constraints

First, we want to find the value of r in which the initial resources minus demand plus the sum of resources going into or out of a base station tends. To do this, we introduce (2.4).

$$C_i^0 - D_i - \sum C_{ij} + \sum C_{ji} \leq r \tag{2.4}$$

Resources cannot be created. They start in the system, C_i^0, can be moved around, C_{ij} and C_{ji}, used toward meeting internal demand, D_i, or not be used at all, X_i. To ensure this, the sum of used resources must be equal zero at all times as in (2.5).

$$C_i^0 - D_i - \sum C_{ij} + \sum C_{ji} + U_i - X_i = 0 \tag{2.5}$$

2.5.4 Mixed Integer Linear Programming Formulation (MILP)

MDP-MILP Formulation

constants

C_i^0	Initial number of carriers allocated to i
D_i	Estimated demand on number of carriers
I	Total number of cells in the system

variables

C_{ij}	Bands of Frequency lent to Neighbor j
C_{ji}	Bands of Frequency borrowed from Neighbor j
U_i	Unused resources
X_i	Excess capacity
r	Maximum number of resources allowed above demand for all base stations

minimize

$$F = r + \frac{1}{I}\sum U_i + \frac{1}{I}\sum X_i \tag{2.6}$$

subject to

$$C_i^0 - D_i - \sum C_{ij} + \sum C_{ji} \leq r \tag{2.7}$$

$$C_i^0 - D_i - \sum C_{ij} + \sum C_{ji} + U_i - X_i = 0 \tag{2.8}$$

$$0 \leq C_{ij} \leq C_i^0 - 1, \qquad i = 1, \ldots, I; j = 1, \ldots, J_i \tag{2.9}$$

$$0 \leq C_{ji} \leq C_i^0 - 1, \qquad i = 1, \ldots, I; j = 1, \ldots, J_i \tag{2.10}$$

2.6 Mathematical Expectations

We represent the efficiency of the system as the ability to it to supply the demand. The load is total demand divided by total resources. Thus, as represented in (2.11), under 100% load, the maximum efficiency is 100%. As the load exceeds the available resources, the efficiency decays by the inverse of the load, since resources used cannot increase event though load increases. The function can be seen in Fig. 5 as the theoretical line.

$$\mathit{Efficiency} = \frac{\mathit{Resources\ Used}}{\mathit{Resources\ Needed}} \tag{2.11}$$

Assume each cell has three resources and a random demand such that the sum of all demands is equal to the number of resources available. The average efficiency is based on the probability of meeting the demand, and we found (2.12). C represents the number of cells and z the total demand. For the case of 100% load where $z = 3 \cdot C$ in the limit, as C goes to infinity, efficiency goes to $1 - (8/27) = 0.7037$.

$$\mathit{Efficiency} = \frac{3 \cdot C}{z} \times \left(1 - \frac{(C-1)\big(z - \frac{4}{3} - \frac{C}{3}\big)}{(z-1)(z-2)}\right) \tag{2.12}$$

For our simulation, the value found was 0.7045 which aligns with the calculated value of 0.7052, with a percent error of 0.1%. This can be seen in Fig. 5 at 100% load. For the value after our optimization, the mathematical formulation is too complex to represent. Therefore we rely on the simulation results. For example, at 100% load, efficiency is 94%. In the next section, we introduce our simulation tool based on Python and the IBM ILOG CPLEX Optimizer.

2.7 Simulation

In our first simulation, using a Python script, we created a ten-by-ten hexagonal grid of base stations. We assumed no prioritization, no cell type, and a uniform distribution of initial resources where each cell was allocated three carriers of 20 MHz. Then, we uniformly randomly assigned a demand for each cell between one and nine carriers summing to a total of 280 carriers, equivalent to a system load of 93%. After processing the demand, we used the optimization algorithm in Section 2.5.4 to move resources and optimize the allocation. The result using (2.1) is plotted in Fig. 3, without and with dynamic allocation.

Next, we repeated the simulation, this time using (2.3) with the result plotted in Fig. 4. While both meet the 280 demand, the difference between simulations is a more spread out excess capacity using (2.3) instead of clusters of resources. This creates a certain fairness and an advantage as it is less likely that a single cell will need more than one extra resource and thus more users will benefit from the extra capacity.

In our third simulation, we varied the total demand value z from 1 (or almost no load) to 750 (which equals three resources per cell times the total number of cells times 250% system load). For each value of z we repeat the simulation 100 times, allocating demands to all base stations by using a function that returns a uniform randomly chosen list of z positive integers summing to total demand. This is accomplished by uniformly

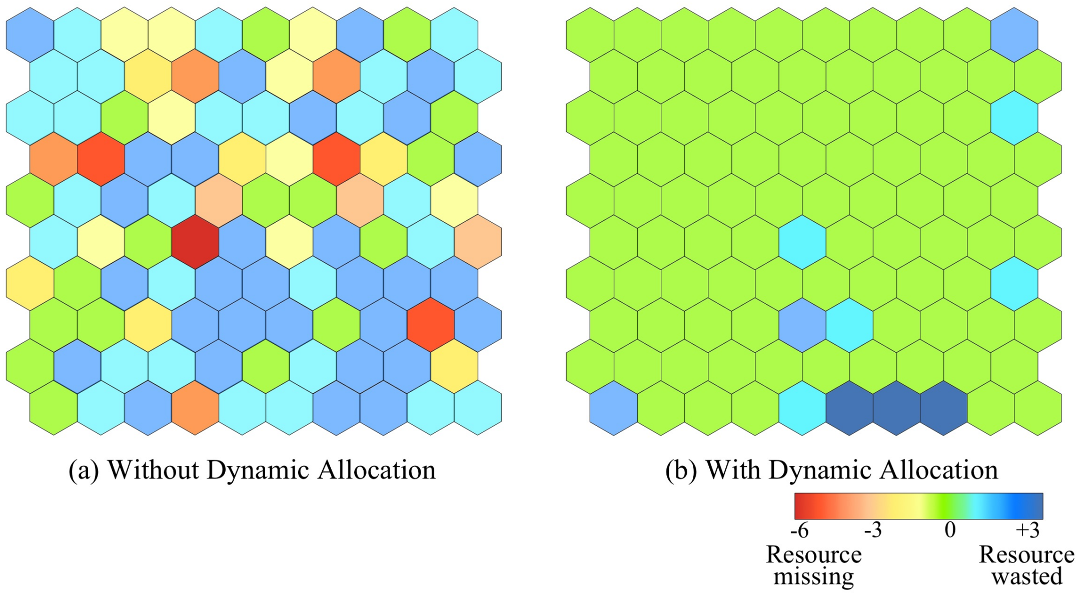

Figure 3: Simulation Results for a Network with 100 Base Stations, $C_i^0 = 3$ and, Based on the Objective Defined in (2.1)

random picking without repetition I numbers between 0 and $MAX\ z$, then calculating the interval between them and allocating to the cells as D_i. In doing so, our goal is to simulate the movement of users inside the system for each total load. Each simulation result came from a ten-by-ten hexagonal grid of base stations where we assumed no sectoring and only macro cells with pre-assigned resources. The simulation results for this first case are displayed in Figs. 5, 6, 7 and 8.

Finally, we simulated for different prioritization. The results are similar to the ones displayed in Fig. 5, 6, 7 and 8, but with a slight worst performance and the same average time.

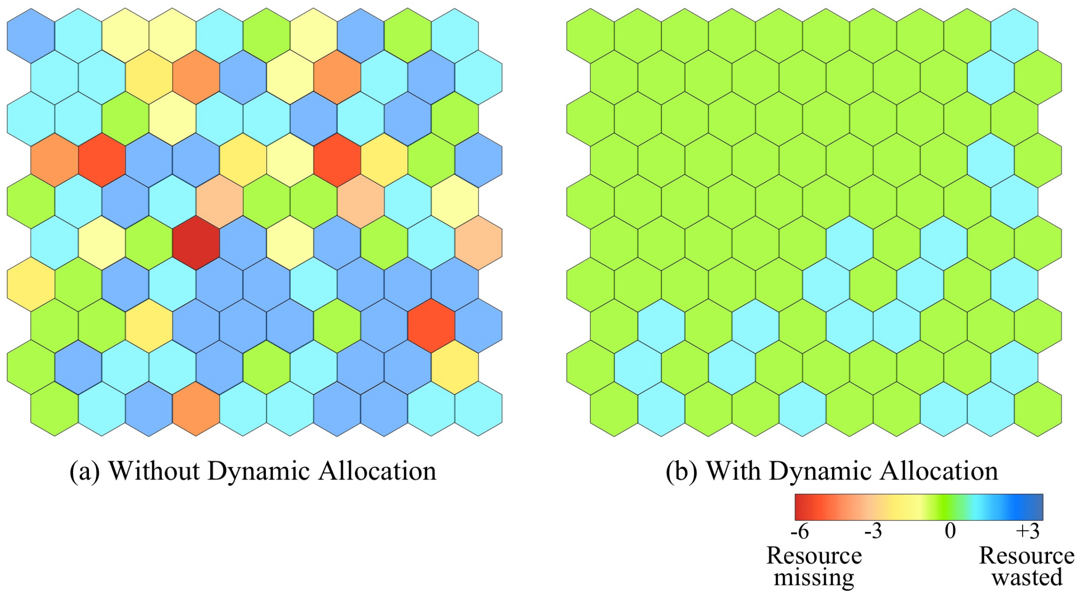

Figure 4: Simulation Results for a Network with 100 Base Stations, $C_i^0 = 3$ and, Based on the Objective Defined in (2.3)

2.8 Discussion

As illustrated in Fig. 4, all spectrum blocks not used as well as areas with peak demand were able to donate and receive resources in a fair and efficient manner. This is not a simple coloring problem, now multiple bands of frequency are being used in the most optimal format allowed by this optimization.

As seen in Fig. 5, based on the mathematical formulation and the simulations, when the system load is between 0% and 35%, meeting the demand is not a problem for the traditional static system. It is also not desired to be in that range since more than 67% of resources are wasted due to gross over-provisioning. As the load increases, we arrive at the point where most of systems are designed to be, using half of the load without

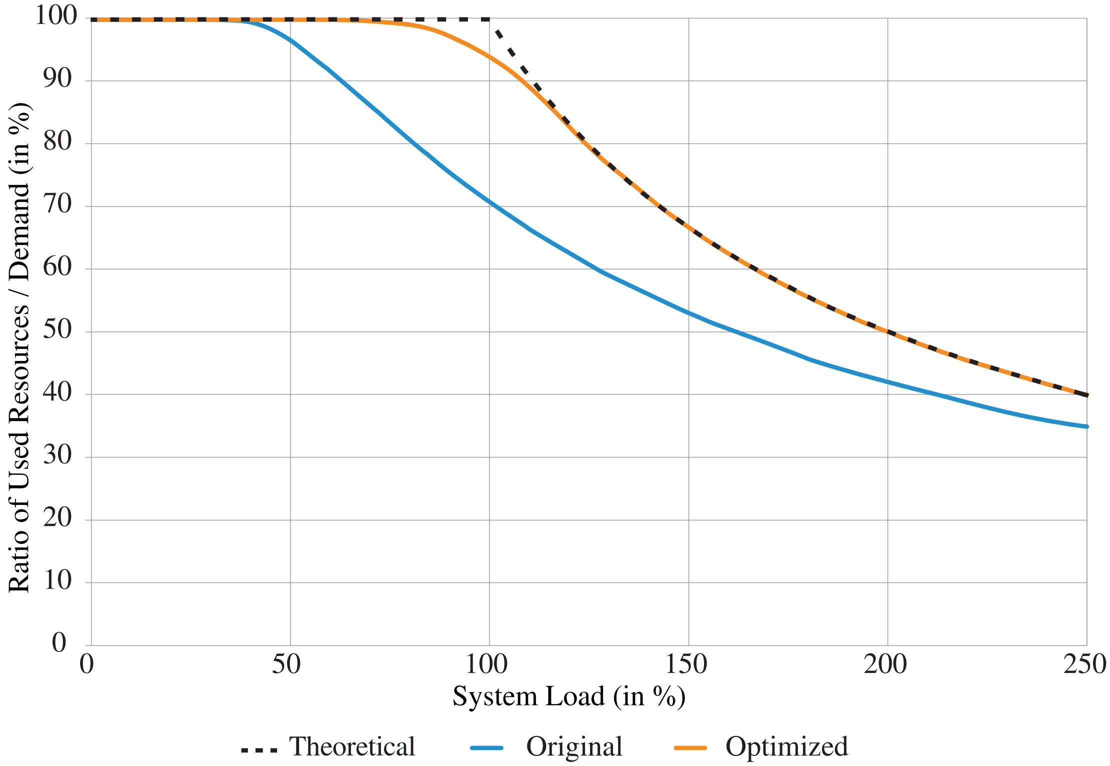

Figure 5: Plot of the Average of 75 000 Simulations for a Network with 100 Cells Displaying Used Resources Divided by Demand.

prejudice to users. However, after this point, as the load increases, it also creates problems for the users as it has to rely on the scheduler to carefully allocate the desired resources in certain areas while other areas have plenty of extra resources. However, the scheduler can only do so much. The impact on the network is the decreased traffic capacity for users in certain regions. Our proposition mitigates this effect. For the desired efficiency ratio of 90% of resources being used for a particular demand, Fig. 5 shows that traditional system will achieve the desired performance with a load of 64%, while with the proposed optimization, this represents a load of up to 109%. Almost twice the original system capacity.

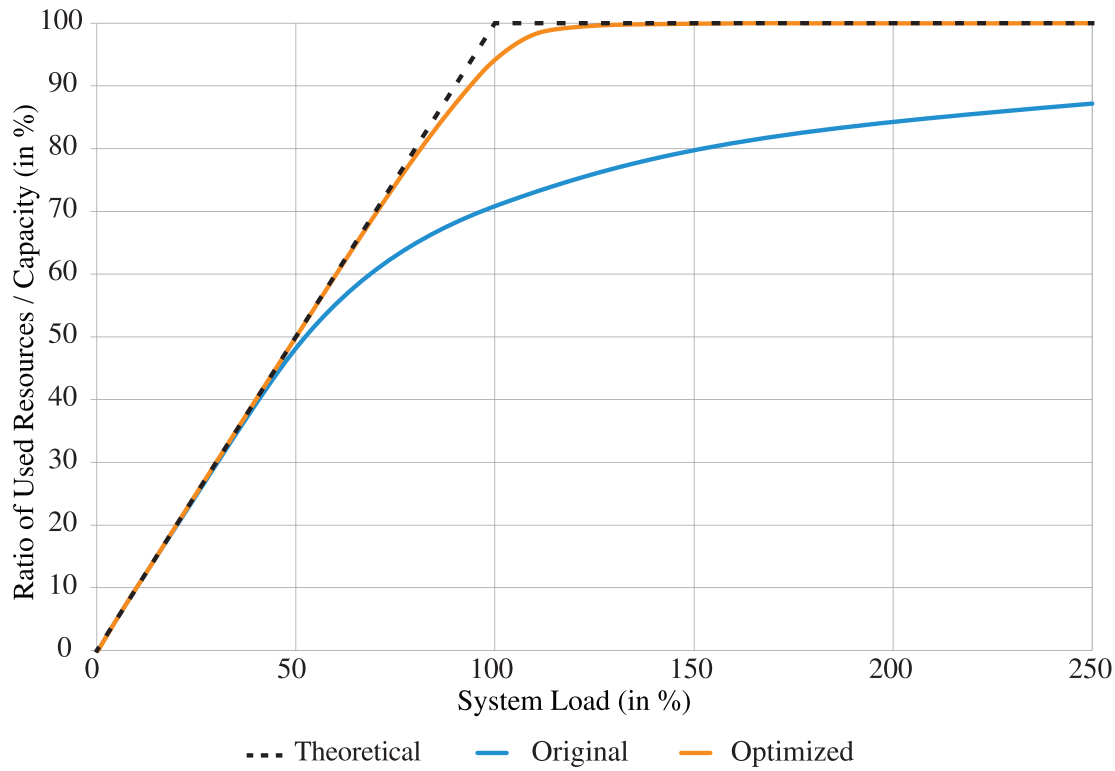

Figure 6: Plot of the Average of 75 000 Simulations for a Network with 100 Cells Displaying Used Resources Divided by Capacity.

