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Non-equity Crowdfunding: Funding Success and Dynamics on Hithit

Master's thesis

Author: Bc. Veronika Machová

Study program: Economics and Finance

Supervisor: doc. PhDr. Martin Gregor, Ph.D.

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Declaration of Authorship

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Prague, May 10, 2019

Veronika Machova

Abstract

Non-equity crowdfunding, as an innovative way of financing new ideas, has been growing enormously over recent years. Crowdfunding projects are often characterized by a predetermined monetary goal and the length of the campaign. Furthermore, potential contributors can observe the level of funding provided by others, which suggests that details of previous contributions play an essential role in funding behavior. We obtain data from the Czech crowdfunding platform Hithit, which allow us to empirically analyze the determinants of success and the funding dynamics of crowdfunding projects. Outcomes from several probit regressions indicate that shorter campaigns and campaigns offering private rewards of lower value are more likely to be successful—but these results do not demonstrate causality. A short campaign signals confidence; this positive signaling effect outweighs the marketing-opportunities effect of a long campaign. Applying fixed effects model to panel data, we show that the amount of contributions is negatively associated with the level of funding already achieved, providing evidence of free-riding effect. However, the effect of past contributions is reversed in the final phase of the campaign as the risk of breakdown increases. Moreover, we found a positive and significant impact of recent marketing activity on social media on the amount of contributions. Our findings help generate a greater understanding of the funding behavior of contributors on Hithit and can be generalized to other platforms with similar features.

JEL Classification	D80, H41
Keywords	crowdfunding, rewards, social media, funding dynamics, success determinants

Title	Non-equity Crowdfunding: Funding Success and Dynamics on Hithit

Author's e-mail	`veronika-machova@centrum.cz`
Supervisor's e-mail	`martin.gregor@fsv.cuni.cz`

Abstrakt

Non-equity crowdfunding, inovativní způsob financování nových nápadů, v posledních letech enormně roste. Crowdfundingové projekty jsou většinou charakterizovány předem stanoveným peněžním cílem a délkou kampaně. Potenciální přispěvatelé mohou navíc pozorovat úroveň financování, kterou poskytují jiní, což naznačuje, že informace o předchozích příspěvcích hrají zásadní roli v chování přispěvatelů. Získali jsme data z české crowdfundingové platformy Hithit, což nám umožnilo empiricky analyzovat determinanty úspěchu a dynamiku financování crowdfundingových projektů. Výsledky z několika probit regresí ukazují, že kratší kampaně a kampaně, které nabízejí soukromé odměny nižší hodnoty, mají větší pravděpodobnost úspěchu—ale tyto výsledky neprokazují kauzalitu. Krátká kampaň signalizuje sebevědomí; tento pozitivní signalizační efekt převažuje nad efektem marketingových příležitostí u dlouhé kampaně. Uplatněním modelu fixních efektů na panelová data jsme zjistili, že výše příspěvků je negativně spojena s již dosaženou úrovní financování, což dokládá existenci free-riding efektu. Dopad minulých příspěvků se však v závěrečné fázi kampaně obrátí, protože se zvyšuje riziko selhání. Navíc jsme prokázali významný pozitivní efekt nedávné marketingové aktivity na sociálních sítích na výši příspěvků. Naše zjištění pomáhají lépe porozumět chování přispěvatelů na Hithitu a lze je zobecnit na jiné platformy s podobnými rysy.

Klasifikace JEL	D80, H41
Klíčová slova	crowdfunding, odměny, sociální sítě, dynamika financování, determinanty úspěchu

Název práce	Non-equity crowdfunding: Úspěch a dynamika financování na Hithitu

E-mail autora	veronika-machova@centrum.cz
E-mail vedoucího práce	martin.gregor@fsv.cuni.cz

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Motivation Non-equity crowdfunding is a modern and fashionable way of organizing a contributions campaign towards a public good. The emergence of online crowdfunding platforms, such as Kickstarter and Indiegogo, has attracted many researchers who have studied this form of innovative financing, growing enormously in recent years. However, the origin of crowdfunding can be traced back already to the provision point mechanism (Bagnoli and Lipman 1989).

This thesis should look into the construction of non-equity crowdfunding campaigns. Voluntary contributions by individuals have been traditionally used to privately finance public goods. However, two aspects differentiate crowdfunding-campaigns from the classic contribution campaigns. First, there is a commitment to a fixed horizon in which the campaign has to collect the funds. A typical crowdfunding project has a predetermined monetary goal to which individuals can contribute any amount of money. The project will be successfully funded only if the goal is reached within a specified time period. Second, details of previous individual contributions (especially the levels) are available unless a contributor wishes his or her contribution to be private.

Crowdfunding websites are characterized by features similar to the provision point mechanism—a concrete fundraising goal is required for each project and total contributions must meet a threshold for the provision of public goods. This institutional feature helps to overcome the incentives of individuals to free-ride as it incentivizes them to contribute (Bagnoli and Lipman 1989). Another solution to the free-rider problem in funding public goods is the use of lotteries. Lotteries were found useful in fundraising as they also increase the provision of public goods (Morgan 2000).

Previous studies on international crowdfunding platforms show that crowdfunding campaigns either succeed, or fail to raise any substantial fraction of their target amount. The support for a project is typically bathtub shaped, with high level of contributions in the first and last weeks and decreasing support in the middle of the funding cycle (Kuppuswamy and Bayus 2018).

We want to see how the existing literature of charitable campaigns fits the setting of crowdfunding. What is the role of the fixed horizon in comparison to a campaign with an infinite horizon? What is the role of the detailed information on the previous contributions, including the information on the distribution?

Hypotheses

Hypothesis #1: Targets are met close to the campaign closing dates because the risk of a breakdown increases.

Hypothesis #2: We can observe accelerated contributions as potential donors respond to calls for contribution that are close to the closing date.

Hypothesis #3: The length of the campaign (30 or 45 days on HitHit) works as a signal for contributors. The shorter campaign, the more confident the author is about its success.

Methodology We will collect data on the dynamics of contributions from Czech crowdfunding platform HitHit, and we will be interested in finding whether targets are met close to the campaign closing dates, and if so, whether we observe accelerated contributions. We will further examine the structure of contributions–in which situations can we observe accelerated contributions? Is the dynamics higher after large contributions, or smaller but more frequent contributions?