Another way of looking is assuming a system load of 100%, or enough resources for the users in the network. Without our optimization, at a given time, on average only 70% of the resources are being used, whereas implementing our solution would increase this to an average of 94%. More resources available equates to higher speeds and greater user experience and satisfaction. Further increasing the load is not desirable as it decays with the reciprocal of the load. As the load increases, we achieve a non-desirable state where resources are less than demand. However, even in this undesirable circumstance, the solution can supply most of the demand, which is not feasible without the optimization.

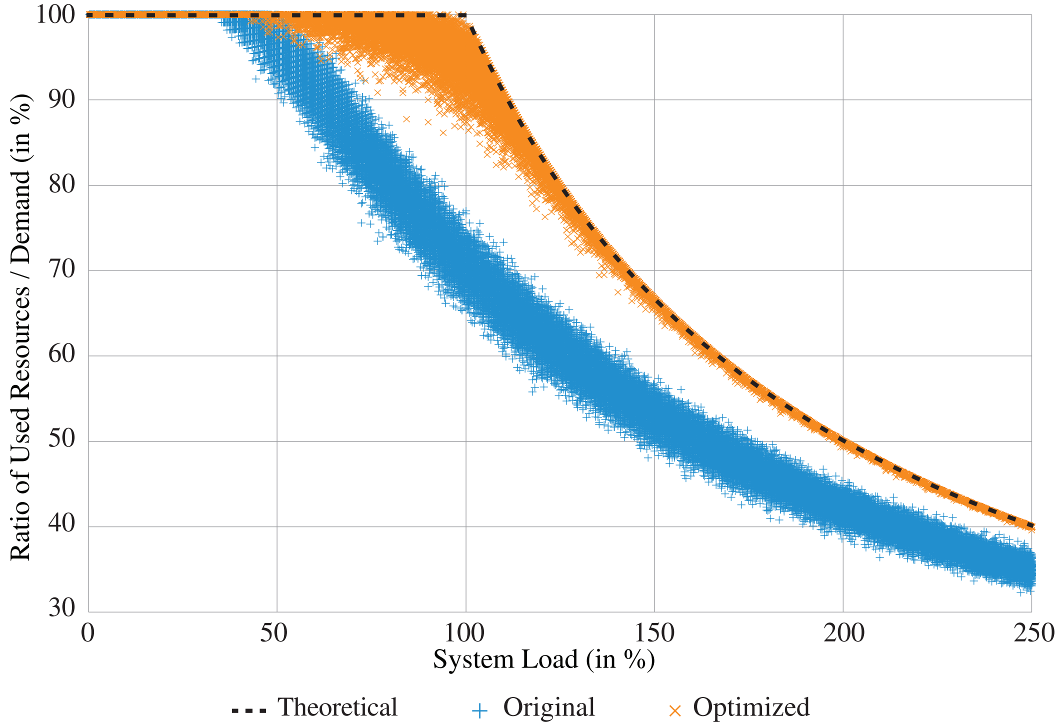

Figure 7: Plot of Each Result of the 75 000 Simulations for a Network with 100 Cells from no Load up to 250% Load.

2.8.1 Using Prioritization Types

One of the most counterintuitive findings was that restraining the number of cells that could donate does not simplify the system nor reduce the processing time. By reducing the number of variables in (2.9) and (2.10), we assume that the system would be able to calculate the optimization faster due to the simpler equation. To do that, we used the types of base stations to reduce the number of neighbors C_{ji} a base station i could have in the pre-processing algorithm. However, in doing so, we found not only no significant improvement in the time of execution but also a degradation in the average efficiency of the system.

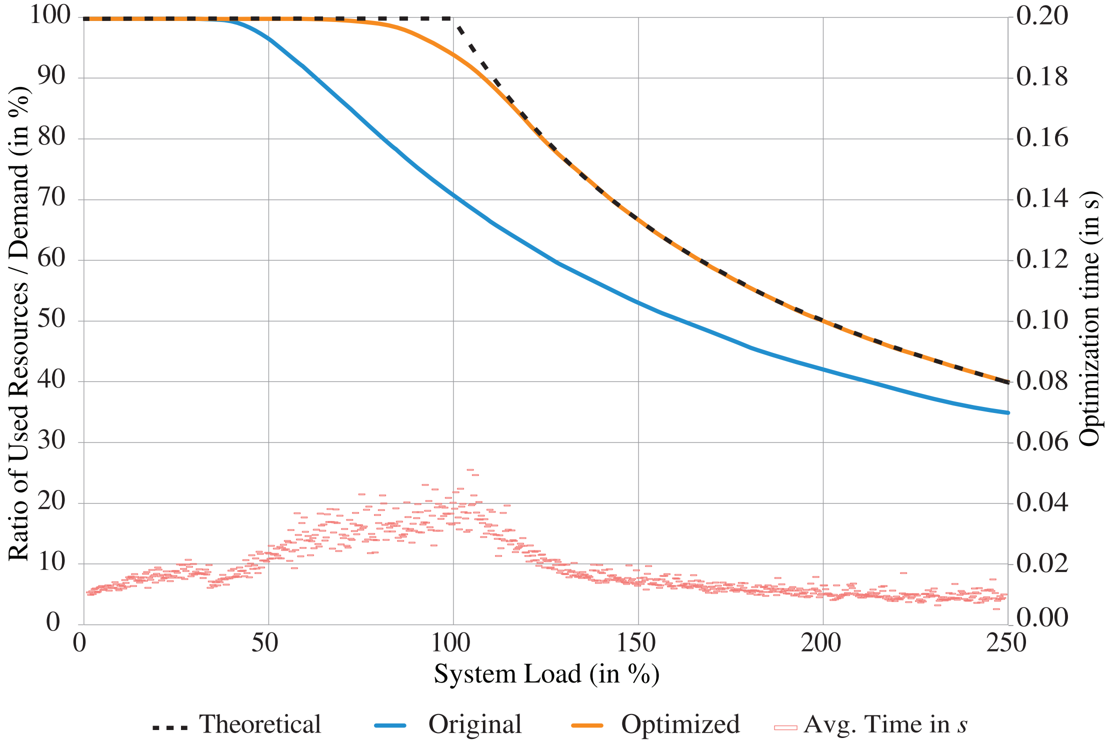

Figure 8: Similar to Fig. 5, But Displaying Processing Time in the Y Axis.

2.8.2 Heterogeneous Networks

The example and simulation results provided here used a ten-by-ten grid of macro cells. This work could easily be extended to a mix of sectored macrocells, picocells, femtocells, COWs, and areas covered by relays. All that is necessary is to define neighbors for the C_{ij} capacity sharing in 2.4 and 2.5. Also, decide which cells need a minimum greater than zero.

2.9 Conclusion

Our study provides an optimization model for the allocation of the number of carriers to cells, suggesting a new approach for future network planning and dynamic provisioning. Service providers who strategically optimize the resources may reduce some of the costs typically associated with the acquisition of carrier blocks and enhance the user experience. There still is, however, a lot to learn about the different ways of implementing this technology.

Optimizations that can improve the system efficiency are needed for wireless providers be able to meet the predicted demand increase. For the research community, we provide an optimization algorithm that can potentially reduce costs and increase the efficiency of the network operation. For the industry, we provide a new solution that has a disruptive potential especially now with the support of Software Defined Networks and Network Function Virtualization to make it work. It increases the quality of service and perceived value from a client perspective. Finally, with a fully connected and mobile society, using the technology in unimaginable ways, with a steep increase in the traffic, devices, and ways of using them, we have tried to provide a step forward to achieve this standard.

2.10 Future Research

The use of this new optimization algorithm opens doors to many future network improvements. We have examined the network requirements from a user demand perspective. In this study, we demonstrated that using this perspective and optimizing the network to address the dynamism of human behavior are important considerations. Future research should address, given the resources blocks available for a service provider, how to select the best ones to reduce interference. This would enable service providers to acquire not only the best resources to expand their network but also make an educated investment in such an expensive resource. The cost of base stations is also affected by which carriers are used. It is important to add in this future study how to incorporate unlicensed bands.

Second, we demonstrated that this algorithm converges to a large number of nodes, however, determining the ideal network size and types of cells for better efficiency will give a significant contribution. Finally, the optimization that is proposed works for picocells and femtocells, however, we suggest exploring the need of resources for those. This would include the investigation of block subdivisions using flexible bandwidth options ranging from 1.4 MHz to 20 MHz.

CHAPTER 3

ALTERNATIVE PATHWAYS TO SUCCEED IN REWARDS-BASED CROWDFUNDING CAMPAIGNS

3.1 Abstract

Crowdfunding campaigns can be an integral part of the process used by founders to gain exposure for their products and acquire financial or social capital for their new ventures. In this essay, we investigate the relationship between the stages of a crowdfunding campaign and success and overfunding in the reward-based community – Kickstarter. Multiple factors contribute to entrepreneurs succeeding in crowdfunding campaigns. Success is defined as. However, prior studies emphasize either only the speed at which the entrepreneurship achieve reward-based goals or the concentration of backers (herding) at each campaign stage. Both have been shown to be predictors of crowdfunding success. However, we propose that the pathways to success are more varied than previously stated. Factors such as the interaction of speed to goal and herding, as well as, the strategic orientation and responses of the entrepreneur founders may matter also. To examine these questions, we use liability of newness as the theoretical lens. This framework allows us to ask questions about the role played by the legitimacy of the entrepreneurs, the products that are the foundation of their crowdfunding campaigns and the ventures themselves. Using mixed-methods and a unique database of over 2,400 crowdfunding projects, we empirically demonstrate that there are alternative pathways to crowdfunding success.

Drawing on emergent patterns, we also develop a typology of alternate pathways that entrepreneurs can take to maximize the financial, human and social capital that support their crowdfunding campaigns. The conceptual and empirical findings of this work extend our understanding of entrepreneurial legitimacy and the roles played by early stage funding strategies in overcoming internal and external liabilities of newness.

3.2 Introduction

Crowdfunding as a source of financing for new business startups has become a popular substitute for traditional sources of funding. While some research has been done to explain the reasons an entrepreneur is successful in this crowdfunding environment, the understanding of the interaction between the early and late stages of the campaign still uncertain. It is also argued that the campaign behavior follows a "bathtub" format, where first and last 20% of the time of the campaign get more contribution than the middle. In this work, we start discussing the connection between the timing of the herding effect and the speed in which the campaign is funded, as well as how the size of the goal moderates this effect. The results of this first study revealed that while the campaign behavior found in the literature exists, we argue that it is only one of the possibilities, and we propose an explanation and taxonomy for the different paths towards crowdfunding success.

Crowdfunding provides entrepreneurial individuals and groups the opportunity to fund cultural, social, for-profit and non-profit ventures using relatively small contributions from a large number of backers [85]. Crowdfunding campaigns also provide entrepreneurs with a mechanism for raising funds outside of regulated financial exchanges by using online social media platforms to facilitate direct interactions between investors and entrepreneurs [3]. Research data from the last Crowdfunding Industry Report [81] show that the crowdfunding market grew 167% in 2014, with crowdfunding platforms raising $16.2 billion. It is predicted to reach $34.4 billion in 2015 surpassing the Venture Capital market. If this alone is not impressive, the World Bank white paper in crowdfunding is foreseeing a deployment of up to $300 billion a year by 2025, with developing countries accounting for $96 billion [22, 84].

Throughout the years, the crowdfunding literature has focused on crowdfunding as a mechanism for early stage funding [3, 20, 45, 85, 103]. This body of research has primarily focused on either the dynamics of the campaign [33, 72], attributes [28, 85], investors [9, 86] or the rewards offered [20] concerning whether the funding goal was achieved.

Generally, the conceptual frameworks and evidence presented in earlier crowdfunding studies focus on five main areas: (1) the entrepreneurial network of the founder (e.g. social capital), (2) the characteristics and possible impact of the campaign (e.g. social movement, backer motivation), (3) timing to achieve the campaign financial goal, (4) herding, and (5) the type of the crowdfunding platform. With respect to entrepreneurial networks, Colombo et al. [33] found evidence that the impact of social capital is mediated by the early stages of the campaign. Preliminary descriptive research suggests that the contributions received right after the start of a campaign largely predicts the success of itself (e.g. [3, 90]). Colombo et al. [33] have extended the literature by looking not only at the contribution itself but also to the number of the backers in the early stage. In their paper, the researcher has explored and found support to the fact that the internal community of crowdfunders affects the number of early backers and capital raised by crowdfunding campaigns.

The characteristics and potential impact have also been examined in crowdfunding studies. Some research has pointed out that both project-level and individual-level quality signals are driving a campaign's success [72]. For example, sustainability and social orientation increase the chances of funding success [9, 28]. Others have examined the geography and how this affect the outcome, finding that it is weakly related [3].

The third body of research is about the timing in the campaign, or more specific if backer support increases when achieving the goal closer to the early or late stage of the campaign, or is it somewhere in between? In this context, Kuppuswamy and Bayus [72] found that backers support increases as the campaign gets closer to reaching their goal, dropping sharply afterwards.

Herding, or the copy of behavior of others towards the same direction, has being explored as a possible explanation for the backer behavior where both irrational and rational herding plays a role in the outcome [25, 115]. In those papers, herding is defined as the cumulative number of backers supporting project i up to day t. It was observed that in loan based crowdfunding, rational herding is present. Rational herding is when the investors follow the behavior of others but in a sophisticated manner by using public available information to moderate their decision [115].

Finally, different entrepreneur goals reflect in a different crowdfunding platform.

Belleflamme et al. [20] found that entrepreneurs should prefer reward-based platforms when financial capital requirements are small, and equity when the needs increase. There is also evidence that investors in equity-based crowdfunding have mainly financial or utilitarian motives [31].

Building upon these earlier studies, more recent crowdfunding studies further draw attention to the attributes of entrepreneur [26], other stakeholders in entrepreneurial networks [31] and to the online and traditional mechanisms that entrepreneurs use to call attention to their campaigns. In this more recent work, the focus has still predominantly been on the success of the campaign itself, and the contributing factors have been considered independently. Crowdfunding campaigns, however, are not the end of the road. These campaigns are micro-events that represent integral parts of the process used by founders to gain exposure for their products and their new ventures [77, 80]. Table 1 lists the main papers in the area and their contributions.

In this work, we conduct two studies to understand the antecedents of successful crowdfunding campaigns and to theorize some roles for crowdfunding in the entrepreneurial process conceptually. In the first one, we build upon two independent conversations on crowdfunding in the finance and entrepreneurship literature. The first conversation from the entrepreneurship literature focuses on the speed to goal. The general suggestion is that some forms of storytelling containing blame and present concern will lead to the goal faster [9], the backer support increases in the proximity of achieving the goal [72] and the importance of the early stage to achieve funding [3].

Table 1: Crowdfunding Literature

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Agrawal et al. [3]	34 funders (Sellaband)	Reward	Exploratory study. Investment patterns are weakly related to the geographic distance between entrepreneur and funder.
Ahlers et al. [4]	104 projects (ASSOB)	Equity	Social & Social capital theory. Intellectual capital have minimal impact on funding success.
Allison et al. [9]	36,665 loans (Kiva)	Loan	Cognitive evaluations. Narratives with social connotation rather than business opportunity lead to better response from backers.
Belleflamme et al. [20]	Conceptual model	Equity vs Reward	Price theory.The goal moderates if the entrepreneur should select reward (small goal) or equity (large goal) based.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Butticè et al. [27]	31,389 projects (Kickstarter)	Reward	Social capital. Serial crowdfunders outperform their novice counterparts mainly due to ”internal” social capital.
Cholakova and Clarysse [31]	155 investors (Sympid)	Equity	Motivation. Equity crowdfunding motivation is financial or utilitarian with no significant non-financial motives.
Colombo et al. [33]	669 projects (Kickstarter)	Reward	Social capital. Internal social capital positively impact the success and is mediated by funders and capital in the early days of the campaign
Davis et al. [35]	102 students (Kickstarter)	Reward	Affective events. Perception of creativity increases the probability of success.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Drover et al. [42]	104 VCs making 1,036 screening decisions	Equity	Certification effects. The crowd can certificate a venture by the venture's offering or market acceptance while angels can certify the financial viability by way of reputation.
Herzenstein et al. [52]	42,694 bids placed on 1,792 auctions (Prosper)	Loan	Herding behavior. Herding effect increases in the proximity of the goal, reducing afterwards. It was also found to increase subsequent performance.
Iyer et al. [61]	194,033 listings with 17,212 funded (Prosper)	Loan	Credit and soft information screening. Investors are 45% more accurate in predicting loan default using the credit score, and 87% more than an econometrician.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Kuppuswamy and Bayus [71]	23,663 projects (Kickstarter)	Reward	Social information (e.g. previously campaign success or failures, goal achieved) can moderate the occurrence of irrational herding behaviors in crowdfunding campaigns.
Kuppuswamy and Bayus [72]	10,000 projects (Kickstarter)	Reward	Speed to goal. The number of backers increases as the project goes closer to the goal, dropping sharply afterwards.
Lehner [73]	36 CF cases of social causes (Multiple)	Equity & Reward	Social capital. While success is based upon the social capital, it is highly moderated by cultural and symbolic capital build during the campaign.
Lu et al. [78]	1,521 projects (Kickstarter)	Reward	Social capital. Promoting the campaign in social media highly positively affect the outcome of the campaign.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Meyskens and Bird [84]	Conceptual model	All	Social venture. The interaction between social and economic value dictates which platform is better for the social venture.
Mollick [85]	48,034 projects (Kickstarter)	Reward	Exploratory study of success. Success is moderated by quality of project, personal networks and geography.
Mollick and Nanda [86]	120 projects (Kickstarter)	Reward	Expert decision making. Funding decision between experts and the crowd converge, but the crowd is more likely to fund a crowdfunding project.
Moss et al. [87]	403,419 loans (Kiva)	Loan	Signaling theory. Signaling autonomy, risk-taking, and competitive aggressiveness under conditions of information asymmetry increase likelihood of receive funding.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Ordanini et al. [90]	Case study (SellaBand, Trampoline, and Kapipal)	Donation & Equity & Reward	Exploratory study. Exploring consumer and organization's perspective for investing, it finds the feeling of patronage, social participation, investment as primary motivators.
Paravisini et al. [91]	2,168 investors (Lending Club)	Loan	Risk Aversion and Wealth. Wealth positively moderates the aversion to risk. This demonstrates that investors' preferences and wealth are not independently distributed.
Parhankangas and Renko [92]	656 projects (Kickstarter)	Reward	Sociolinguistics and language expectancy. Linguistic style and building a personal connection positively increases the chance of crowdfunding success for social entrepreneurs, but has no impact in commercial campaigns.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Short et al. [103]	N/A	All	Literature review. Highlights that literature is new and there is *"fertile ground for future efforts seeking to build knowledge surrounding crowdfunding phenomena."*
Skirnevskiy et al. [105]	19,351 projects (Kickstarter)	Reward	Serial crowdfunding. Family and friends early support are replaced by loyal backers in subsequent campaigns by the same founder. This creation of social capital increases the likelihood of success in follow-up campaigns.
Sonenshein et al. [106]	512 loan (Prosper)	Loan	Role of social narratives. Accounts we found to increase the perceived trustworthiness but also to hurt the loan performance.

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Table 1: Crowdfunding Literature (continued)

Name	Data Set Size (Platform)	Type	Literature / Theory / Key Findings
Younkin and Kashkooli [114]	63 US crowdfunding platforms	All	Exploratory. Look at how crowdfunding can address problem relate to coordination, gatekeeping, inexperience, patronage, and differentiation.
Zhang and Liu [115]	49,693 loans (Prosper)	Loan	Herding. It was observed rational herding, where the investors follow the behavior of others but in a sophisticated manner, not only by following other investors but also by using public available information to moderate their decision.

The second conversation from the finance literature focuses on the campaign characteristics. While this conversation has more breadth and considers variables from multiple levels of analysis, many studies focus on the number of unique backers at a given stage in the campaign [3]. The term used in these studies to describe high concentrations of backers at a given stage of a funding campaign is herding [52, 58, 115].

We bridge these conversations and examine the interaction effect of speed to goal and herding on whether entrepreneurs achieve success in their crowdfunding campaigns. In addition, we investigate whether the stage of the campaign that herding takes place matters to whether the crowdfunding goal set by the entrepreneur is exceeded. The unique data set we use for these examinations is comprised of daily status snapshots of 2,463 Kickstarter projects, of which 64% or 1,653 projects were successfully funded. This data set is used quantitatively to validate our question of when is the right time for the entrepreneur to take action on the campaign and how it will result in the crowdfunding campaign being successfully funded.

In the second study, we took a more qualitative approach with the aim of developing a typology of alternative pathways to succeed in reward-based crowdfunding campaigns. The literature in crowdfunding is still in its early stages [20, 24, 103]. There are many valuable insights about the factors that contribute to campaign success to be uncovered. As the starting point, we used computer software to model the backer profile, reward and funding for each Kickstarter campaign. We then searched for patterns across the campaigns. Once we uncovered the patterns, we analyzed the content of the campaign profile on Kickstarter and used a crawling tool for Twitter and Facebook to capture any posts on social media during the campaign duration. Our motivation for performing study two arrives from the accepted premise in the entrepreneurship literature that the attributes of individual entrepreneurs and their ventures differ [35, 85]. Hence, what may be an appropriate path for one entrepreneur, regarding staging and achieving their goals may not be the best-case scenario for another entrepreneur.

To examine the questions raised in Study 1 and Study 2, we use liability of newness [7, 109] as the theoretical lens. In the entrepreneurship literature, liabilities of newness is described as the constellation of problems a new venture faces associated with their newly founded status that renders them particularly prone to failure [109]. ”In the formative stage, a new venture is no more than a commercial experiment; a set of assumptions or hypotheses about market needs, product specifications, resource availability and production, and organizational capabilities that need to be tested by practice” [108] pp. 81. The liabilities of newness framework allows us to conceptualize the effects of legitimacy and the timing of strategic responses to performance feedback on crowdfunding campaign pathways and success.

We make several contributions to the literature. First, Shepherd [102] and Davidsson [34] both call for scholars to examine entrepreneurship phenomena using contingency frameworks that factor time into the model. Our findings of Study 1 demonstrate that while the growing literature identifies speed [4] and herding [33, 72, 78, 115] as independent factors that contribute to goal attainment [4, 78] and over funding [85, 86], a better understanding of their interaction needs investigation as well. In particular, the literature demonstrates that the individuals that are more likely to herd in the early stage are family, friends, and fools. The implication of using only this crowd is that the entrepreneurs pull on their strong ties, their narrow networking and they were not able to optimize this to the weaker ties [47]. The conversation of understanding of who is being herding and under what time condition is an important contribution to the crowdfunding literature. This work is the first to relate herding and the temporal effect of speed and their interaction effects on the outcome of a crowdfunding campaign.

Second, our theoretical framework draws attention to the consequences of rational and irrational herding [115] and the effects of simultaneous versus sequential funding strategies [56]. We expand the concept of speed and herding as main predictors of crowdfunding success [4] to include different patterns of success beyond the ones identified in the literature. Further, the typology we develop in Study 2 contributes with four combinatory patterns of herding, bystander or substitution and deadline effects that are alternative pathways to crowdfunding success. Our study findings highlight that asking how fast the entrepreneur achieve the goal (speed) is not enough. Theoretically, scholars also need to understand the investment archetype in the early and the latter stages. Practically, entrepreneurs should consider staging the timing of social media campaigns, since, in some contexts, the release of new information may be more efficient when it is more sequential than simultaneous with the campaign launch [19, 56].

Finally, entrepreneurship is a process. Crowdfunding success is not the end. It is the beginning. Successful crowdfunding campaigns provide signals about the legitimacy of entrepreneurs and their projects. Our study offers entrepreneurs routes that they can take to navigate their liabilities of newness and maximize the benefits of the financial, human and social capital [16] that they accumulate from their crowdfunding campaigns. In so doing, we set the stage for future research to further expand about relationships between the early stage crowdfunding activities and new venture start-up, performance and growth. We also adjust the stage for future analyses that explore the relationship between entrepreneurial learning at this pre-venture stage and the entry and exit decisions of various stakeholders who do business in different organizational and institutional settings. Those entrepreneurs might engage in creating solutions as proposed in chapter 2 by optimizing and reducing the cost of operations and thus introducing a competitive advantage that will allow them to compete with incumbents.

By integrating our knowledge of engineering with entrepreneurship, we can create new tools to advance entrepreneurship research. This integration has been done in this dissertation to create our unique data set without relying upon a third party. Those engineering tools have been used in this dissertation to enable not only the data collection to study one but also the analysis for study two. Across the contributions that this relation might create is the use of machine learning technics to explore big data. We used this approach to enable the quantitative study of entrepreneurship and to optimize the process in which we do research.

The essay proceeds as follows. First, we provide a review of the crowdfunding phenomena and the current finance and entrepreneurship literature on speed and herding. Next, we develop the theoretical framing the Study 1 hypotheses and discuss the methodology and empirical findings of Study 1. In our discussion of the Study 1 findings, we introduce the motivation for Study 2. We then proceed to discuss the methodology for the qualitative data collection that supports Study 2 and the typology of crowdfunding campaign archetypes that emerged from the data. We conclude the work with the implications of our empirical findings and developed typology for future research.

3.3 Theoretical Development

How ventures are financed is one of the fundamental questions of entrepreneurship research [29]. While one of the most common sources of financial capital is the three Fs – friends, family, and fools [21, 70] – the entrepreneurs can also acquire funds via (1) government agencies and research administrators, (2) venture capitalists (VC's), (3) corporate venture capitalists, (4) crowdfunding contributors, and (5) angel investors [45].

Crowdfunding approaches can take the form of online charity donations, equity shares, product or service rewards, and peer-to-peer lending [31, 48, 72]. Crowdfunding offers not only the financial benefits but also a sense community, a belief in trust and reciprocity, and emotional connection. To appear legitimate, the entrepreneur pursuing crowdfunding needs to craft their campaign to strategically demonstrating the contributions to the community (local or with similar interest) and the returns (financial or emotional) a member can acquire from investing in the campaign.

In this essay, we examine crowdfunding from a product or service reward-based perspective. Previous research has used this reward-based perspective for a variety of reasons including the availability of public data, affective events theory defined as the motivation of backers engaging into reward-based projects (e.g. obtain a novel product, support the entrepreneur's dream, or even become part of the larger creative community)

[35]. It has also looked from the perspective of investigating the factors driving a campaign's success [72], both at the project-level quality signals (e.g. preparedness [85], narrative [45], and the use of social media [27]), and individual-level quality signals (e.g. gender [85], the role of experts in decision making [86], and project creator social capital [28, 33]).

3.3.1 Liabilities of Newness

One of the cornerstones of entrepreneurship research is to understand and identify actions that entrepreneurs take to secure resources such as financial capital, social capital and strategic relationships [108] required to bring a product or service to the market. The 'liability of newness' can hinder the entrepreneur of acquiring those resources [7, 109]. To overcome this liability, members of an external audience need to perceive the venture legitimate [7, 44, 45, 77, 116]. A venture is perceived as legitimate if the stakeholders and external members view it as "desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" [110].

Butticè et al. [27] suggest that the relationship between the entrepreneur's social capital and a successful campaign are closed associated (see [33, 85]). The researchers base this suggestion on the VC literature where it is accepted that entrepreneurs rely on personal contacts to gain access to early stage funds. When extended to the context of crowdfunding, however, the researchers find that backers are sharing same values as an early supporter of repeated campaigns and that the early stage relationships are formed by a greater number of weak ties [47]. They also find that funds raised for subsequent ventures are enabled by the social capital developed in the campaign. Colombo et al. [33] found full mediation on the positive impacts of internal social capital driving success by investors and fund raised in the early stage of the campaign.

From the strategic relationship perspective, the entrepreneurs develop strategies that allow them to create relationships with potential customers and stakeholders. For instance, crowdfunding campaigns can act as a for of certification of new ventures in a similar manner to the certification they can obtain from an angel investor [42]. A justification for that is related to the Wisdom of the Crowd [111], where subsequent studies found two consequences. First, between the decisions of crowds and the one from experts, the crowd is more likely to fund the campaign [86]. Second, the is a higher accuracy in the ability to predict default than using the borrower's credit score in loan-based platform [61]. Some elements of social capital can be complementary to the strategic relationship, with some differentiation. Social capital looks at forms to the create a connection, while strategic relationship uses these connections to put a plan into action and benefit from it [47].

Examining the financial capital, many researchers have looked at the crowdfunding platform as a financial tool. This perspective drive back to the question of how ventures are financed is one of the fundamental questions of entrepreneurship research [29]. In this literature, Cholakova and Clarysse [31] found that the sole motivation for an investor in equity-based crowdfunding is basically financial or utilitarian. Other forms of crowdfunding also indicate the financial goal, even if there is a hint of the greater good reasoning behind, for instance, Calic and Mosakowski [28] found that sustainability orientation positively affects the outcome of a reward-based campaign.

While examining the relationship between the forms of securing financial capital, social capital and strategic relationships, two bodies of literature are used but not at the same time, herding and speed to goal. The connection between they might reveal different aspects not observed before. In Section 3.4, we explore each literature and their connection.

3.4 Herding of Backers and Speed to Goal (Study 1)

3.4.1 Effects on Crowdfunding Campaign Success

Herding in the literature is defined as the mimic of the behavior of others. For example, the sense of community or belonging developed by reading, watching or listening to the same things can make people pursue common interests [2, 101]. This can make a product or service more popular, leading to advantages and funding success. A simpler form of model herding behavior is described in [13] where a group of individuals makes the same decision in sequence. There each has knowledge of the previous decision, yet he or she do not have access to private reasoning. In this context, rational herding is when the backers draw their decision in the same external factor. Irrational herding, on the other hand, is alleged to be the one present in reward-based campaigns and occurs when the backer relies upon the decision of previous investors to assess the legitimacy instead of performing its due diligence [115]. In relation to the liabilities of newness in crowdfunding campaigns, we argue that irrational herding creates an advantage for the funder as creates network externalities [25]. In explaining this concept, Katz and Shapiro [64] say that the utility perceived by a customer of a product increases the consumption of the good by other agents also increases. Khanna and Mathews [65] also found that herding can result in better aggregate information and more accurate decisions. If herding can reduce the external liabilities of newness by creating network externalities, then it can be used to measure a perceived legitimacy.

Speed is defined as the time from start of a campaign to the moment it is fully funded, meaning the goal set has been achieved, consistent with a previous investigation [3, 10, 9, 4]. Looking at narratives, Allison et al. [10] found language that leads to more rapid or slower funding. Allison et al. [9] found that campaign about the opportunity to help others is faster funded than the ones framed as a business opportunity. For purposes of this work, we define speed in the early stage as the first one-sixth of the campaign and speed in the late stage as the last one-sixth, following the definition from Mollick [85]. Concerning the liabilities of newness in crowdfunding campaigns, we argue that achieving the goal faster creates a validation for new investors and thus reducing the external liabilities.

Taking both speed to goal and herding of backers into consideration, prior studies have already established that campaigns are likely to succeed if herding takes place in the early stages of a reward-based campaign [3, 33, 71, 115]. These studies make this suggestion because they found strong support of early stage friend, family, and fools investing creates irrational herding which leads to achieving the campaign goal. We argue, however, that campaigns are also likely to succeed if herding occurs at the latter stages of the campaign. There are some reasons why we suspect this to be the case. First, backer support increases as the campaign near its target goal [72]. Second, when the campaign approached its deadline, people do not want to be left out of a good bargain similarly to online auctions [12, 71, 100]. Based on these arguments, we introduce our first hypothesis which states that:

Hypothesis 1: Rewards-based crowdfunding campaigns are likely to succeed when herding occurs in the latter stage of the campaign.