The panel data collected from the crowdfunding platform will include, for each project: category of the project, target amount, day of the campaign, the amount of contributions, number of contributors, and percent of the target amount raised on a given day. Moreover, marketing data about the campaigns, such as the number of new posts and the number of likes, comments, and shares, will be collected from a Facebook page of each project.

Formally, we can construct a window (e.g. last 5 or 10 days before the campaign met the target) and check whether the amount of contributions collected in the window is determined by proximity to the closing date. For this analysis, data on marketing activity on Facebook will be very helpful to serve as control variables. The activity on social media is expected to have a positive effect on the amount of contributions. Moreover, we will estimate the market value of rewards provided to contributors and include this measure of private prizes, which plays an important role in reward-based crowdfunding, in the regression. We will be also interested in the effect of the category of a project, target amount, video, and length of the campaign.

Projects with smaller goals, of shorter duration, and having a video are more likely to succeed (Kuppuswamy and Bayus 2018) and therefore these variables seem to be correlated with unobserved quality.

Apart from the main model on the dynamics of contributions, we will also apply another model on the determinants of campaigns' success as a complement to descriptive evidence. We will work with two datasets and examine the effect of the length of the campaign, category, target amount, and video. Our first dataset will consists of more than 2,000 projects on HitHit until July 2018. Then, we will use information from our panel data and run the regression on smaller sample of projects, but we will be able to include also the measure of marketing activity on Facebook, the measure of private prizes, and the amount raised in the beginning of a campaign as explanatory variables.

Since a crowdfunding campaign can be seen as a special example of a dynamic campaign with strategic uncertainty about the outcome, we will try to apply a dynamic global game model in the theoretical part.

Expected Contribution A detailed comparison with classical charitable campaigns will be made. In contrast to previous literature on charitable campaigns, we will be interested in the role of the fixed horizon. We will construct a model of voluntary contributions during a crowdfunding campaign. We will define the differences between a non-equity crowdfunding campaign and a classical campaign and include them into a standard campaign model similar to that of Hindriks and Myles (2006).

After collecting the data, we will empirically analyse how the dynamics of a crowdfunding campaign is affected by the information on previous contributions and the distribution. Our work will not only extend the literature of non-equity crowdfunding, but better understanding the dynamics of a crowdfunding campaign and the determinants of success will be useful also for authors of projects and potential donors. We will compare our findings about Czech crowdfunding platform with results of other empirical studies made on data from other platforms, such as Kickstarter and Indiegogo.

Outline

1. Introduction
2. Motivation and Literature Review: the literature on charitable fundraising and non-equity crowdfunding
3. The mechanism of crowdfunding campaigns: A detailed description of the

mechanism and comparison with classic contribution campaigns in charitable campaigns

4. Modeling of voluntary contributions during a campaign with a finite horizon
5. Data: I will describe the data on the dynamics of contributions obtained from crowdfunding platforms.
6. Methodology: Explanation of methods used when analyzing the time profile of campaigns
7. Results: Discussion of the results
8. Conclusion: Summary of main findings and their implications for future research

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Author

Supervisor

Chapter 1

Introduction

Non-equity crowdfunding is an innovative form of financing which has been growing enormously in recent years. It involves relatively small contributions of many individuals. Three key aspects differentiate a crowdfunding campaign from a traditional contribution campaign. First, the financing of a project is not geographically constrained. Second, campaigns are characterized by a fixed horizon and a predetermined monetary goal—the project will get funded only if the goal is reached within a specified time period. Third, details on previous contributions are publicly available, which suggests the level and timing of prior contributions play an important role in the funding behavior of potential contributors, and thus in the overall success of the project. Previous studies show that crowdfunding campaigns either succeed or fail to raise any substantial fraction of their goal. Understanding the funding dynamics involved, the motivations of potential contributors, and the determinants of success for such projects, are therefore of high importance.

The objective of this thesis is to analyze the determinants of success and funding dynamics on Czech non-equity reward-based crowdfunding platform Hithit—the biggest crowdfunding platform in the Czech republic, founded in 2012. We work with two datasets. The first dataset consists of 2023 projects launched on Hithit between November 2012 and June 2018, and is used for a cross-sectional analysis of success determinants. The second dataset comprises 56 projects on Hithit and serves both for analysis of success determinants and of funding dynamics. These panel data were manually collected from the Hithit website in the period September 2018 to January 2019. We extracted marketing data from a Facebook page of each project in the panel. Moreover, we created our own measure of private prizes, to enable us to distinguish between campaigns with a public good component and those which are primarily sales campaigns.

The study begins with an investigation of the determinants of success in crowdfunding projects. In this cross-sectional analysis, we apply the probit model as we are interested in the effects on the probability of success. The thesis examines the effects of a campaign's length, the value of private rewards, and other possible success determinants. Our results indicate that the length of a crowdfunding campaign is negatively associated with its success, which is in line with previous research. We show that the positive signaling effect of a short campaign dominates the marketing-opportunities effect of a long campaign. Interestingly, crowdfunding projects which offer rewards of higher market value are less likely to be successful. It is important to stress that the results of our analysis of success determinants cannot demonstrate causality, as project characteristics are not selected randomly.

In the panel data analysis, we go on to examine the relationship between the amount of contributions a project receives and its past level of funding, and the change in this relationship in the final phase of the funding cycle. Moreover, we explore the role of recent marketing activity on Facebook in a project's funding dynamics. The fixed effects model is employed for this purpose. As expected, the amount of contributions a crowdfunding project receives on a given day is positively and strongly related to previous marketing activity on social media—but also negatively associated with the level of funding already achieved. This pattern has been previously observed by Kuppuswamy & Bayus (2017) and can be explained by a diffusion of the sense of responsibility as well as incentives to free-ride. Conversely, we show that the effect of the level of funding already achieved on the amount of contributions made is reversed in the final stage of the campaign. Such accelerated contributions are linked with increased risk of breakdown.

The thesis is structured as follows: Chapter 2 provides a review of literature on the topics of the provision of public goods and crowdfunding campaigns. Chapter 3 describes different types of crowdfunding and the development of crowdfunding markets, with attention to the current situation in the Czech Republic and around the world. Chapter 4 presents our hypotheses. Chapter 5 contains informations about the datasets used and key variables. In Chapter 6, the data is explored and a preliminary analysis conducted. Chapter 7 explains the methodology applied to the cross-sectional data and contains an empirical analysis of the projects' success determinants. Chapter 8 describes the panel data methodology and provides outputs for all the regressions used in examining the projects' funding dynamics. Chapter 9 discusses the results. Finally, Chapter 10 summarizes the findings and concludes the thesis by suggesting the implications of these and ideas for future research.

Chapter 2

Literature Review

2.1 Provision of Public Goods: Provision Points, Lotteries, and Seed Money

Crowdfunding is based on voluntary contributions from a large number of individuals who finance the production of goods or provision of services. There is great variability in the goals of crowdfunding projects, yet many of them provide goods that can be characterized as public, yield public goods as a secondary benefit, or yield positive externalities to specific communities. Therefore, we may apply lessons from charitable contribution campaigns to the analysis of crowdfunding with a public good component. Nevertheless, in a basic donation-based model of the provision of public goods, contributors do not expect any direct private returns from their contributions (Bose & Rabotyagov 2018), while in reward-based crowdfunding people raise funds in return for rewards (private prizes), and the benefits are both public and private.

Pure public goods are defined as goods that satisfy two important properties: they are nonexcludable (no one can be excluded from consumption irrespective of whether they have paid) and nonrivalrous (when one person consumes the good, it does not reduce the quantity available for other consumers). The properties of public goods lead to each consumer relying on others to purchase the good and this incentive to free-ride then causes inefficiency in allocation (Andreoni 1998; Bagnoli & Lipman 1989; Hindriks *et al.* 2006). In a static setting in which potential donors simultaneously (and noncooperatively) provide voluntary contributions, it is well known that the equilibrium is not Pareto efficient—not enough of the public good is purchased, which demonstrates the failure of private actions to provide a public good.

Impure public goods satisfy these conditions only to some extent—they can be excludable at a cost or become congested beyond some level of use. Nonetheless, what is crucial is that private purchase of the good generates uncompensated positive externalities for the other donors, which generates a wedge between private benefits and social benefits (as the sum of all private benefits). Most public goods are threshold public goods—they cannot be produced in small fractions.

For threshold-level public goods, Hindriks *et al.* (2006) suggest alternative Pareto-improving allocation mechanisms for the private provision of public goods. They analyze two different forms of a fundraising campaign game with an infinite horizon in which a public good is provided only if a target level is achieved. In a contribution campaign, contributions are made immediately, while in a subscription campaign, players make donation pledges that are paid only after the target level is met. They consider one public good and two (identical) individuals who alternate in making contributions. They show that allowing players to add to their contributions can lead to an efficient outcome, but only in the subscription campaign game, which is always successful if the project is worthwhile. The players commit to contributing in the future but bear no costs if insufficient contributions are pledged. In the contribution campaign game, on the other hand, not enough money is ever raised because contributions are sunk in the past and there is a lack of credible commitment to contributing in the future. Since the maximum amount that can be raised never reaches the sum of all the individual benefits from the project, the contribution campaign game cannot lead to efficient private provision of the public good.

Several solutions to the problem of free-riding have been offered. Bagnoli & Lipman (1989) provide an example of a mechanism—now known as the provision point mechanism—that leads to an efficient outcome under the assumption of a complete information economy. In a simple contribution game, the public good is provided only if the total contributions reach a certain threshold. When insufficient money is contributed, all contributions are refunded. Bagnoli & Lipman (1989) prove that the outcome of the game is efficient even when the public good can take on finitely many values. The provision point mechanism is crucial for the evolution of crowdfunding because crowdfunding platforms are characterized by features similar to this mechanism—a concrete fundraising goal is required for each project and total contributions must meet a certain threshold. If the project does not succeed, its originator does not receive any money.

The provision point mechanism was later evaluated empirically. Bagnoli & McKee (1991) conducted a series of laboratory experiments with groups of five or 10 people. The voluntary contribution game was played for over fourteen periods; all the players had complete information about the threshold, the income of all group members, and their valuations of the public good. The results confirm that the efficient provision of a public good can be achieved through the provision point mechanism, as proposed by Bagnoli & Lipman (1989). The public good was successfully and efficiently provided through voluntary contributions in 53 of 55 observations—the players contributed exactly the amount needed for the provision of the good. Moreover, the outcome is Pareto efficient even with groups of players with considerable differences in incomes or valuations. However, larger groups are slower to converge to the equilibrium (Bagnoli & McKee 1991). Bose & Rabotyagov (2018) argue that even though the threshold encourages people to contribute, the provision point mechanism does not completely solve the problem because of lack of coordination between potential contributors, who may contribute nothing for the public good.

Andreoni (1998) examined the effect of seed money in charitable capital campaigns launched by charitable organizations, which provide public goods when a certain threshold of contributions is reached. Capital campaigns are characterized by large fixed costs and typically have two phases: a quiet phase and a public phase. During the quiet phase, a considerable part of the campaign goal is provided by major gifts from government grants or 'leadership givers.' The value of the gifts is then publicly announced, and the remaining funds are raised by a larger population of donors. Andreoni (1998) argues that seed money increases the total amount of contributions. More specifically, he shows that seed money can eliminate a Nash equilibrium with zero contribution that exists in the model of charitable giving in the absence of seed money.

List & Lucking-Reiley (2002) conducted an experiment that tests the effectiveness of the provision point mechanism and seed money policy in a real charitable university capital campaign—based on theories by Bagnoli & Lipman (1989) and Andreoni (1998), respectively. The experimental evidence shows that both mechanisms increase the amount of contributions in a real charitable campaign, but the effect of seed money is significantly larger than the effect of the provision point mechanism. However, unlike in laboratory settings, the contributions that do not reach the threshold in terms of the seed money policy are used for other purpose at the university and are therefore not completely wasted. List & Lucking-Reiley (2002) show that the provision point mechanism increases the total value of contributions and average amount of each contribution but has no positive effect on the number of donors. The refund policy does not change the outcome from not providing the good to an efficient one as predicted by Bagnoli & Lipman (1989). Consistent with Andreoni (1998), an increase in seed money leads to a considerable increase in the total value of contributions, as well as the number of donors and average amount of a contribution.

Morgan (2000) suggests a different solution to the free-riding problem—the use of lotteries, which lead not only to a contribution to a public good, but also a chance to win a private prize—a large reward for a small lottery price. He argues that, unlike lotteries, the provision point mechanism suggested by Bagnoli & Lipman (1989) has two limitations: Preferences must be known to set the threshold level appropriately to reach the efficient outcome, and commitment power to refund all contributions in the case of the failure of the project is required. Morgan (2000) finds that the use of lotteries is an effective way of financing public goods as it lessens the free rider problem (but does not eliminate it completely). Lotteries are welfare improving and increase the provision of a public good. Lotteries outweigh the positive externality from public goods because when an individual purchases a lottery ticket, it lowers the probability of winning of other people (Bose & Rabotyagov 2018). Moreover, as the lottery prize increases, the amount of the public good is closer to first-best level (Morgan 2000). The finding holds for heterogeneous agents with quasi-linear preferences and lotteries with a fixed amount for the prize; the provision of public goods does not increase in the case in which the prize is a constant fraction of the total contributions.