3.4.2 Effects on Rewards-Based Crowdfunding Campaign Overfunding

The typical successful crowdfunding campaigns of entrepreneurs as discussed in the literature are composed of three stages that depict a ”bathtub” [71]. Initially, there is an early stage that draws heavily on social capital and family, friends and fools to break initial inertia [3, 33, 71, 115]. The second stage is where bystander or substitution effect occurs [10, 71, 72, 85]. In this stage, backers do not fund the campaign expecting others to take action [71]. The third stage is the deadline effect, whereby funders invest heavily until the deadline in fear of being left out [12, 71, 100].

Our study extends this structure reasoning that after the deadline effect starts, or late herding, there is nothing to stop the project to growth other than the deadline itself. The deadlines call for one’s action, where a temporal distance often has the opposite effect [74]. This has been widely observed in many environments. For example, in the online auction, Ariely and Simonson [12] created a framework for the dynamic decision where a bidder does not want to lose the opportunity. In crowdfunding, not investing would represent not being able to buy until, and even if, it is available for retail sells, paying a higher price and losing the bragging right of being one of the first to support an innovative product. Others have found support for the opposite effect where backer support for a crowdfunding campaign will reduce after the goal is achieved [72]. Accordingly, our next hypothesis states that:

Hypothesis 2: For the campaigns that succeed, latter herding increases the over-funding ratio.

3.4.3 Project Goal Moderating Effects

One of the most cited articles in crowdfunding compares two of types of crowdfunding: reward and equity [20]. They state that the goal size moderates if the entrepreneur should select reward (small goal) or equity (large goal) based. While it defines that there is a relationship between the entrepreneur that launches a campaign to raise funds using reward-based or equity-based communities, our research looks throughout the glasses of the goal size in the reward-based environment. For our hypotheses 1 and 2, we argue that the interaction is moderated by the size of the goal of the crowdfunding campaign. If the goal is too small, the entrepreneur faces the risk of not being able to raise enough capital, however, setting the goal too high will attenuate the effect of herding needed to the success of the campaign.

Prior loan-based crowdfunding research has suggested that goal – the total amount of funds requested – is a major factor in the financing success [9, 46]. In reward-based campaigns, funders are also concerned how attainable a project goal is and likely to invest if they believe it will meet the goal [71]. Lehner [73] found that ”only when a certain threshold was crossed of a ’critical mass’” that the contribution as mentioned earlier starts. However, there is a gap in the literature where the role of the goal in the reward-based crowdfunding financial success is not studied empirically. Accordingly, our last hypothesis states that:

Hypothesis 3: The size of the project goal moderates the herding and speed effects of crowdfunding campaigns.

3.5 Methods

We test out hypotheses in the context of reward-based crowdfunding campaigns. We collected data publicly available at the Kickstarter website, which is the largest and most popular online reward-based crowdfunding platform in the world [86]. From its launch date in June 2012 up to their 8^{th} anniversary in 2017, 125,000 campaigns have been successfully funded and more than \$3 billion raised. Entrepreneurs can create campaigns with duration between 3 and 60 days seeking funding for the most diverse projects as long as it provides a non-monetary reward in the form of product or service to the investor. Projects on Kickstarter are categorized into thirteen main categories: art, comics, dance, design, fashion, film and video, food, games, music, photography, publishing, technology, and theater.

3.5.1 Sample

The core of our data were collected on Kickstarter from November 30, 2014 to April 30, 2015. We used a novel web scraping method to capture all available information every six hours for each campaign, which is unique insofar as it allows us to examine the full dynamics of the investment process. This process not only captured the information publicly available at the Kickstarter platform but also captured the interactions happening on social media platforms (Facebook and Twitter) and details such as previous successful and unsuccessful campaigns on the profile of the founder. This resulted in 500,127 observations. The focus is only on the projects which we were able to capture from the first one-sixth until the conclusion. The scraping program automatically censored the data in the left side by only capturing campaigns started after the beginning of the scraping process. We censored in the right side of the data by excluding all campaign in which we did not have the full temporal event by the end of April, reducing our sample to 323,435 observations. From this subset, we grouped each project by its unique id and excluded all projects that were cancelled, suspended or purged out due to the violation of the Kickstarter policy (e.g. breaking the law, offer prohibited items, violating trademarks or patents). The motivation to exclude the observations and not consider them as failure is that they do not reflect a complete campaign with early and late stage. This yielded a sample of 2,463 projects, of which 67% or 1,653 were successfully funded.

Kickstarter provides a discover page for users to browse all campaigns, we used this website to discover all new projects starting by looking every hour in those pages during the data collection. To extend the capture beyond newly listed, recommended and popular campaigns, and to reduce bias in the data, we also captured the discover page for each of the 13 categories presents in the platform. To validate the data collected, we used the official total number of newly created projects per month. Kickstarter had a total 1,906 projects set up in December 2014 [66], we were able to captured a sample of 710 campaigns, resulting in a sampling rate of 37.3%. As demonstrated, our sample is not necessarily representative of the overall population of Kickstarter projects, we kept that in mind when discussing our results. For the complete dataset, the average duration of a project is 31.8 days, and average raised amount is $32,563.00 with an average of 364 backers (122 in the first 1/6, and 92 in the last 1/6 of the campaign).

The detail method used for the data collection can be found on the Appendix B.

3.5.2 Dependent Variables

3.5.2.1 Campaign Success or Failure

We use Kickstarter's all-or-nothing principle to create a dichotomous variable, Status, which is equal to one if the creator achieved funding of 100% or more of the goal set in the beginning of the campaign and zero otherwise. In Kickstarter, if the creator accumulated less than 100% of the funds from their goal they do not receive any funds. We found the distribution to be bimodal, in line with previous literature [27, 33]. This can be demonstrated by using the Hartigan dip test which measures the multimodality in a sample [51]. The binary relationship between ratio of funds raised and the goal set by the entrepreneur can be seen in the Hartigan dip test results (See Table 2 and Fig. 9). Our data are significant at 0.001% with modes around 0% and 100%, similar results were found by Butticè et al. [27]. This corroborates to the consideration of the project's final status as a dummy variable (success/failure dichotomy), and thus requiring the use of the Logistic regression.

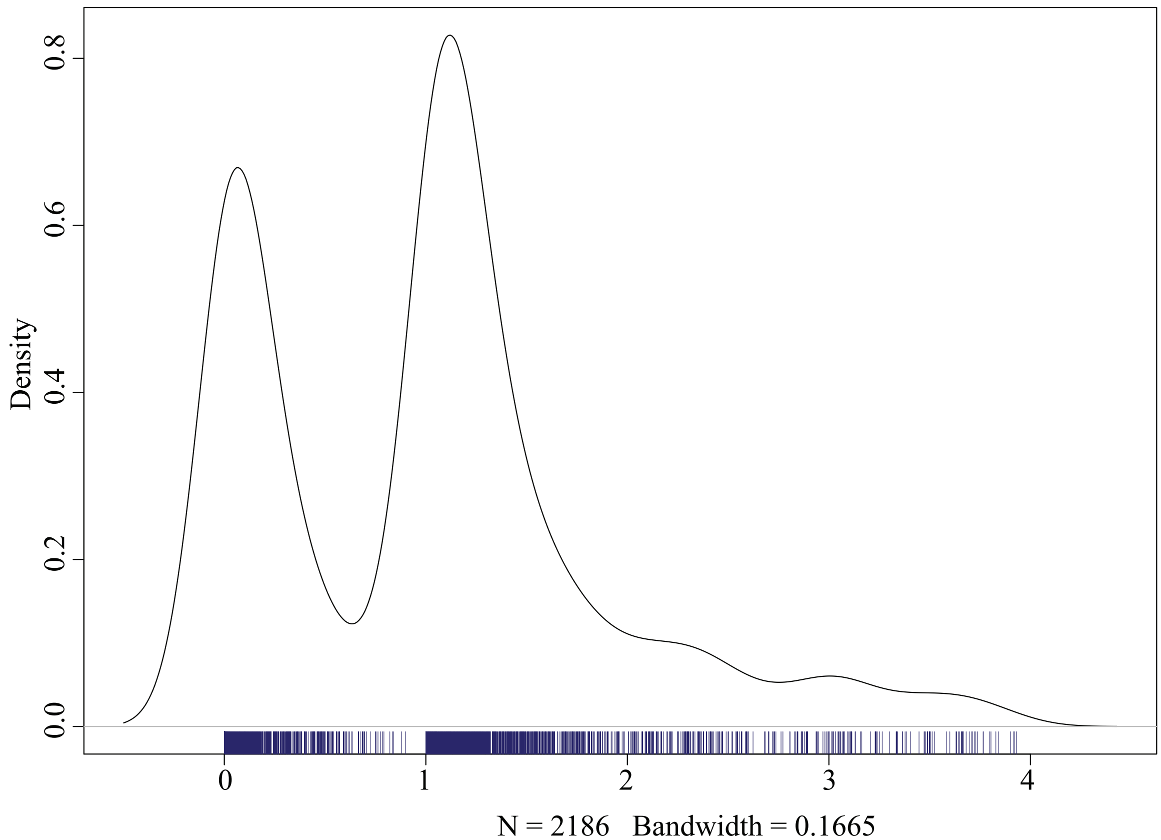

Figure 9: Hartigan Dip Density Test

3.5.2.2 Percentage of Goal Funded

To test our third hypotheses, we require a measure of goal proximity. As Kivetz et al. [67] note, perceptions, and preferences are receptive to relative rather than absolute quantities as found in many research in psychophysics, judgment, and decision-making.

Table 2: Descriptives of Data from Hartigan Dip

Modes	0	1	2
Length	802	1125	166

Thus, we define percentage of the goal funded as the ratio of project total funding divided by project goal.

3.5.3 Independent Variables

3.5.3.1 Early and Late Backers

To measure herding both in the early and late stages, we look at the delta of the number of investors in a period. This is consistent with previous studies like Burtch [25]. Then, the first one-sixth of the total time is conventionally considered the critical point of early stage [33]. Thus, the extent of early herding is measured with as the number of backers in this period of the project. Similar to the measure of early backers, we also included a measure of the number of backers at the last sixth of the total time of the project. The measure of Late Backers enables us to compare the effect difference between different timings of herding.

3.5.3.2 Logarithm of the Goal ($Log(Goal)$)

Defined as the total amount of money the founder seeks to raise through crowdfunding [85], in Kickstarter, the corresponding variable is called project goal. This has been used as an independent variable in many prior studies [19]. A creator of a project is required to specify the project goal at the time of creation of the Kickstarter project.

The goal is not the upper boundary of the final amount of funds founders can raise, but it provides a good indicator of a project's scale, complexity and the amount of time and skill required to fulfill promises. In our analysis, we first convert all currencies to the corresponding dollar value using the average currency exchange monthly rate to make all values comparable and take the logarithm of the goal and center it at its mean.

3.5.4 Control Variables

We included several control variables. First, we considered the duration of the campaign (*duration*), as longer campaigns might have more time to raise funds and act to change the status quo. It represents the beginning to end duration of a project which is set by the creator before the project starts. The rules of Kickstarter restrict the project duration to be anywhere from one to sixty days. Our second control is the (*past creator performance*) which is measured as the number of previously successful projects. This information is available to all the backers and has been used in the previous study as a proxy of social capital developed through previous campaigns [27]. Third, when creating the project page, creators can specify the different rewards supporter will get in return for their pledges. We recorded the number of the various types of reward being offered, but not its contents (*number of rewards*). Finally, social capital created by the usage of social media can influence the outcome of the campaign, to control for that we create two metrics to meet the time of our independent variable of early and late backers, namely (*early social media*) and (*late social media*). This is a measure of the log of the total number of interactions about the campaign on Twitter, the number of Facebook shares and the number Facebook likes.

3.6 Model and Analysis

For our first dependent variable, since it is binary, we use a logistic model to test the hypotheses. The general logistic model is displayed in (3.1) where $Pr(Y_i = 1)$ is the probability that the campaign i is successful and β is a vector of logistic coefficients associated with the matrix of independent variables X. The β indicates a given variable's influence on the chances – expressed in log odds – that a campaign is funded. The size of the goal of the campaign has been found to influence the backer decision, which could bias the test statistics and confidence intervals produced by the logit estimator [54]. Thus, we split the goal at the average in our robustness tests to address this departure from the independence assumption.

$$\ln\left(\frac{Pr(Y_i = 1)}{1 - Pr(Y_i = 1)}\right) = A_0 + \beta X \tag{3.1}$$

To test the moderating hypotheses, we add the interaction term, X_1X_2, to the logit model and extend the general model in (3.2). However, as with other non-linear models, the coefficient for the interaction term, β_{12}, is not an estimate or test of the hypothesized moderation effect for two related reasons. First, the scale of interest and the logit coefficient are different. Whereas the hypotheses predict the effect of the goal on the probability of a campaign being funded, the main β coefficients, β_1 and β_2, are interpreted as the natural log of the odds ratio. The β coefficient of the interaction term, β_{12}, on the other hand, are the natural log of the ratio of two odds ratios. One cannot interpret a ratio of odds ratios in the form of a likelihood [63, 68]. Thereby, the coefficient of the interaction term representing the direction, magnitude, and statistical significance cannot be directly interpreted as a predictor of the probability of being successful. Second, the logit coefficient for the interaction term does not truly indicate the interaction effect [54]. The calculation for the interactive effect of two interacted dummy variables can be found in Plummer et al. [95]. Then, the interaction effect of X_1 and X_2 could be statistically significant even if the logit coefficient, β_{12} is not significant [63].

$$\ln\left(\frac{Pr(Y_i = 1)}{1 - Pr(Y_i = 1)}\right) = A_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 \tag{3.2}$$

Therefore, it is important to test the hypotheses and interpret the results in terms of the average marginal effects of the independent variables and their interactions [54]. The marginal effect is the change in probability of the predicted outcome (i.e., campaign success) as result of an one-unit change in the independent variable.

3.7 Results

3.7.1 Logit

Table 3 displays the descriptive statistics and Table 4 displays the correlation table of the dataset we used in logistic regressions. This dataset includes both successful and failed projects. Our final sample includes 2,463 projects with 1,653 successfully funded. On average, we have more early backers than late backers, early and late social media are centered in zero.

Table 5 displays the logistic regression coefficients and table 6 displays the odds

Table 3: Descriptive Statistics for Logistic Regression

Statistic	N	Mean	St. Dev.	Min	Max
Success	2,463	0.67	0.47	0	1
Early Backers	2,463	122.31	455.98	0	14,209
Late Backers	2,463	92.12	324.68	0	8,135
Log (Goal)	2,463	0	1.56	−8.70	6.98
Duration (days)	2,463	31.79	9.72	2.96	60.00
Previous successful campaigns	2,463	0.38	1.90	0	29
Number of Rewards	2,463	11.31	7.85	2	147
Early Social Media	2,463	0	6.23	−23.49	7.74
Late Social Media	2,463	0	10.54	−18.11	12.29

Table 4: Correlation Table for Logistic Regression

	1	2	3	4	5	6	7	8
Success								
Early Backers	0.16***							
Late Backers	0.18***	0.82***						
Log (Goal)	-0.07***	0.25***	0.26***					
Duration (days)	-0.10***	0.03	0.03	0.20***				
Previous successful campaigns	0.12***	0.10***	0.06**	-0.03	-0.10***			
Number of Rewards	0.26***	0.14***	0.16***	0.31***	0.04*	0.05*		
Early Social Media	0.37***	0.15***	0.15***	0.23***	0.01	0.04	0.29***	
Late Social Media	0.58***	0.18***	0.21***	0.25***	0.02	0.05*	0.34***	0.50***

Note: *p<0.05; **p<0.01; ***p<0.001

ratio and the average marginal effects used for testing the hypotheses. The table 5 also reports the pseudo R^2 and the log-likelihood statistics for each model. We also conduct the Hosmer-Lemeshow X^2 goodness of fit statistic for each of the models. While the test itself is not reported, none of them suggested misspecification.