On the other hand, Morgan (2000) acknowledges that the lottery mechanism and its private gains might actually reduce a taste for altruism in charitable campaigns—there is a crowding-out effect on intrinsic motivation. Another disadvantage of lotteries comes from the finding that higher value prizes are more effective—though large prizes may be too expensive and impractical for authors of crowdfunding projects (Bose & Rabotyagov 2018). Zheng *et al.* (2017) examine the effect of lotteries on crowdfunding outcomes empirically based on a dataset from a Chinese reward-based crowdfunding platform that uses the lottery mechanism to attract more contributors. They show that the lottery indeed increases the total number of contributors to a project (by 21% on average), but it reduces the total value of funds raised (by 61% on average) and therefore also the probability of success of the project (projects with lotteries are 9% less likely to reach their target). The reason is that the lottery mechanism encourages people who would not otherwise support the project to contribute. On the other hand, it discourages funders who would contribute anyway from donating a higher amount—they choose the lottery, which is often offered at lower minimum value of a contribution, instead of a reward or donating without a reward.

Bose & Rabotyagov (2018) examined the effect of using a provision point mechanism combined with a lottery in a laboratory experiment. They found that a small prize lottery with a threshold requirement performs better than the provision point mechanism alone because of the risk-loving preferences of individuals. It increases the average amount of individual contributions, the total value of contributions, and the probability of success in reaching the target amount.

2.2 Crowdfunding Campaigns

Non-equity crowdfunding is a modern and fashionable way of organizing a contribution campaign, which substantially reduces transaction costs (Cecere *et al.* 2017). It involves relatively small contributions by many individuals. Three aspects differentiate a crowdfunding campaign from a traditional contribution campaign. First, the financing of projects is not geographically constrained, which is one of the main advantages. Second, there is a commitment to a fixed horizon within which the campaign collects the funds. A typical crowdfunding project has a predetermined monetary goal to which individuals can contribute any amount of money. The project will be successfully funded only if the goal is reached within a specified time period. Once the project reaches the goal, it can continue to receive more contributions until its closing date. Third, the details of previous contributions are publicly available. However, contributors may not have complete information about the others.

Individuals have heterogeneous motivations for participating in crowdfunding campaigns. They can be either intrinsically motivated to contribute (because of altruism or because they want to feel good about themselves), or extrinsically motivated as they can benefit from the public benefits or receive private prizes for their contributions (Allison *et al.* 2015). Agrawal *et al.* (2014) identifies several reasons for people engaging in non-equity crowdfunding projects. First, contributors want to support a certain product, service, or idea they like (without receiving any private reward). Second, contributors participate in the associated online community. They may value the social activity or direct communication with the project's creators. Third, people engage in crowdfunding because they can obtain early access to a new product (prebuying). Lastly, crowdfunding platforms are used to formalize donation contracts. Cecere *et al.* (2017) find a high level of prosocial motivations of funders, and argue that, in non-equity crowdfunding, contributions are associated mainly with altruism and social interaction rather than with prebuying. The decisions of the social community about whether or not to contribute influence the funding decisions of individuals to a large extent (Cecere *et al.* 2017).

Gerber *et al.* (2012) and Hemer (2011) argue that rewards play an important role in crowdfunding campaigns as interest in rewards may be the primary motivation for contributions. Cecere *et al.* (2017) shows that prebuying increases the number of contributors, but not the average value of the contribution. On the other hand, intangible rewards (such as a thank-you letter or public acknowledgment) positively influence the value of the contribution but do not have any significant effect on the decision to contribute. Financial rewards can crowd out the intrinsic motivations of funders to contribute to a campaign—the offer of a financial reward reduces the probability of success of a project (Cecere *et al.* 2017).

Coordination between creators of projects and contributors takes place on a crowdfunding platform. Most of the crowdfunding platform's business is based on a transaction fee for successful projects, a percentage of the total amount of money raised. If a project is not successful, the creator of the project does not pay any fee. Therefore, an adverse selection risk arises. The mechanism does not efficiently eliminate bad projects. The objective of a crowdfunding platform is to maximize the number of successful projects and the total value of contributions. To achieve this goal, a large community of creators and contributors is required, as is a platform that attracts high-quality projects, reduces the risk of fraud, and enables efficient matching between ideas and contributions (Agrawal *et al.* 2014).

2.3 The Distribution of Outcomes and Determinants of Success

Previous studies of international non-equity crowdfunding platforms show that the outcome (in percent of goal) is bimodal—crowdfunding campaigns either succeed or fail to raise any substantial fraction of their target amount. It is highly unlikely that a project raises between 50 and 99% of its target funds (Alaei *et al.* 2016; Crosetto & Regner 2014; Kuppuswamy & Bayus 2017; Mollick 2014). Agrawal *et al.* (2014) argue that the outcomes of crowdfunding projects are highly skewed, even in a sample of successful projects alone. Crosetto & Regner (2014) and Mollick (2014) show that projects usually succeed by small margins and that few successful projects pledge much more than their target amount. This is because potential contributors are less interested in financing projects that have already reached their goal (Kuppuswamy & Bayus 2017).

Only around half of campaigns reach their target amount of funds (Etter *et al.* 2013). Hence, empirical studies have tried to explain the success of campaigns, especially in early stages. Etter *et al.* (2013) introduce a model that predicts the success of crowdfunding projects, using information about money pledges and social features (tweets and projects/backers graphs on Kickstarter). Their predictor is able to attain more than 76% correct predictions only four hours after the campaign has started. The analysis of Crosetto & Regner (2014) confirms that the success of a campaign can be predicted quite early with a high degree of accuracy. However, it also shows that majority of the projects that are eventually successful do not seem to be on a successful path in two thirds of the project's duration.