In Table 5, models 1 and 2 report the logit coefficients estimates for the isolated early and late backers model, respectively. By comparing these coefficients estimate with the one in model 3, we notice the effects are robust even under collinearity.

3.7.1.1 Hypothesis Tests Logit

Models 4, 5 and 6 shows that the two positive relationships are conditioned on the $goal$. At the mean, one more backer in the early stage can lead to 3.3% increase in the odds of success, while one more backer in the late stage can lead to 8.9% increase in the odds of success. This result supports Hypothesis 1 (The positive effects on campaign success from herding is stronger when herding occurs in the latter stage of the campaign). The project goal further negatively moderates both positive relationships. If the Goal is doubled, the effect of early backers is reduced by 0.006, and the effect of late backers on project success is reduced by 0.020 (supporting Hypothesis 3 where the size of the project goal moderates the herding and speed effects of crowdfunding campaigns).

3.7.2 Tobit

Table 7 shows the descriptive statistics and Table 8 displays the correlation table of the dataset we used for Tobit regression. This dataset only includes the projects that are successful, as we are interested in the Raised-Goal ratios that are not zero. In both data

Table 5: Logistic Regression Results

	Dependent variable: Success					
	(1)	(2)	(3)	(4)	(5)	(6)
Early Backers	0.021***		0.012***	0.046***	0.011***	0.032***
	(0.002)		(0.002)	(0.004)	(0.002)	(0.004)
Late Backers		0.053***	0.041***	0.042***	0.100***	0.086***
		(0.005)	(0.005)	(0.004)	(0.009)	(0.009)
Log(Goal)	−1.001***	−0.997***	−1.101***	−0.989***	−0.986***	−0.988***
	(0.062)	(0.062)	(0.067)	(0.066)	(0.067)	(0.066)
Duration (days)	−0.021**	−0.024***	−0.023**	−0.018*	−0.023**	−0.020**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Previous successful campaigns	0.233	0.301*	0.192	0.068	0.120	0.058
	(0.129)	(0.132)	(0.133)	(0.141)	(0.138)	(0.142)
Number of Rewards	0.069***	0.050***	0.046***	0.023	0.031*	0.022
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Early Social Media	0.076***	0.088***	0.082***	0.059***	0.075***	0.064***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Late Social Media	0.122***	0.095***	0.099***	0.091***	0.077***	0.077***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Early Backers X Log(Goal)				−0.013***		−0.006***
				(0.001)		(0.001)
Late Backers X Log(Goal)					−0.024***	−0.020***
					(0.002)	(0.002)
Constant	−0.093	−0.152	−0.352	−0.764**	−0.710*	−0.927**
	(0.259)	(0.266)	(0.272)	(0.286)	(0.287)	(0.294)
Pseudo R-squared	0.4755	0.5091	0.5226	0.5642	0.5670	0.5804
Observations	2,463	2,463	2,463	2,463	2,463	2,463
Log Likelihood	−815.167	−762.989	−742.002	−677.372	−672.910	−652.093
Akaike Inf. Crit.	1,646.335	1,541.979	1,502.003	1,374.743	1,365.820	1,326.186

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 6: Odds Ratio and Average Marginal Effects

	Odds Ratio (Std. Err.)	a.m.e.
Early Backers	1.0325^{***} (0.0074)	0.0000355
Late Backers	1.0896^{***} (0.0142)	0.0000953^{*}
Log (Goal)	0.3722^{***} (0.0252)	-0.0010963^{***}
Duration (days)	0.9803^{**} (0.0070)	-0.0000221^{**}
Previous successful campaigns	1.0601 (0.1682)	0.0000647^{*}
Number of Rewards	1.0218 (0.0132)	0.0000240^{***}
Early Social Media	1.0658^{***} (0.0161)	0.0000707^{**}
Late Social Media	1.0804^{***} (0.0090)	0.0000858^{***}
Early Backers X Log (Goal)	0.9938^{***} (0.0015)	-0.0000069
Late Backers X Log (Goal)	0.9802^{***} (0.0029)	-0.0000221
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$	

sets, the correlation between Early Backers and Late Backers are between 0.74 and 0.99. This high correlation is expected, as good projects can attract a large number of followers and backers, both in the beginning and in the end. However, as we will show in the later section, the two variables exhibit a very different effect on the success and overfunding of the projects, and the difference is robust to the collinearity between each other.

Table 9 displays the Tobit regression results. Models 1, 2 and 3 are similar to the one presented previously about Table 5, and serve as a robustness check for multi-collinearity. Model 6 is used to test the Hypothesis 3. At the mean of Goal, increasing one more early backers leads to 0.6% increase in the predicted value of Raised-Goal ratio while increasing one more late backer leads to an increase of 1.4%. Both effects are again negatively moderated by the size of the goal. The moderating effects for early backers, when the goal is doubled, is reduced by 0.1% while the late backers is reduced by 0.4%.

Table 7: Descriptive Statistics for Tobit Regression

Statistic	N	Mean	St. Dev.	Min	Max
Raised-Goal Ratio	1,653	3.4211	7.2562	1.0000	99.4360
Early Backers	1,653	165.6134	425.9265	0	6,340
Late Backers	1,653	128.4525	335.8605	0	5,695
Log(Goal)	1,653	−0.0505	1.5197	−6.9123	4.6007
Duration (days)	1,653	31.0940	9.1877	3.0000	60.0000
Previous successful campaigns	1,653	0.5263	2.2954	0	29
Number of Rewards	1,653	12.7502	8.4301	2	147
Early Social Media	1,653	1.6212	3.3645	−23.4906	7.7430
Late Social Media	1,653	4.2536	6.9012	−18.1132	12.2926

Table 8: Correlation Table for Tobit Regression

	1	2	3	4	5	6	7	8
Raised-Goal Ratio								
Early Backers	0.26***							
Late Backers	0.26***	0.74***						
Log(Goal)	-0.21***	0.36***	0.37***					
Duration (days)	-0.05*	0.06*	0.07**	0.24***				
Previous successful campaigns	0.07**	0.10***	0.04	-0.04	-0.12***			
Number of Rewards	0.00	0.13***	0.13***	0.35***	0.09***	0.02		
Early Social Media	0.00	0.21***	0.19***	0.40***	0.16***	-0.03	0.22***	
Late Social Media	0.03	0.15***	0.20***	0.43***	0.17***	-0.04	0.20***	0.38***

Note: *p<0.05; **p<0.01; ***p<0.001

Table 9: Tobit Regression Results

	Dependent variable: Raised-Goal Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Early Backers	0.006***		0.004***	0.011***	0.004***	0.006***
	(0.0004)		(0.001)	(0.001)	(0.001)	(0.001)
Late Backers		0.008***	0.005***	0.005***	0.017***	0.014***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(Goal)	−2.117***	−2.104***	−2.222***	−2.032***	−1.929***	−1.927***
	(0.134)	(0.134)	(0.133)	(0.128)	(0.127)	(0.126)
Duration (days)	−0.002	−0.002	−0.001	0.003	−0.004	−0.002
	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Previous successful campaigns	0.072	0.140*	0.091	−0.030	0.024	−0.00000
	(0.071)	(0.070)	(0.070)	(0.067)	(0.066)	(0.066)
Number of Rewards	0.057**	0.056**	0.057**	0.063***	0.069***	0.069***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)
Early Social Media	0.081	0.109*	0.087	0.047	0.052	0.046
	(0.054)	(0.054)	(0.053)	(0.051)	(0.050)	(0.050)
Late Social Media	0.150***	0.127***	0.137***	0.117***	0.093***	0.095***
	(0.027)	(0.027)	(0.026)	(0.025)	(0.025)	(0.025)
Early Backers X Log (Goal)				−0.003***		−0.001**
				(0.0002)		(0.0004)
Late Backers X Log (Goal)					−0.005***	−0.004***
					(0.0003)	(0.0005)
Constant	0.777	0.812	0.587	0.082	0.202	0.121
	(0.650)	(0.649)	(0.641)	(0.614)	(0.602)	(0.602)
Pseudo R-squared	0.4755	0.5091	0.5226	0.5642	0.5670	0.5804
Observations	1,653	1,653	1,653	1,653	1,653	1,653
Log Likelihood	−5,440.205	−5,437.318	−5,415.840	−5,340.372	−5,310.411	−5,306.855
Wald Test	404.242***	411.439***	465.791***	668.366***	754.063***	764.441***

Note: *p<0.05; **p<0.01; ***p<0.001

3.7.3 Robustness check

To validate our test, we performed a split test of our population. This new sample was randomly selected and represents 70% of the observations. The results are displayed in table 10. By doing the split test as explained in 3.6, the results can be found in tables 11 and 12. It is interesting to observe that the size of the goal does affect the results as previously predicted in the hypotheses 3, and as the goal get smaller, the effect on the outcome from the early and late stages flips. One explanation for the difference is that when the goal is small, early backers are sufficient to ensure the goal is met, but as the goal increases, late backers play a greater role in the funding outcome.

3.8 Discussion

While prior research has independently shown that herding and the type of investor matters, we are the first to look at the interaction of both. Colombo et al. [33] emphasizes the significance of receiving a robust support by backers in the early stage of the campaign, and our results show that while this is important, the latter stage needs even stronger support when the goal is higher.

We expect the behavior to all campaigns to be similar to the one proposed by Kuppuswamy and Bayus [71], where family and friends create the early herding and eventually fades giving space to the bystander effect, followed by the deadline effect driving the campaign towards its goal. However, we find that while the early herding is important, later herding increases the chances of achieving the goal and overfunding, even more if the goal is larger.

Table 10: Logistic Regression Robustness Check

	Dependent variable: Success					
	(1)	(2)	(3)	(4)	(5)	(6)
Early Backers	0.019^{***}		0.011^{***}	0.039^{***}	0.011^{***}	0.029^{***}
	(0.002)		(0.002)	(0.005)	(0.002)	(0.005)
Late Backers		0.055^{***}	0.043^{***}	0.043^{***}	0.090^{***}	0.078^{***}
		(0.006)	(0.006)	(0.006)	(0.010)	(0.009)
Log(Goal)	-0.967^{***}	-0.961^{***}	-1.069^{***}	-0.939^{***}	-0.963^{***}	-0.944^{***}
	(0.073)	(0.072)	(0.079)	(0.077)	(0.079)	(0.076)
Duration (days)	-0.032^{***}	-0.034^{***}	-0.034^{***}	-0.031^{***}	-0.033^{***}	-0.031^{***}
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Previous successful campaigns	0.193	0.239	0.134	0.010	0.075	0.008
	(0.131)	(0.130)	(0.132)	(0.143)	(0.134)	(0.144)
Number of Rewards	0.074^{***}	0.046^{**}	0.045^{**}	0.024	0.033^{*}	0.024
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Early Social Media	0.075^{***}	0.092^{***}	0.086^{***}	0.064^{***}	0.081^{***}	0.069^{***}
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Late Social Media	0.122^{***}	0.091^{***}	0.095^{***}	0.090^{***}	0.078^{***}	0.078^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Early Backers X Log(Goal)				-0.012^{***}		-0.006^{***}
				(0.001)		(0.001)
Late Backers X Log(Goal)					-0.021^{***}	-0.018^{***}
					(0.002)	(0.002)
Constant	0.239	0.182	0.016	−0.258	−0.295	−0.458
	(0.315)	(0.324)	(0.331)	(0.342)	(0.343)	(0.350)
Pseudo R-squared	0.4755	0.5091	0.5226	0.5642	0.5670	0.5804
Observations	1,725	1,725	1,725	1,725	1,725	1,725
Log Likelihood	−563.548	−523.041	−509.096	−472.834	−472.239	−458.124
Akaike Inf. Crit.	1,143.097	1,062.082	1,036.192	965.667	964.478	938.248
Note:						$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 11: Logistic Regression Goal $\leq$ \$6,000.00

	Dependent variable: Success					
	(1)	(2)	(3)	(4)	(5)	(6)
Early Backers	0.197***		0.164***	0.275***	0.171***	0.274***
	(0.020)		(0.020)	(0.030)	(0.021)	(0.030)
Late Backers		0.206***	0.131***	0.143***	0.225***	0.203***
		(0.024)	(0.023)	(0.024)	(0.034)	(0.036)
Log(Goal)	−0.730***	−0.808***	−0.890***	−0.229	−0.623***	−0.104
	(0.103)	(0.100)	(0.111)	(0.137)	(0.119)	(0.150)
Duration (days)	−0.027**	−0.035***	−0.026**	−0.024*	−0.025*	−0.024*
	(0.010)	(0.009)	(0.010)	(0.011)	(0.010)	(0.011)
Previous successful campaigns	0.118	0.220	0.009	−0.030	0.038	0.020
	(0.226)	(0.185)	(0.226)	(0.260)	(0.248)	(0.266)
Number of Rewards	0.033	0.066**	0.021	0.021	0.014	0.019
	(0.024)	(0.022)	(0.025)	(0.027)	(0.026)	(0.027)
Early Social Media	0.033*	0.073***	0.039*	0.025	0.039*	0.024
	(0.015)	(0.015)	(0.016)	(0.017)	(0.016)	(0.017)
Late Social Media	0.090***	0.062***	0.063***	0.065***	0.058***	0.061***
	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)	(0.011)
Early Backers X Log(Goal)				−0.195***		−0.180***
				(0.029)		(0.030)
Late Backers X Log(Goal)					−0.153***	−0.093*
					(0.035)	(0.038)
Constant	0.033	0.308	−0.592	−0.988*	−0.775	−1.140**
	(0.366)	(0.360)	(0.396)	(0.427)	(0.411)	(0.437)
Pseudo R-squared	0.5660	0.5069	0.5976	0.6345	0.6115	0.6387
Observations	1,245	1,245	1,245	1,245	1,245	1,245
Log Likelihood	−333.514	−378.927	−309.203	−280.814	−298.554	−277.605
Akaike Inf. Crit.	683.028	773.855	636.407	581.627	617.108	577.210
Note:				*p<0.05; **p<0.01; ***p<0.001		

Table 12: Logistic Regression Goal ≥ \$6,000.00

	Dependent variable: Success					
	(1)	(2)	(3)	(4)	(5)	(6)
Early Backers	0.017***		0.010***	0.017***	0.010***	0.013***
	(0.002)		(0.002)	(0.003)	(0.002)	(0.003)
Late Backers		0.044***	0.035***	0.034***	0.057***	0.053***
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Log(Goal)	−1.351***	−1.378***	−1.642***	−1.261***	−1.186***	−1.056***
	(0.136)	(0.150)	(0.171)	(0.175)	(0.171)	(0.158)
Duration (days)	−0.003	−0.002	−0.001	0.0001	−0.003	−0.002
	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Previous successful campaigns	0.076	0.228	−0.013	−0.144	−0.073	−0.161
	(0.174)	(0.191)	(0.186)	(0.177)	(0.171)	(0.186)
Number of Rewards	0.063***	0.028	0.029	0.022	0.017	0.015
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
Early Social Media	0.040	0.087*	0.046	0.028	0.042	0.032
	(0.037)	(0.041)	(0.037)	(0.036)	(0.040)	(0.039)
Late Social Media	0.198***	0.113***	0.128***	0.131***	0.104***	0.107***
	(0.022)	(0.016)	(0.018)	(0.020)	(0.018)	(0.019)
Early Backers X Log(Goal)				−0.007***		−0.003**
				(0.001)		(0.001)
Late Backers X Log(Goal)					−0.019***	−0.017***
					(0.002)	(0.002)
Constant	−2.050***	−1.870***	−2.258***	−2.321***	−2.264***	−2.308***
	(0.445)	(0.448)	(0.473)	(0.484)	(0.485)	(0.488)
Pseudo R-squared	0.5280	0.5818	0.6032	0.6193	0.6386	0.6425
Observations	1,218	1,218	1,218	1,218	1,218	1,218
Log Likelihood	−370.029	−327.870	−311.109	−298.433	−283.333	−280.272
Akaike Inf. Crit.	756.058	671.740	640.218	616.865	586.666	582.545
Note:						*p<0.05; **p<0.01; ***p<0.001

We are also the first one to explore the relation between herding and overfunding. The explanation we find is that while in the earlier stage herding helps the founder to achieve the goal, the bystander effect will reduce or stabilize the growth of this campaign. Closer to the end, we will have backers investing to help the campaign to progress to the goal or to exceed the target (when they do not want to be left out of a bargain).

Although prior studies have provided insights into the retrospective outcomes of the actions of entrepreneurs in their crowdfunding campaigns, there is still a lot to learn about the strategic selection of the right crowdfunding model for entrepreneurial projects [20].

3.9 Pathways to Succeed in Reward-Based Crowdfunding (Study 2)

Every entrepreneur is unique and likely to execute its campaign differently, varying based on their ability to learn and respond to the different challenges of the campaign. For this reason, while we agree with prior findings that entrepreneurs who effectively execute the previously mentioned bathtub campaigns are likely to succeed, we suggest that there are other paths to crowdfunding success.

During our study 1, we observed four patterns of funding behavior during the campaign: a constant raise of funds, not presenting major changes during the campaign; an initial flat slope that was followed by rapid growth; rocket growth proceeded by a loss in momentum and gradually flatten out, and early stage momentum followed by stabilization than a later stage momentum and rally. Those are summarized in Table 14. To further explain this finding we explored the patterns in successful Kickstarter campaigns using ad hoc tests and content analysis. Using software to scrape the internet for qualitative event histories of each campaign, the study 2 provide rich descriptions for exemplary campaigns. Finally, using non-linear modeling, we explored the pattern of each funding projects and determine the parameters estimates of each curve [15].

3.9.1 Profiles

In this modeling, the estimated value of m indicates the shape of the curve and thus the patterns of funding. Specifically, the Profile A is represented by $m = 1$ which mirrors a linear line; Profile B is represented by $m > 1$ with the curve having a slow start, but picking up exponentially; $m < 1$ representing Profile C where the curve matches a rapid rise in the beginning and then flattens after the inflection point; and, finally, a cubic polynomial model as it fits well a typical S-curve of the funding process. To further remedy the possible misfitting, we generated a plot of funds raised versus relative time of the campaign, and visually inspected the fit results to confirm our findings. The distribution of campaigns can be found in Tables 13 and 14.

Table 13: Distribution of Campaigns

Profile	Description	# of Projects	% of Total Projects	% Successful
A	Linear	410	19.2 %	90 %
B	Exponential	865	40.4 %	15 %
C	Logarithmical	390	18.2 %	99 %
D	Bathtub	475	22.2 %	100 %

Note: Total Sample size: 2,140 crowdfunding projects.

Table 14: Ad-Hoc Study, Patterns Descriptions

Profile	Goal Met	Speed	Herding	Case Example
A	Early	Continuous	Early	”Universal Remote Control” Responded backers feedback. Kept engagement across the entire duration of the campaign.
B	Late	Exponential	Late	”Innovative Building Blocks” Late backers trust. Continuous updates in the duration of the campaign.
C	Early	Discontinuous	Multiple	”3D Headphone” Strategically created. Limited goal.
D	Early	Decrease Momentum	Early/ Late	”Pocket-Sized Software Defined Radio” Entrepreneur not active during the middle of campaign. Sense of community.

Drawing on our study findings, we present a typology of four profiles of successful crowdfunding campaigns. The Type A profile, with early herding causing steep acceleration, creates a continuous speed or momentum, which can result in failure or success depending on whether the strength of the early herding effect. The Type B profile lacks the early stage herding effect but then builds an exponential momentum is typical in cases where entrepreneurs have poor marketing strategies, lack of backers trust but great products. The Type C profile, on the other hand, may promote products that either is not strong enough to overcome ”bystander effects” mid-campaign but still achieves success because of the earlier herding or that were strategically created this way. Finally, the Type D profile with two waves of herding effects was typical in campaigns where entrepreneurs interjected new rewards or successfully pivoted their campaign midstream based on feedback.

3.9.2 Profile A

The first curve (Profile A) has a linear function with a constant increase in the raised funds, not presenting major changes during the campaign. This profile has an early acceleration, usually meeting its goals in the first few days of the campaign, achieving a continuous speed or momentum throughout its duration. The strength of the early herding effect can result in failure or success depending on the steep of the growth.

In this case, the entrepreneurs continually respond to changes in the environment. They perceive demands from clients and respond accordingly keeping the momentum in their campaign going. One of those cases is a universal remote control. Reaching the goal on the first day of their campaign, they listened to the feedback of the users which wanted more of one design that was sold out, and responded creating new levels of rewards to address the request. Those actions are not limited to availability of a product but extend to the creation of new features in the product. Those new features are also introduced as new virtual goals, offered only if a certain financial threshold is met. We define it as virtual as they only exist as a promise between the entrepreneur and the backers, while common practices, it is not part of the platform.

Primarily, responding to the feedback of users is not an easy quest. One important characteristic of those ventures is that they are focused on their product and the response to feedbacks are only those adopted if they enhance their product vision. This approach enables entrepreneurs to limit their time investment in developing features that will increase the value-added perception of most customers. One example is a guitar analog headphone amplifier which looks like those rectangular prism portable battery chargers. Some customers wanted a clip on it to attach to different places, like a pocket knife. However, this would have introduced a cheaper look for the stainless-steel body of the product increasing functionality at the price of reducing the added value of the design.

Secondly, setting a realistic goal in not only the sense of the amount of money required but also the one of production capacity can assist the entrepreneurs in securing the funds required to succeed in all or nothing campaigns. Creating an unlimited reward tier for a product which inflicts a change in the fixed cost of production could harm the entrepreneur timeline to deliver the product. While this does not seem like a formal concern today, as most of the campaign do not deliver on time and backers already expect those delays, moving forward, it is likely to create changes in the crowdfunding environment to protect investors from those issues.

3.9.3 Profile B

The second curve (Profile B) has an exponential function with an initial flat slope that was followed by rapid growth. The Type B profile that lacks the early stage herding effect but then builds constant momentum is typical in cases where entrepreneurs have poor marketing strategies but great products. One example is the innovative building blocks. Their market strategy and price placement did not receive much attention in the early stages of the campaign. At the 80% completion date, after hitting their goal, they released a video of the product being manufactured, and it was the turning point for the campaign. They have doubled the number of backers and reached 180% of their initial goal.

In this second profile, activities were made by the entrepreneur to assisted them to reach their success. First, the prototype was completed during the early stage of the campaign, but only early adopters were willing to cope with the productions risks. As they achieved the goal and were able to alleviate the production risks, the perceived legitimacy it needed to motivate new backers to invest increased. Second, constant updates about the status of development assisted them in achieving the momentum and creating a sense of community. This community environment also strengths the concept of shared value – the entrepreneur undertakes practices that enhance the competitiveness of a company while simultaneously create advantages to the communities in which it operates. Stakeholders then will work for the success of the campaign, because this will create an advantage beyond the product they will receive. It is known that firms that can create value for multiple stakeholders may have an unusual success [96, 97, 112].

3.9.4 Profile C

The third curve (Profile C) has a logarithmic function, with rocket growth proceeded by a loss in momentum and gradually flattened out. This Type C profile, when compared with the others, may promote products that are not strong enough to overcome

”bystander effects” mid-campaign but still achieves success because of the earlier herding. We can illustrate this type of campaign with a 3D headphone that tracks motion and simulates a significant number of different speakers placed around the subject. Reaching the goal on the first day and being select as ”staff pick,” the campaign skyrocket in the first week.

As rewards levels started to hit their limit, fewer people were willing to pay the premium for a more expensive version, with this the number of backers was limited. This can occur by design and be a form of crowdfunding strategical planning. This entrepreneur during the duration of the project was able to adapt to unexpected events like hitting the goal in 2 days. It also undertook a similar attitude to Profile A regarding addressing requests of customers in a limited form – changes supporting the vision of the product. No significant variations in the campaign were made other than introducing new batches of the product at different prices to engage and motivate early backers and achieve the virtual goal.

This profile may signal a better strategical planning when compared with Profile A. After reaching the goal, boundaries in the number of products available to be sold can restrict the number of customers willing to acquire it. One entrepreneur may engage in this form of action to limit the amount of capital raised, as one may argue it might not be of the best interest to raise a greater amount than the goal to keep the expected delivery time and the production costs. However, on the other hand, this can also be due to a lack of planning when the entrepreneur does not adapt and fails to recognize the opportunities and the market needs.

3.9.5 Profile D

The fourth curve (Profile D) had an s-shape, representing a power function, with early stage momentum followed by stabilization than a later stage momentum and rally. The Type D profile with two waves of herding effects was typical in campaigns where entrepreneurs interjected new rewards or successfully pivoted their campaign midstream based on feedback. A good example is a Pocket-Sized Software Defined Radio, or a portable shortwave ham radio with GPS for backpackers and hikers that want to have communication in the middle of nowhere. The creator was a first-time entrepreneur that developed this as his hobby. Not only his product received third place finalist in an important prize, but also it was featured at a German Ham Radio Magazine.

After the campaign launch, it was also featured in two different gadgets websites in the first week, and the entrepreneur spent many hours actively explaining the underlying cost and technical challenges at specialized forums where interested investors would be present. However, the entrepreneur had to travel in the middle of the campaign without access to the internet. He could access back his campaign only shortly before the deadline when he actively answered the comments and engaged with his potential customers achieving the goal on the last day of the campaign.

This profile demonstrates the importance of the engagement of the entrepreneur throughout the campaign. An entrepreneur desiring to achieve its goals need to be actively engaged with the customers to address concerns that may arise. Doing so in the early stages will create the sense that the entrepreneur cares about the users, it will create a personal connection. If the entrepreneur fails to do that, it will result in a reduction of trust between the parties and thus a downfall in the number of new backers. If the creator does not reverse this trend, it may result in the failure of the project, however, reversing will capture back some of the lost trust, leading to an increase of investment. Also, being transparent regarding quality and costs will help the entrepreneur to gain the confidence of backers where they will perceive the campaign as an opportunity for a high benefit-cost ratio. The earlier those are addressed, sooner the investors will come.

3.10 Discussion

Our findings suggest that entrepreneurs, who strategically craft the timing of their explanations and promotion of their new venture, may reduce some of the uncertainty typically associated with entrepreneurship [7, 80]. The ability to tell those stories becomes then an integral part of the process used by founders to construct, acquire capital, and generate new wealth for the new ventures [7, 80].

Crowdfunding campaigns can be an integral part of the process used by founders to construct, acquire capital, and generate new wealth for the new ventures [77, 80]. Some stakeholders are more likely to engage with entrepreneurs in the latter stages (i.e., Venture Capital Firms, Relationship Partners) once the entrepreneur has legitimacy [55]. Crowdfunding campaigns provide a way for entrepreneurs to gain legitimacy with these latter stage stakeholders. A speedy or successfully backed crowdfunding campaign, especially a reward-based campaign, is not a guarantee of entrepreneurial success in the long-term. For an entrepreneur investing in crowdfunding, while it is essential to have early support from family and friends [33], we found strong support to the late stage as well. The energy shall be used for the entire campaign, but the focus should be in the first and last week. The goal should also reflect the genuine need of the entrepreneur and not be inflated. This will increase the herding effect and result in a higher overfunding.

Our study findings and developed typology suggest that entrepreneurs who strategically craft the timing of their explanations and promotion of their new venture may reduce some of the uncertainty typically associated with entrepreneurship [7, 80]. It highlights the importance of responding to users feedbacks and thus creating a sense of community. It also opens the discussion towards the different paths of success within the crowdfunding campaign. There still is, however, a lot to learn about the strategic selection of the right crowdfunding model for entrepreneurial projects [20]. It also shed light on strategic actions that entrepreneurs can take to maximize the financial, human and social capital that they extract from their crowdfunding campaigns.

3.11 Limitations and Future Research

Future research should validate the bystander effect during the middle of the campaign and explore the relationship between the backer motivation after reaching the goal. It should also address some limitations. First, while we tested our models on a relatively large sample, using only one platform (Kickstarter) and representing 37% of the campaign in that period might suggest that additional research is needed to verify whether our results hold on different crowdfunding platforms and time frame. Second, only a limited part of the variables in our database were used, the use of the full panel structure of our datasets might provide different insights (for instance allowing us to distinguishing backers before reaching the goal and those after them, analyze failure and the reasons for it to happen). Finally, exploring the motivation of the founder differentiating between social and for-profit goal should result in a contribution to the area of social entrepreneurship.

Future research can also examine $country$ differences in the relationship between the early and late stages of a crowdfunding campaign and its relationship to success and overfund in the reward-based community Kickstarter. As ad hoc tests, we looked at the positive effects on campaign success from herding in the latter stage of the campaign by the geographic region of the founder. For the campaigns that succeed, we also looked at whether latter herding increases the overfunding ratio by the geographic region of the founder. To be able to fully capture this international nature and compare findings across different creation regions, we separated into continents aggregating currencies within (e.g. Australian Dollars is Oceania, Canadian Dollars and US Dollars are North America, Euro and British Pound are Europe). Campaign founders are required to have an address, bank account, and government-issued ID and be a permanent resident of a selected list of countries.

At the mean of the $goal$, in North America, one extra backer at the early stage can lead to 5% increase in the odd of success, while one more backer in the late stage can lead to 14%. Europe has a similar result with 3% in the early stage and 14% in the late stage. However, in Oceania, the results are even stronger for the late stage, 5% and 42%. For overfunding, the effects were stronger in Europe, followed by North America. The findings shed light on strategic actions that entrepreneurs in different geographic regions can take to maximize the financial, human and social capital [16] that they extract from their crowdfunding campaigns. Entrepreneurship is a process, and crowdfunding success is not the end. Campaigns provide signals about the legitimacy of the entrepreneur and their projects.

3.12 Conclusion

In this work we make several contributions to the literature. First, Shepherd [102] and Davidsson [34] both call for scholars to examine entrepreneurship phenomena using contingency frameworks that factor time into the model. Our findings of Study 1 demonstrate that while the growing literature identifies speed [4] and herding [33, 72, 78, 115] as independent factors that contribute to goal attainment [4, 78] and overfunding [85, 86], a better understanding of their interaction needs investigation as well. In particular, the literature is clear that the individuals that are more likely to herd in the early stage are family, friends, and fools. The implication of using only this crowd is that you really pull on your strong ties, your narrow networking and you were not able to optimize this to the weaker ties [47]. The conversation of understanding of who is being herding and under what time condition is an important contribution to the crowdfunding literature. This work is the first to relate herding and the temporal effect of speed and their interaction effects on the outcome of a crowdfunding campaign.

Second, our theoretical framework draws attention to the consequences of rational and irrational herding [115] and the effects of simultaneous versus sequential funding strategies [56]. We expand the concept of speed and herding as main predictors of crowdfunding success [4] to include different patterns of success beyond the ones identified in the literature. Further, the typology we develop in Study 2 contributes four combinatory patterns of herding, bystander/substitution and deadline effects that are alternative pathways to crowdfunding success. Our study findings highlight that asking how fast the entrepreneur achieve the goal (speed) is not enough. Theoretically, scholars also need to understand the investment archetype in the early and the latter stages. Practically, entrepreneurs should consider staging the timing of social media campaigns since, in some contexts, the release of new information may be more efficient when it is more sequential than simultaneous with the campaign launch [19, 56].

Finally, entrepreneurship is a process, and crowdfunding success is not the end. It is the beginning. Successful crowdfunding campaigns provide signals about the legitimacy of entrepreneurs and their projects. Our study offers entrepreneurs routes that they can take to navigate their liabilities of newness and maximize the benefits of the financial, human and social capital [16] that they accumulate from their crowdfunding campaigns. In so doing, we set the stage for future research to further expand about relationships between the early stage crowdfunding activities and new venture start-up, performance and growth. We also adjust the stage for future analyses that explore the relationship between entrepreneurial learning at this pre-venture stage and the entry and exit decisions of various stakeholders who do business in different organizational and institutional settings.

CHAPTER 4

CONCLUSIONS AND FUTURE RESEARCH

4.1 Telecommunications and Computer Networking

This paper provides an optimization model for the allocation of frequencies to base stations, regardless of size, to serve the different demand needs. This optimization to improve the organic efficiency is needed for wireless providers be able to meet the predicted demand increase.