Previous literature has also explored many determinants of the decision to contribute to a project. There is a high level of consensus that a *lower funding goal* increases the chance of success, as does a *shorter campaign duration*, possibly because it functions as a sign of confidence (Crosetto & Regner 2014; Etter *et al.* 2013; Kuppuswamy & Bayus 2017; Mollick 2014; Zheng *et al.* 2017). Etter *et al.* (2013) and Kuppuswamy & Bayus (2017) show (based on data from Kickstarter) that campaigns that fail have goals that are between three and four times higher on average. However, the funding goal is positively related to the average value of a contribution (Beier & Wagner 2015).

The description and design of a project are also important determinants of success as they work as signals of high project quality (Mollick 2014). Mollick (2014) and Zheng *et al.* (2017) show that projects having a *video*, *more pictures*, and a *longer description* are more likely to succeed. Beier & Wagner (2015) argue that the presence of video is positively related to the number of contributions and the overall success of a campaign, but not to the average value of a contribution. *Spelling errors* in the description of a project are negatively correlated with success (Mollick 2014). Kuppuswamy & Bayus (2017) claim that having a *colon* in the title is associated with greater success.

Crosetto & Regner (2014) also analyzed the effect of *rewards* (based on data from Startnext, the largest crowdfunding platform in Germany). They divide rewards into five categories: (1) a simple thank you, (2) preselling, (3) an unrelated service such as dinner or a meeting, (4) an invitation (e.g. to a production), and (5) branded clothing. They suggest that preselling, invitations and clothing have a positive impact on campaign success, while unrelated services are negatively correlated with success. Projects with a higher share of preselling rewards and rewards that publicly show contributors' support are more likely to be successful. Kuppuswamy & Bayus (2017) argue that campaigns with more reward categories are associated with greater success.

Communication with potential contributors has a large impact on the success of a campaign. Projects with more updates on a blog or on the project page are more likely to succeed (Crosetto & Regner 2014; Mollick 2014). The frequency of updates is positively related to the total success of the campaign, the number of contributions, as well as the average value of a contribution (Beier & Wagner 2015). *Network size*, measured as the total number of project fans and the number of friends on online social networks, is positively correlated with success (Crosetto & Regner 2014; Mollick 2014).

Many project creators use social media such as Facebook and Twitter to promote their campaigns. This channel is fast and far-reaching and therefore plays a crucial role in crowdfunding. It can increase the quality of interactions with potential contributors and the subsequent success of a campaign. Beier & Wagner (2015) claim that it is the details of the use of the social media channel that is important. They find no evidence that the use of social media platforms is positively correlated with the success of a project. Lu *et al.* (2014) point out the importance of other external channels of promotion outside social media, which should be used together with the latter to stimulate the crowdfunding campaign.

Lu *et al.* (2014) analyzed how social media helps crowdfunding campaigns to succeed. They discovered that there is a strong correlation between early promotional activities on social media and the results of projects. The effect of social promotion on social media on final outcomes is even larger than the effect of project properties, such as duration of a campaign or the funding goal. The success of a campaign is mainly determined by the design of the project's promotion campaign, while the number of contributors is more correlated with the volume of promotional activities.

Social buzz on social media platforms—in the form of shares and tweets—works as another signal of a project's quality. It can play a crucial role in persuading potential contributors to support a project. Thies *et al.* (2014) argue that the number of shared posts on Facebook is the main factor for project success and that its predictive power increases over time.

Du *et al.* (2017) propose three contingent policies—*seeding*, *feature upgrades*, and *limited-time offers*—which seek to encourage pledging and improve the success rates of projects. Seeding reduces the amount of funds needed to achieve a project's goal; feature upgrades encourage more contributors to pledge; and limited-time promotional offers aim at encouraging people to contribute early. The positive effect of contingent policies is greatest in the middle of a campaign when support for a project typically decreases. Du *et al.* (2017) show that contingent policies, together with the adjustment of project features during the campaign, may be even more important than fixed project characteristics such as the target amount.

2.4 The Funding Cycle and Project Dynamics

Support for a project is typically bathtub-shaped, with high level of contributions in the first and last weeks and decreasing support in the middle of the funding cycle (Crosetto & Regner 2014; Kuppuswamy & Bayus 2017). In the middle of the cycle, even initially successful projects usually slow down because the propensity to contribute decreases as potential contributors believe that the target amount will be reached regardless of their contribution (Agrawal *et al.* 2014; Kuppuswamy & Bayus 2017).

Agrawal *et al.* (2014) argue that family members and friends play a crucial role at the beginning of a campaign. They support the project early and therefore generate a signal for later contributors as a result of the details of the project's level of previous individual contributions that are publicly available. Potential contributors can usually observe: the aggregate contribution, the number of contributors, the campaign funding target, and the remaining duration of the campaign. They are often provided with limited or selective information about a project (Thies *et al.* 2014). They evaluate the value and trustworthiness of a campaign by observing the behavior of previous funders.

There are different views regarding the impact of available information about previous contributions on the behavior of funders. Thies *et al.* (2014) argue that each additional contributor increases the reputation of the project, which leads to a multiplying effect. Agrawal *et al.* (2014) show—based on data from crowdfunding platform Sellaband—that the propensity of individuals to contribute to a project grows quickly with the amount of contributions accumulated and can lead to herding. Potential contributors rely on accumulated funds as a signal of quality. Thus, herding behavior can be rational and efficient if early contributors have adequate information about the project. On the other hand, a large amount of contributions from family and friends may give incorrect information, as it reflects the size of author's social network rather than the quality of the project. The herding pattern has also been observed by Alaei *et al.* (2016) and Cecere *et al.* (2017), who find a positive effect of past contributions on the funding decision. Zhang & Liu (2012) point out that the acceleration of contributions on online platforms is most remarkable as the end date approaches.

On the other hand, Kuppuswamy & Bayus (2017) show that contributions to a project are negatively related to past contributions. Many potential contributors do not support a project that has already received a lot of funds as they believe that it will reach the funding goal anyway. This effect is later reduced in the final stage of the campaign because potential contributors perceive the real threat that other people may not contribute enough. As a result, in this stage, there is a sharp increase in contributions to projects that eventually succeed. Rising support at the end of the funding cycle is also due to the increase in project public updates, which encourage potential funders to contribute. Kuppuswamy & Bayus (2017) observe that successful projects are more likely to have an update in the last week.

List & Lucking-Reiley (2002) find that individuals contribute more when they know that the funding for a project is near its goal. Crosetto & Regner (2014) argue that the increase in contributions in the final phase of a campaign is mainly due to contributions to campaigns that have already reached their target amount rather than to an attempt to make unfunded projects successful. Their analysis shows that 18.7% of all contributions are made after the funding goal has already been reached. Preselling rewards are the main motivation for contributors after a project's funding goal has been met.

Thies *et al.* (2014) use a panel vector autoregression model to investigate the interconnection between activities on social media and the behavior of contributors on a crowdfunding platform. The results show that there is a positive effect of social buzz on contributions, but a negative effect in the opposite direction. This suggests that individuals look for feedback about the project from their social network before deciding to fund the project, but that they do not share the campaign on social media after contributing. Yesterday's shares on Facebook have a positive and significant impact on today's amount of contributions. However, this effect is not observable in a subsample of unsuccessful campaigns.

Alaei *et al.* (2016) and Du *et al.* (2017) provide a dynamic model in which potential contributors arrive sequentially and decide whether to contribute to a crowdfunding project. Alaei *et al.* (2016) introduce 'anticipating random walks' process to analyze the behavior of contributors. They argue that individuals estimate the chance of success before deciding to contribute and show that potential contributors prefer not to contribute if they think that the campaign will not be successful. The absence of contributions then discourages others from contributing, and a vicious cycle emerges.

One of the reasons for this is that making a contribution is not costless—even when the project is not successful, the contributor cannot use the money until the end of the campaign. If the campaign fails to meet the threshold, the public good is not provided, the contributor does not get any reward (in case of reward-based crowdfunding), and he or she does not have the opportunity to use the funds for other purposes until the campaign is over. As a result, a project may not succeed even when there are enough individuals for whom it is valuable.

On the other hand, when individuals are optimistic about a campaign's success and make contributions, other people who arrive later estimate that the probability of success is high and contribute too, creating a virtuous cycle (Alaei *et al.* 2016). Alaei *et al.* (2016) conclude that an information disclosure policy is favorable for projects with a high level of contributions in the beginning of the campaign, while for projects with a slow start, revealing the pledge amount may discourage potential contributors.

Chapter 3

Crowdfunding

3.1 Types of Crowdfunding

With equity crowdfunding, contributors become investors who invest money in return for equity in the venture. Investors have partial ownership of a young developing company and receive profits if the company does well, but they can lose their investment if the company fails. Another type of crowdfunding, similar to equity crowdfunding, is credit-based crowdfunding (also known as debt crowdfunding or peer-to-peer lending). It is an alternative way of financing—instead of borrowing from a bank, individuals borrow from a crowd. Lenders and borrowers are connected directly by means of internet platforms, and lenders (investors) receive a financial return with interest. On the other hand, non-equity crowdfunding does not offer the contributors any equity or shares in the profits of the project, and it is much less regulated.

There are two basic types of non-equity crowdfunding: reward-based crowdfunding, which is the most prevalent today, and donation-based crowdfunding. With donation-based crowdfunding, contributors donate (typically small) amounts of money to specific causes or projects without expecting anything in return, apart from the feeling of satisfaction from supporting a project that seems worthwhile to them. Donors can sometimes receive a thank you or a special mention, but not a product or service with a clear monetary value.

With reward-based crowdfunding, contributors raise money for a project in return for rewards, which vary according to the level of contribution. Symbolic goods are offered for low-value contributions, while goods or services with a significant monetary value are offered for larger contributions. The reward can be a simple thank-you message, a postcard, or a T-shirt, but also the prepurchasing of new products or services. As Mollick (2014) points out, there is usually no legal obligation for the originator of a project to deliver the reward. Moreover, the description of a reward is often relatively vague and the product or service typically does not exist at the time that the potential contributor decides whether to support the campaign or not (Thies *et al.* 2014).

3.2 Crowdfunding around the World

Historically, crowdfunding was used for art and other creativity-based projects and was dominated by a single platform. Today, hundreds of crowdfunding platforms exist around the world, though only a few of them have a global reach. As Agrawal *et al.* (2014) points out, indirect network effects play an important role in crowdfunding and other online markets because the value of a platform to project creators increases with the number of contributors and vice versa. The first crowdfunding platform was Sellaband, a platform for music projects founded in 2006 in Amsterdam; it was followed by Indiegogo in 2008 and Kickstarter in 2009. Both of the latter are reward-based platforms in which project contributors receive tangible, though nonfinancial, benefits. Today, Kickstarter and Indiegogo remain the most powerful non-equity crowdfunding platforms in the world.

3.3 Crowdfunding in the Czech Republic

Crowdfunding platforms in the Czech Republic copy the design and mechanisms of platforms such as Kickstarter and Indiegogo. The first non-equity crowdfunding platform, Fondomat, appeared in 2011. Fondomat was followed by around a dozen other platforms, but many of them ceased being active and exited the market after few years. The most successful are the reward-based crowdfunding platforms, Hithit and Startovač. Fundlift is the first Czech equity-based crowdfunding platform, founded in 2016.

3.4 Hithit

Hithit is a reward-based, non-equity crowdfunding platform founded in 2012. Today, it controls 70% of the entirety of the Czech and Slovak crowdfunding market. Up to the present day, over 2,000 projects have been launched on

Hithit, and successful projects have raised over 100,000,000 CZK (4 million EUR). Hithit is a crowdfunding platform that is used mainly for financing new ideas and creative projects, for example, music albums, films, innovative or design products, and the like. There are 15 categories of projects: *Technology*, *Design*, *Dance*, *Games*, *Community*, *Music*, *Theater*, *Food*, *Literature*, *Photography*, *Film*, *Art*, *Sport*, *Fashion*, and *Education* (Hithit 2019). Hithit is not a platform for funding general business expenses or charity projects (with exceptions).

The projects on Hithit are active for exactly 30 or 45 days. The originator of a project can decide on the length of the project before it is launched. Once the project is published, the originator can edit the text, video, and pictures of the project, or upload new rewards, but he or she cannot change the name of the project, the already published rewards, and, most importantly, he or she cannot change the target amount to be raised or the length of the project. During the campaign, the money from contributors arrives in a special account through on-line transfers or ordinary bank account transfers, and neither the author of a project nor Hithit have access to it before the end of the campaign. Each contributor chooses a reward as a private prize for his or her contribution. The reward can be a product, a service, or an experience (Hithit 2019).