For the academic environment, we provide an introduction to a new discussion of the future of wireless networks, and we give directions for future research. First, how to improve the carrier allocation allowing also reduced interference. Second, how to incorporate unlicensed bands. Third, the optimal distribution of cell types. Finally, the effect of picocells and femtocells with this technology need to be explored.

For the industry, we provide a new direction that has a track record but until now lacked the technology to make it work. This also increases the quality of service and perceived value from a client perspective. Finally, with a fully connected and mobile society, using the technology in unimaginable ways, with a steep increase in the traffic, in the number of devices, and in the ways of using them, we are required to search new ways of creating the future. This article provides a helpful piece.

Using this new optimization algorithm opens door to many future network improvements and we propose some streams of research that can benefit from implement it. First, given the resources blocks available for a service provider, questions regarding which frequency blocks should be allocated to each base station and how to optimize the distribution to reduce interference should be investigated. This would enable service providers to acquire not only the best resources to expand their network but also make an educated investment in such an expensive resource. Second, we demonstrated that this algorithm converge for a large number of nodes, however, determining the ideal network size for a better efficiency will give a important contribution. Third, this article drive in the idea that planning for network expansions and new locations should not be a burden for service providers.

4.2 Entrepreneurship and Innovation

Future research should validate the bystander effect during the middle of the campaign and explore the relationship between the backer motivation after reaching the goal. It should also address some limitations, (1) use of the full advantage of the panel structure of our datasets, (2) distinguish late backers before reaching the goal and those after them, (3) analyze failure and reason for so.

Future research can also examine $country$ differences in the relationship between the early and late stages of a crowdfunding campaign and its relationship to success and overfunding in the reward-based community Kickstarter. As ad hoc tests, we looked at the positive effects on campaign success from herding in the latter stage of the campaign by the geographic region of the founder. For the campaigns that succeed, we also looked at whether latter herding increases the overfunding ratio by the geographic region of the founder. To be able to fully capture this international nature and compare findings across different creation regions, we separated into continents aggregating currencies within (e.g. Australian Dollars is Oceania, Canadian Dollars and US Dollars are North America, Euro and British Pound are Europe). Campaign founders are required to have an address, bank account, and government-issued ID and be a permanent resident of a selected list of countries.

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In this work we make several contributions to the literature. First, Shepherd [102] and Davidsson [34] both call for scholars to examine entrepreneurship phenomena using contingency frameworks that factor time into the model. Our findings of Study 1 demonstrate that while the growing literature identifies speed [4] and herding [33, 72, 78, 115] as independent factors that contribute to goal attainment [4, 78] and overfunding [85, 86], a better understanding of their interaction needs investigation as well. In particular, the literature is clear that the individuals that are more likely to herd in the early stage are family, friends, and fools. The implication of using only this crowd is that you really pull on your strong ties, your narrow networking and you were not able to optimize this to the weaker ties [47]. The conversation of understanding of who is being herding and under what time condition is an important contribution to the crowdfunding literature. This work is the first to relate herding and the temporal effect of speed and their interaction effects on the outcome of a crowdfunding campaign.

Second, our theoretical framework draws attention to the consequences of rational and irrational herding [115] and the effects of simultaneous versus sequential funding strategies [56]. We expand the concept of speed and herding as main predictors of crowdfunding success [4] to include different patterns of success beyond the ones identified in the literature. Further, the typology we develop in Study 2 contributes four combinatory patterns of herding, bystander/substitution and deadline effects that are alternative pathways to crowdfunding success. Our study findings highlight that asking how fast the entrepreneur achieve the goal (speed) is not enough. Theoretically, scholars also need to understand the investment archetype in the early and the latter stages. Practically, entrepreneurs should consider staging the timing of social media campaigns since, in some contexts, the release of new information may be more efficient when it is more sequential than simultaneous with the campaign launch [19, 56].

Finally, entrepreneurship is a process, and crowdfunding success is not the end. It is the beginning. Successful crowdfunding campaigns provide signals about the legitimacy of entrepreneurs and their projects. Our study offers entrepreneurs routes that they can take to navigate their liabilities of newness and maximize the benefits of the financial, human and social capital [16] that they accumulate from their crowdfunding campaigns. In so doing, we set the stage for future research to further expand about relationships between the early stage crowdfunding activities and new venture start-up, performance and growth. We also adjust the stage for future analyses that explore the relationship between entrepreneurial learning at this pre-venture stage and the entry and exit decisions of various stakeholders who do business in different organizational and institutional settings.

4.3 Future Research

The work here presented has provided room for improvement of many aspects of telecommunications market and the crowdfunding research. We expect to further develop the optimization to enable the use of partial carriers and fast adaptation. We also expect to use the full extent of the data collected in the crowdfunding campaign for more research in other aspects of this area.

4.4 Summary of Publications

4.4.1 Conference Proceedings

There are five main conference papers presented, in Telecommunication, first the was presented at the IEEE Workshop in Smart Cities in Kansas City [36], the second conference was the Wireless Telecommunication Symposium in Chicago, IL [37]. In Entrepreneurship and Innovation, we presented my work at three conferences, the first was Rent in Antwerp, Belgium [38] where we were also invited to participate in their

Doctoral Seminar. The second was Babson Conference, a very selective and prestigious conference in Entrepreneurship [39]. Finally, the Academy of International Business in Dubai [104].

4.4.2 Journal Papers Under Review

The work presented on Chapter 2 was submitted to the IEEE Transactions on Vehicular Technology and is currently under review.

APPENDIX A

MATHEMATICAL JUSTIFICATION OF EFFICIENCY DISTRIBUTION

A.1 Introduction to the Problem

After creating the simulation, our results pointed to an average efficiency of a system composed of n base stations with r resources allocated for each of them. When the demands would meet the total number of resources, the efficiency would be on average around 70%. Changing variables would not change the value found.

A.2 Approach to Solution

Assuming each cell to have three resources and a random demand such the sum of all demands is equal to the number of resources available, the average efficiency based on the probability of meeting the demand is defined by (A.1). C represents the number of cells and z the total demand. In the limit, as C goes to infinity, efficiency goes to $1-(8/27)=0.7037$.

$$\textit{Efficiency} = \frac{3 \cdot C}{z} \times \left(1 - \frac{(C-1)\big(z - \frac{4}{3} - \frac{C}{3}\big)}{(z-1)(z-2)}\right) \tag{A.1}$$

For our simulation, we assumed $z = 100$ and $C = 3$. Replacing those values in (A.1) we find an efficiency of 0.7052. The value for efficiency obtained was 0.7045. This result is aligned with the calculated value of 0.7052, with a percent error of 0.1%. For the optimized value, the mathematical formulation is too complex to represent. Thus we rely on the simulation results. In the next section, we introduce our simulation tool in Python and IBM ILOG CPLEX Optimizer.

A.3 Matlab Code

```
clear all;
close all;
numberofcells=100;
capacitypercell=3;
totaldemand2=(numberofcells*capacitypercell)/3:5:(
   numberofcells*capacitypercell)*2.5;

C=numberofcells;
z=totaldemand2;
cap_unmetratio=(C-1).*(z-1/3.*(4+C))./(z-1)./(z-2);
cap_metratio=1-cap_unmetratio;
cap_used=capacitypercell.*numberofcells.*cap_metratio;
demand_metratio=cap_used./totaldemand2;

successratio=1./beta;
lengthsuccess=length(successratio);
successratio=min([ones(1,lengthsuccess);successratio]);

figure(1);
plot(Demandratio,demand_metratio,'k-');
ylabel('Efficiency = Met Demand / Total Demand');
xlabel('Total Demand / Total Capacity');
```

```
grid on;
title('Counting Capacity Result')
```

A.4 Results

The proposed (A.1) creates the following plot displayed in Fig. 10. This is alined with the results found in the simulation on Chapter 2. While brief, this concludes the mathematical assumptions presented in the chapter as mentioned above.

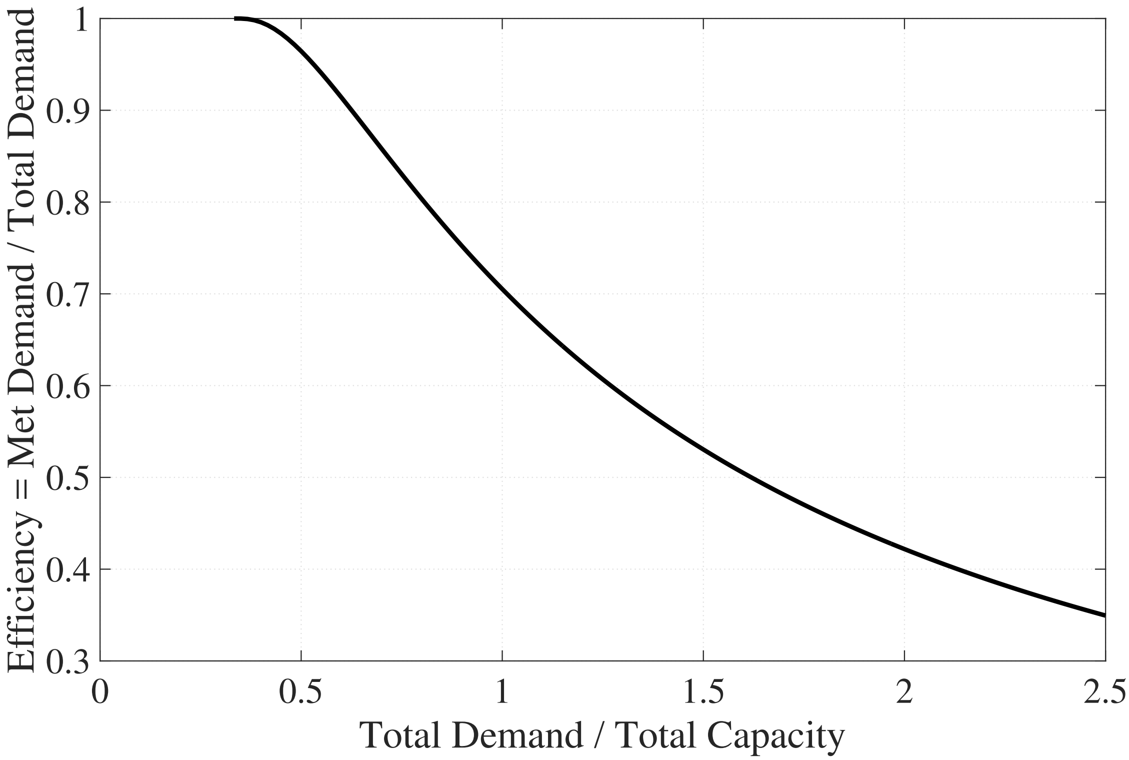

Figure 10: Theoretical Result of Allocation of Three Resources per Cell Without Optimization

APPENDIX B

TUTORIAL IN WEB SCRAPING KICKSTARTER

B.1 Introduction

This Appendix summarizes the process used to capture the data from Kickstarter. First, we present the project planning, calculating requirements, selecting variables to be measured and determining service providers. Second, we present the Python Libraries used. Finally, we provide the code used for reference.

B.2 Dimensioning Resources

There are three main components that determine the success of the data collection. First, guarantee that enough storage is available and that the influx of data will not overflow the server capacity. Second, ensure minimal time between start and finish of data collection to reduce any biases. Last, balance cost (financial and resources) to get the best performance at a low cost.

B.2.1 Storage

Data Structure is presented in Table 15. For each single point collection, it was expected to have the size of 783 bytes based on the size of the data field. Kickstarter, prior the data collection, had an average close to 1,500 projects active per month. This would come to a total of 7,500 projects measured from start to end if we assume an average duration of each project of 30 days. The projects of the 6th months and the projects started prior the data collection would be dropped since we would not be able to measure them from start to end.

With the data collection happening every 6 hours, for each 30 days project we estimated that the storage space needed is $783\ bytes * 30 * 4 = 93,960\ bytes$ or 91.8 KB. For the total of 7,500 project, the total storage space required is estimated to be around 672 MB.

B.2.2 Processing Power

The processing and writing time of this scraper is very light, no multicore processing was incorporated in the code making a single virtual core enough for the task. The allocation of a virtual machine was for all days of the month with around 600 Mib of data egress.

B.3 The Server Selection

The first component of the scraper is a cluster of servers hosted at the cloud. For this case we used Google Cloud Engine™.

The scrapper used to collect the date is composed. First, a virtual machine running Linux was set up using Google Cloud Engine™. This server is responsible to execute two tasks, first a crontab schedule and execute pre-assigned scripts, second, it informs the researcher if any problem occurs.

Table 15: Structure of Database

Name of Variable	Format	Size	Size in Bytes
ID	Integer		4
Project ID	Varchar	20	21
URL	Varchar	255	256
Status	Integer		4
Duration	Float		8
End Time	Datetime		8
Time of Collection	Datetime		8
Title	Varchar	255	256
Length of Description	Integer		4
Number of Pictures	Integer		4
Number of Videos	Integer		4
Number of Twits	Integer		4
Number of Facebook Shares	Integer		4
Number of Facebook Likes	Integer		4
Number of Facebook Comments	Integer		4
Number of Updates	Integer		4
Number of Comments	Integer		4
Number of FAQ	Integer		4
Number of Previous Projects	Integer		4
Number of Previous Successful Projects	Integer		4
Number of Backed Projects	Integer		4
Category	Varchar	45	46
Location	Varchar	45	46
Creator	Varchar	45	46
Backers	Integer		4
Raised	Integer		4
Currency	Varchar	5	6
Goal	Integer		4
Rewards	Integer		4
Total			783

Note: Each index record contains a 6-byte header.

B.4 Libraries

We used two main libraries to execute the code, Beautiful Soup and MySQLdb. Python relies in libraries to execute specific tasks otherwise not available.

B.4.1 BeautifulSoup

Beautiful Soup is a Python library created to automatize screen-scraping projects. It has three features that makes one of the best tools available for the goal of getting information publicly available. First, it allows an user to navigate, search and modify a parse tree in a very simple and Pythonic way. Second, it converts documents to Unicode and UTF-8, making it straight forward when thinking about encodings. Finally, it utilizes $lxml$ and $html5lib$ giving a mix of flexibility and speed.

B.4.2 MySQLdb

MySQL has become the most popular open source database. The library MySQLdb provides an higher-level interface to Python to interact with the MySQL database. While the basic connection is easy to implement, in one server with internet access it is essential to provide a deep and complex security process to avoid any exploit in the code.

B.5 Codes

In this section we present two important snippets of code used.

B.5.1 Finding New Projects

This script is responsible to acquire new links as campaigns start. It goes to a list of tables of content from Kickstarter and check if there is any new project listed that was not previously in the database. If there is a new project, it adds to the database with a live status.

```
#!/usr/bin/python

import sys, getopt, urllib2, os
from bs4 import BeautifulSoup
from subprocess import call

total = 0
u1 = ["www.kickstarter.com/discover/recommended",
"www.kickstarter.com/discover/categories/technology",
"www.kickstarter.com/discover/categories/art",
"www.kickstarter.com/discover/categories/comics",
"www.kickstarter.com/discover/categories/crafts",
"www.kickstarter.com/discover/categories/dance",
"www.kickstarter.com/discover/categories/design",
"www.kickstarter.com/discover/categories/fashion",
"www.kickstarter.com/discover/categories/film&video",
"www.kickstarter.com/discover/categories/food",
"www.kickstarter.com/discover/categories/games",
"www.kickstarter.com/discover/categories/journalism",
"www.kickstarter.com/discover/categories/music",
"www.kickstarter.com/discover/categories/photography",
"www.kickstarter.com/discover/categories/publishing",
```

```
"www.kickstarter.com/discover/popular",
"www.kickstarter.com/discover/categories/theater"]

for x in xrange(0,len(u1)):
 try:
  page = urllib2.urlopen(u1[x]).read()
 except urllib2.HTTPError, e:
  print "Error: ", e.code
  pass
 except urllib2.URLError, e:
  print "Error: ", e.args
  pass
 except Exception, e:
  print "Error: ", e
  pass

 soup = BeautifulSoup(page, "lxml")
 previous = ’’
 for link in soup.findAll(’a’, href=True):
  url = link[’href’]
  if url[:10] == "/projects/":
   full_url = "www.kickstarter.com%s"%(url)
   if previous != full_url:
    call(["/usr/bin/python","/home/url.py","-i",full_url])
   previous = full_url
   total = total + 1
print "Total of %d traced" %total
```

B.5.2 Acquiring Data

This script starts by reading the list of projects acquired as described in Section B.5.1. If the project is listed as live, it checks the status of the project for any changes (e.g. completed, deleted, cancelled) and creates a new entry copying the variable listed on Table 15.

```python
#!/usr/bin/python
# -*- coding: utf-8 -*-

import sys, getopt, urllib2, dateutil.parser, datetime
import MySQLdb as mdb
from bs4 import BeautifulSoup, UnicodeDammit
from re import sub
from decimal import Decimal

# database connection
db = mdb.connect('localhost', 'scrapper', 'scrapper', '
   scrapper');

def prepdb( value_to_be_corrected):

  if isinstance(value_to_be_corrected, str):
    return value_to_be_corrected.encode('utf-8')

  elif isinstance(value_to_be_corrected, list):
    return value_to_be_corrected[0].encode('utf-8')

  else:
```

```
    return value_to_be_corrected.encode('utf-8')

def preparesql( request ):
  opening = "INSERT INTO data (ProjId , Url , Status , Duration , EndTime , Now , Title , LenDescription , NrPic , NrVid , NrTwits , NrFbShares , NrFbLikes , NrFbComments, NrUpdates , NrComments , NrFAQ , PrevProj , SuccessedProj, BackedProj, Category, Location , Creator , Backers , Raised , Currency , Goal , Rewards) VALUES (" closing = """ );"""
  return "%s%s%s" % (opening, request, closing)

def getdata( row, url ):
  #"This prints a passed string into this function"

  # ----- VARIABLES -----
  d3 = datetime.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
  PreviousProjFullFunded = 0
  PreviousProj = 0
  secondpart = ''
  action = 'live'

  # ----- Initiation -----

  try:
    page = urllib2.urlopen(url).read()
  except urllib2.HTTPError, e:
    print e.code
```

```
  action = 'Error'
  return action, None
except urllib2.URLError, e:
  print e.args
  action = 'Error'
  return action, None
except Exception, e:
  print "Error: ", e
  action = 'Error'
  return action, None
new_page = UnicodeDammit.detwingle(page)
soup = BeautifulSoup(new_page, "lxml")

# ----- Colecting variables ------

#ProjectID from Kickstarter [out0] ProjId VARCHAR(20)
idd = soup.find('div', id="backers_count")
out0 = prepdb(idd.data['class'])

#URL from Kickstarter [out1] Url VARCHAR(255)
out1 = url

#Status of the project [out2] Status INT (0 - live, 1 -
   successful, 2 - submitted, 3 - canceled, 4 - failed, 5
    - purged)
status = soup.find('div', id="main_content")
try:
  status1 = status['class']

```

```
except TypeError:
  # No such meta tag found, assume live.
  status1 = [' ', 'Project-state-live', ' ', 'Project-ended-false']
  print "Status detection Error - Assuming Live"

if status1[1] == 'Project-state-live':
  if status1[3] == 'Project-ended-false':
    out2 = 0
  else:
    action = 'Error'
    return action, None
# Project-ended-true
elif status1[1] == 'Project-state-successful':
  out2 = 1
  action = 'successful'
elif status1[1] == 'Project-state-submitted':
  out2 = 2
# Project-is_starred-false Project-ended-true
elif status1[1] == 'Project-state-canceled':
  out2 = 3
  action = 'canceled'
  return action, None
# Project-is_starred-false Project-ended-true
elif status1[1] == 'Project-state-failed':
  out2 = 4
  action = 'failed'
elif status1[1] == 'Project-state-purged':
  out2 = 5
```

```
 action = 'purged'
else:
 action = 'Error'
 return action, None

totaltime = soup.find(id="project_duration_data")

#Total time duration of campain [out3] Duration FLOAT
out3 = float(prepdb(totaltime['data-duration']))

#End time of campain [out4] EndTime DATETIME
endtime = dateutil.parser.parse(prepdb(totaltime['data-
   end_time']))
out4 = endtime.astimezone(dateutil.tz.tzutc()).strftime("
   %Y-%m-%d %H:%M:%S")

#Now [out5] Now DATETIME
out5 = d3

#Title [out6] Title VARCHAR(255)
title = soup.find('h2',"mb1")
out6 = prepdb(title.get_text().replace('\n', '').replace(
   '\r', '').replace("'",''))

#Number of words used [out7] LenDescription INT
text = soup.find('div','full-description')
out7 = len(text.get_text(" ", strip=True).split())

#Number of pictures [out8] NrPic INT
```

```
out8 = len(text.findAll('img', src=True))

#Number of videos [out9] NrVid INT
out9 = len(text.findAll('video','has_webm'))

#TWITTER: Nr of twits [out10] NrTwits INT
twurl = "http://urls.api.twitter.com/1/urls/count.json?
   url=%s" %(url)
twstat = urllib2.urlopen(twurl).read()
twsoup = BeautifulSoup(twstat, "lxml")
twshares = twsoup.get_text().split("\"")
twshares = twshares[2] #add to db as TwitterShares
out10 = int(twshares[1:-1])

#FACEBOOK: Find facebook stat
fburl = "http://api.facebook.com/restserver.php?method=
   links.getStats&urls=%s" %(url)
fbstat = urllib2.urlopen(fburl).read()
fbsoup = BeautifulSoup(fbstat, "lxml")

#FACEBOOK: Nr of Shares [out11] NrFbShares INT
out11 = int(fbsoup.share_count.get_text())
#FACEBOOK: Nr of Likes [out12] NrFbLikes INT
out12 = int(fbsoup.like_count.get_text())
#FACEBOOK: Nr of Comments [out13] NrFbComments INT
out13 = int(fbsoup.comment_count.get_text())

#Updates in KS [out14] NrUpdates INT
updates = soup.find(id="updates_nav")
```

```
try:
 out14 = int(prepdb(updates['data-updates-count']))
except ValueError:
 print "Out14 integer Error - FIXED"
 out14 = int(round(float(prepdb(updates['data-updates-
    count']))))
except TypeError:
 print "Error at Out14 - NrUpdates"
 out14 = -1

#Comments in KS [out15] NrComments INT
comments_ct = soup.find(id="comments_count")
try:
 out15 = int(prepdb(comments_ct['data-comments-count']))
except ValueError:
 print "Out15 integer Error - FIXED"
 out15 = int(round(float(prepdb(comments_ct['data-
    comments-count']))))
except TypeError:
 print "Error at Out15 - NrComments"
 out15 = -1

#NrFAQs in KS [out16] NrFAQ INT
faq = soup.find(id="project-faqs")
try:
 out16 = len(faq('div','faq-question'))
except TypeError:
 print "Error at Out16 - FAQ"
 out16 = -1
```

```
#NrPrevProj in KS [out17] PrevProj INT
#NrSuccessedProj in KS [out18] SuccessedProj INT
#NrBackedProj in KS [out19] BackedProj INT
creator_details = soup.find(’div’,’NS_projects__creator’)
creator_details2 = creator_details.find_all([’span’,’a’], ’grey-dark’)

#Has previous projects and has backed
try:
  if creator_details2 is not None:
    if prepdb(creator_details2[1].get_text()) == ’First created’:
      out17 = 0
      out18 = 0
    else:
      out17b = creator_details2[1].get_text().split(" ")
      out17 = int(prepdb(out17b[0]))
      srurl = "https://www.kickstarter.com%s" %(creator_details2[1][’href’])
      srpage = urllib2.urlopen(srurl).read()
      srsoup = BeautifulSoup(srpage, "lxml")
      srproject = srsoup.find_all(’div’,’badge-success’)
      if srproject is None:
        out18 = 0
      else:
        out18 = len(srproject)
```

```
    out19b = prepdb(creator_details2[3].get_text().split(" "))
    out19 = out19b[0]

  #No previous projects and has not backed any project
  else:
    print "possible error at variables out17 to out19"
    out17 = -1
    out18 = -1
    out19 = -1
except AttributeError:
  out17 = -1
  out18 = -1
  out19 = -1
  print "Error at Out17 - Out 19 PreviousProjects"

#Category [out20] Category VARCHAR[45]
category = soup.find('div', id="project_share")
try:
  out20 = prepdb(category.previous_sibling.previous_sibling.get_text().replace('\n', '').replace('\r', '').replace("'",''))
except AttributeError:
  out20 = 'Error'
  print "Error at Out20 - Category"

#Location [out21] Location VARCHAR[45]
location = soup.find('span', "ss-icon ss-location margin-right")
```

```
try:
 out21 = prepdb(location.next_sibling.next_sibling.get_text().replace(’\n’, ’’).replace(’\r’, ’’).replace("’",’’))
except AttributeError:
 out21 = ’Error’
 print "Error at Out21 - Location"

#Creator [out22] Creator VARCHAR[45]
creator1 = soup.find(’div’, "NS_projects__header center")
creator = creator1.p.next_sibling.next_sibling.b
try:
 out22 = prepdb(creator.get_text().replace(’\n’, ’’).replace(’\r’, ’’).replace("’",’’))
except AttributeError:
 out22 = ’Error’
 print "Error at Out22 - Creator"

#Total of Backers [out23] Backers INT
backers_count = soup.find(’div’, id="backers_count")
try:
 out23 = int(prepdb(backers_count.get_text().replace(’\n’, ’’).replace(’\r’, ’’).replace(",",’’)))
except AttributeError:
 out23 = -1
 print "Error at Out23 - Backers"
except ValueError:
 print "Out23 integer Error - FIXED"
```

```
    out23 = int(round(float(prepdb(backers_count.get_text().
        replace('\n', '').replace('\r', '').replace(",",'')))
        ))

achieved = soup.find('div', id="pledged")
#Total Money Achieved [out24] Raised INT
try:
    out24 = int(prepdb(achieved.data['data-value']))
except AttributeError:
    out24 = -1
    print "Error at Out24 - Raised"
except ValueError:
    print "Out24 integer Error - FIXED"
    out24 = int(round(float(prepdb(achieved.data['data-value
        ']))))

#Currency [out25] Currency VARCHAR[5]
try:
    out25 = prepdb(achieved.data['data-currency'])
except AttributeError:
    out25 = 'Error'
    print "Error at Out25 - Currency"

#Goal [out26] Goal INT
try:
    out26 = int(round(float(prepdb(achieved['data-goal']))))
except AttributeError:
    out26 = 'Error'
    print "Error at Out26 - Goal"
```

```
#Rewards [out267 Rewards INT
if out2 != 0:
  try:
    wyg = soup.find('ul', "list mt2")
    tipos = wyg['data-reward-count']
    out27 = int(prepdb(wyg['data-reward-count']))
  except ValueError:
    print "Out27 integer Error - FIXED"
    out27 = int(round(float(prepdb(wyg['data-reward-count'
        ]))))
  except AttributeError:
    out27 = -1
    print "Error at Out27 - Rewards"
else:
  try:
    wyg = soup.find('ul', "list mt2 pledgeable")
    tipos = wyg['data-reward-count']
    out27 = int(prepdb(wyg['data-reward-count']))
  except ValueError:
    print "Out27 integer Error - FIXED"
    out27 = int(round(float(prepdb(wyg['data-reward-count'
        ]))))
  except AttributeError:
    out27 = -1
    print "Error at Out27 - Rewards"
```

```
 request = "’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’
     , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%
    s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ ,
    ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’ , ’%s’" % (out0 ,
    out1 , out2 , out3 , out4 , out5 , out6 , out7 , out8
    , out9 , out10 , out11 , out12 , out13 , out14 , out15
     , out16 , out17 , out18 , out19 , out20 , out21 ,
    out22 , out23 , out24 , out25 , out26, out27)

 sql_database = preparesql(request)
 return action, sql_database

with db:

 cursor = db.cursor()

 cursor.execute("SELECT * FROM url_db WHERE completed=0")

 total_projects = cursor.rowcount
 print "Log of scrapper\n Total Projects to Scan: %d" %
    total_projects

 for i in range(total_projects):
  row = cursor.fetchone()
  for x in xrange(4):
   try:
    cursor2 = db.cursor()
    print "Line %s of %s - Link: %s"%(i+1, total_projects
       , row[1])
```

```
action, sql_database = getdata(row[0], row[1])

if action != 'live':

  if action == 'successful':
    print "Project changed for [1] %s" %(action)
    cursor2.execute("UPDATE url_db SET completed=1
        WHERE Id='%s'" % (row[0]))
  elif action == 'canceled':
    print "Project changed for [3] %s" %(action)
    cursor2.execute("UPDATE url_db SET completed=3
        WHERE Id='%s'" % (row[0]))
  elif action == 'failed':
    print "Project changed for [4] %s" %(action)
    cursor2.execute("UPDATE url_db SET completed=4
        WHERE Id='%s'" % (row[0]))
  elif action == 'purged':
    print "Project changed for [5] %s" %(action)
    cursor2.execute("UPDATE url_db SET completed=5
        WHERE Id='%s'" % (row[0]))
  elif action == 'Error':
    print "Project changed for [6] %s" %(action)
    cursor2.execute("UPDATE url_db SET completed=6
        WHERE Id='%s'" % (row[0]))
  else:
    print "Fatal Error"
    pass
else:
  cursor2.execute(sql_database)
```

```
   db.commit()
   cursor2.close()
  except mdb.Error, e:
   db.rollback()
   print "Error %d: %s" % (e.args[0],e.args[1])
   continue
  else:
   break

try:
 db.commit()

except mdb.Error, e:

 if db:

  db.rollback()

 print "Error %d: %s" % (e.args[0],e.args[1])

 sys.exit(1)
```

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VITA

Pedro Tonhozi de Oliveira was born on May 18, 1988, in Curitiba, Paraná, Brazil where he graduated from UTFPR (Federal University of Technology – Paraná) formerly known as CEFET (Federal Center for Technological Education) in 2005. In 2006, he was honored by Rotary International with one-year high school exchange program to Germany, where he lived in the city of Weißenhorn. During this time, he attended the Nikolaus-Kopernikus-Gymnasium Weißenhorn and the Robert-Bosch-Schule Ulm. In the later, he developed his first technology prototype, a GPS tracking technology using geolocation. During his bachelor, he returned to Germany under the Erasmus exchange program to study one year at the Leibniz Universität Hannover. During this time he studied Telecommunications, Automotive Electronics, Entrepreneurship for Engineers and Alternative Power Engineering. In 2011, he received a Bachelor of Science in Electrical Engineering (Telecommunications & Electronics) from the Federal University of Paraná, Brazil.

Pedro has worked over three years for the GVT as a Telecommunications Switch Engineer. GVT was later bought by Telefonica and was considered the best Brazilian broadband for five consecutive years (2009-2013). After leaving GVT in early 2012, he served as the field engineer for NORTENG in the Oil & Gas Industry on several notable projects including the Petrobras FAFEN-SE Air Compression plant. In 2013, he started his Doctor of Philosophy degree at the University of Missouri-Kansas City.

During his Ph.D. he was awarded in 2014 by the School of Graduate Studies a research grant in the value of $6,500. He was invited for and attended the doctoral consortium of Rent Conference in Belgium 2016, Early Career Consortium of the Academy of Management Entrepreneurship Division (2017) and have presented conference papers at IEEE Smart City Workshop 2016 (Kansas City, MO), Wireless Telecommunication Symposium 2017 (Chicago, IL), Rent Conference 2016 (Antwerp, Belgium), Babson College Entrepreneurship Research Conference 2017 (Norman, OK) and the Academy of International Business 2017 (Dubai, UAE). He has reviewed for Springer Journal of Telecommunication Systems and Journal of Small Business Management. He has also served as a program committee chair, organizing committee chair, session chair, and reviewer for the Brazilian Student Graduate Conference for the 2016 Harvard and the 2017 University of Southern California edition.