After the 30 or 45 days, Hithit evaluates the success of the project. If the campaign is successful, the author receives all the contributions, less the commission, and delivers the rewards to all contributors. The commission is 9% of the amount collected for projects under 200,000 CZK and is agreed individually for larger projects (Hithit 2019). If the project does not succeed in collecting the required amount of money, neither the creator of the project nor Hithit get anything, all the contributions are refunded, and the contributors do not receive any rewards. The use of the provision point mechanism and a finite time horizon on Hithit thus protects contributors as they either get their money back (in the case of failure) or receive their reward (in the case of success) in a reasonably short time. In addition, this all-or-nothing mechanism should motivate creators to set realistic target amounts for funds to be collected. An overambitious project may raise no funds at all.

Chapter 4

Hypotheses

Based on the literature research, we formulate the following hypotheses:

Hypothesis 1. *The duration of a crowdfunding campaign is negatively associated with its success.*

The effect of a campaign's length is twofold. Obviously, a longer campaign provides more opportunities to attract attention to the crowdfunding project, and therefore collect higher amount of contributions. However, campaign length is also a signal of confidence as it is not selected randomly but depends on unobservable confidence. Duration (30 or 45 days on Hithit) works as a signal for contributors. The shorter the campaign, the more confident the originator is about its success. The two effects work in the opposite directions, and we cannot separate them as we do not have a measure of confidence. Hypothesis 1 entails that the signaling effect is strong enough to dominate the opportunity effect. We expect that shorter campaigns are more likely to succeed and receive a higher percentage of their funding goal.

Hypothesis 2. *Crowdfunding projects that offer private rewards of high market value are more likely to suceed.*

While interest in private rewards of high value may be the primary motivation for some contributors in reward-based crowdfunding, these valuable 'private prizes' can have a negative effect on the funding decision of intrinsically motivated individuals—intrinsic motivation is crowded out. Hypothesis 2 therefore empirically tests whether the prize effect dominates the crowding-out effect. We assume that the ratio of the estimated market value of a reward to the amount of a contribution is positively associated with the success of the project.

Hypothesis 3. *The amount of contributions a crowdfunding project receives on a given day is positively and strongly related to recent marketing activity on social media.*

Project promotion and interaction with potential contributors on Facebook and other social media platforms play an important role in crowdfunding, for several reasons. First, they attract attention to the existence of the campaign. Next, they reduce uncertainty about the nature of the campaign. Moreover, they provide a signal of the contributions of others and can generate herding effects (the motivation for herding can be informational or reputational, and so forth). We assume that the value of contributions (as a percentage of a project's funding goal) on a given day reflects the appearance of a new Facebook post on that day or the day before as contributors respond to the calls for contributions.

Hypothesis 4. *The amount of contributions a crowdfunding project receives on a given day is negatively associated with its level of funding already achieved.*

Studies on crowdfunding have found both positive and negative effects of past contributions on the funding decision of potential contributors. Our hypothesis is in line with Kuppuswamy & Bayus (2017), who noted that there is a diffusion of responsibility in crowdfunding. They argue that potential contributors do not support a project that has already received substantial funds as they believe that it will reach its funding goal anyway. As the level of financing of each project is publicly available, individuals infer their own personal responsibility to contribute from the size of a group that can provide sufficient funding. The likelihood of contributing decreases when the number of individuals needed to reach a project's funding goal is smaller. Therefore, we expect that the value of contributions (as a percentage of a project's funding goal) on a given day is negatively related to the value of past contributions because of greater incentives to free ride.

Hypothesis 5. *The effect of the level of funding already achieved on the amount of contributions a crowdfunding project receives on a given day is less negative in the final stage of the campaign.*

Due to the finite time horizon of crowdfunding campaigns, campaign dynamics is not only affected by the value of past contributions, but also by the number of days remaining until the end of a campaign (the time dimension).

The diffusion of responsibility effect decreases in the final stage of the campaign as potential contributors perceive the real threat that other people will not contribute enough, and they are more likely to help to achieve the project's goal—the finite time horizon reduces free-riding. We can therefore observe accelerated contributions in the final phase of a campaign because the risk of a breakdown increases. In addition, as the end of the campaign approaches, there is a higher chance that a (small) contribution will be pivotal in determining the success of the campaign. On the other hand, there can also arise the problem of 'contributor of the last resort'—a person who is ready to provide sufficient funding with a large contribution if the project is not on a successful path (it can be the originator him- or herself).

Chapter 5

Data and Key Variables

5.1 Dataset 1

The first dataset consists of 2,023 projects that ran on the Czech crowdfunding Hithit from November 2012 to June 2018. It was provided by one of the platform's managers. It includes basic information about each project's characteristics and final outcome in terms of success, total amount pledged, and the number of contributors. This dataset is used mainly for descriptive purposes and for a cross-sectional analysis, which is the first step before the main analysis of the panel data.

5.2 Dataset 2

Data for the panel analysis comes from publicly available information on the Hithit website. We manually collected information on each project's characteristics and its dynamics—the amount of money pledged and the number of contributions on each day of the campaign. We also extracted marketing data about the campaigns, such as the number of new posts and the number of reactions to them (likes, comments, and shares) from the Facebook page of each project. For this reason, we only focus on projects that contain a link to a Facebook page. Projects that do not have a Facebook page are not used in the analysis. This dataset includes 56 projects that ran on Hithit from September 2018 to January 2019.

5.3 Key Variables

The following list provides definitions of variables used to analyze Dataset 1 and Dataset 2. Not all variables are used together.

Goal: The variable *Goal* is the target amount of money to be collected for project i (in CZK).

Success: *Success* is a dummy variable that is equal to one if project i is successful (i.e., it reaches its funding goal), and zero otherwise.

Money pledged: The variable *Total amount pledged* is the total amount of money (in CZK) collected during the funding cycle of project i.

Percent of goal: The variable *Percent of goal reached* is the percentage of project i's goal that is collected during its whole funding cycle. The variable *Percent of goal* is defined as the percentage of project i's goal collected on day t. The variable *Cumulative percent of goal* is the cumulative percentage of project i's goal collected up to and including day t.

Contributions: The variable *Total contributions* is the total number of contributions to project i during its funding cycle. The variable *Average contribution* is defined as the average amount of money (in CZK) per contribution to the project i (i.e. *Total amount pledged* divided by *Total contributions*). The variable *Contributions* is the number of contributions for project i collected on day t.

Length: *Length* is a dummy variable that is defined as the length of the funding cycle of project i (in days). It can be either 30 or 45 days.

Project category: *Project category* is defined by dummy variables for the category in which project i is classified: *Technology*, *Design*, *Dance*, *Games*, *Community*, *Music*, *Theater*, *Food*, *Literature*, *Photography*, *Film*, *Art*, *Sport*, *Fashion*, or *Education*. Each project on Hithit can be assigned to one or two categories.

Video: *Video* is a dummy variable which is equal to one if project i has a video, and zero otherwise.

Reward categories: The variable *Reward categories* is the number of different rewards of project i from which contributors can choose when contributing to the project.

Private prizes: The variable *Private prizes value* is defined as the estimated market value of all rewards which are delivered to contributors to project i. We estimated the market value of each reward by searching for the market values of similar products or services. We acknowledge that these are merely rough estimates as the descriptions of the rewards are often relatively vague, the products or services typically do not exist yet, and they can be quite unique. However, we find it important to include a measure of the value of private prizes because these change the character of crowdfunding campaigns. The variable *Private prizes coefficient* is the ratio of *Private prizes value* to *Total amount pledged*. The lower the coefficient, the more symbolic are the goods or services provided relative to the value of contributions. Projects with very high coefficients for private prizes are typically sales promotions with little or no public good element.

Facebook posts: The variable *Total Facebook posts* is the total number of posts that were posted on project i's Facebook page by the project's authors during its funding cycle. We count only those posts that contain a reference to the project run on Hithit—either directly by including a hyperlink to the project, or indirectly by mentioning the campaign (the post involves the name of the project or the word "Hithit"). The variable *Posts per day* is defined as *Total Facebook posts* divided by *Length*. It is the average number of posts on project i's Facebook page posted in one day of its funding cycle. *New post* is a dummy variable that is equal to one if there is at least one new post on project i's Facebook page on day t, and zero otherwise.

Facebook reactions: The variable *Total Facebook reactions* is the total number of reactions (likes, comments, and shares) to posts that were posted on project i's Facebook page by the project's authors during its funding cycle. The variable *Reactions per post* is defined as *Total Facebook reactions* divided by *Total Facebook posts*. It is the average number of reactions (likes, comments, and shares) to one post on project i's Facebook page. The variable *Facebook reactions* is the number of reactions to posts that were posted on project i's

Facebook page by the project's authors during day t.

First week and Last week: The variable *First week* is equal to one if project i is in the first week of its funding cycle on day t, and zero otherwise. The variable *Last week* is equal to one if project i is in the final week of its funding cycle on day t, and zero otherwise. These variables are included to reflect the idea that projects typically receive more contributions in the initial and final phases of the funding cycle.

Post funded: The variable *Post funded* is equal to one if project i has already reached its goal on day $t-1$, and zero otherwise. In the post-funded phase, a project can continue receiving contributions until the end of a campaign. We expect that the behavior of potential contributors will be different in this phase, as has been argued by Kuppuswamy & Bayus (2017) because there is no risk of a breakdown present. In addition, free-riding behavior is present mainly before a project reaches its goal.

Campaign duration: The variable *Campaign duration* is the ratio of the cumulative number of days that have passed for project i up to day t to the length of project i's funding cycle in days.

Chapter 6

Descriptive Statistics and Preliminary Analysis

6.1 Dataset 1

The first step in our analysis involves reviewing the values present in the datasets. The first dataset consists of 2,023 projects on Hithit in the period from November 2012 to June 2018. The most well-represented category is *Music* (454 projects), followed by *Community*, *Art*, and *Literature*. The least well-represented category is *Games* (42 projects), followed by *Dance*, *Fashion*, and *Photography*. The number of projects assigned to each category can be seen below:

Music	454
Community	391
Art	385
Literature	370
Education	254
Film	227
Sport	181
Design	129
Food	126
Technology	118
Theater	117
Photography	74
Fashion	65
Dance	49
Games	42

Table 6.1 provides information about the mean, median, minimum and maximum values of the key variables, along with their standard deviations and standard errors. The average goal is slightly more than 120,000 CZK, but median value is much lower (75,000 CZK). The most ambitious project had a goal of 2.5 million CZK. On average, projects collected around 70,500 CZK and 62% of their funding goal. The median value of money received per project is two times smaller. The highest amount of money collected was more than 2.4 million CZK. The highest outcome in terms of the percentage of goal reached is 718.5 %. Of all projects, 69 (3.4%) did not receive any money at all. On average, projects received approximately 91 contributions, but the median value is only 37. The project with the most contributions received 3,634. The average contribution was 830 CZK. The average number of reward categories from which contributors could choose was 13.5, and the project with highest number of reward categories offered 82 different rewards.

Table 6.1: Summary statistics of key variables (Dataset 1)

	Mean	**Median**	**Minimum**	**Maximum**	**Std. dev.**	**Std. error**
Goal (CZK)	120,564.40	75,000.00	1,700.00	2,500,000.00	155,072.34	3,447.75
Total amount pledged (CZK)	70,427.11	35,190.00	0.00	2,421,090.00	138,400,23	3,077.08
Percent of goal reached	62.29	37.30	0.00	718.50	63.03	1.40
Reward categories	13.50	12.00	2.00	82.00	7.57	0.17
Total contributions	90.73	37.00	0.00	3,634.00	192.85	4.29
Average contribution (CZK)	830.16	646.86	0.00	32,990.00	1,120.38	24.91

Table 6.2 summarizes the binary variables. Of all projects, 952 (or 47.06%) were successfully funded. The majority of projects (1,627, or 80.43%) included a video on the campaign's page on Hithit website. Most of the authors chose the longer duration for their campaign (45 days); only 12.7 % of campaigns (257 projects) lasted 30 days.

Next, we report on correlations between project characteristics and success. Table 6.3 compares the mean values for successful and unsuccessful projects. We can see that on average, unsuccessful projects have higher goals, but the difference is only around 17,000 CZK (14.9% higher). The average amount of money collected is approximately 135,200 CZK per successful project and 12,900 CZK for each unsuccessful project. On average, successful projects

Table 6.2: Summary statistics of binary variables (Dataset 1)

	Yes	No
Success	952	1,071
Video	1,627	396
	30 days	**45 days**
Length	257	1,766

received 120% of their goal; projects that failed reached only 11% of goal. Projects that succeed have, on average, more reward categories (15.7, compared to 11.5 for unsuccessful projects). Moreover, not only do they receive more contributions, but the average contribution is also higher—approximately 1,000 CZK for successful projects compared to 680 CZK for projects that fail. Even though we cannot use these statistics to assess causality, they are useful to better understand the features of reward-based crowdfunding on Hithit.

Table 6.3: Mean values of key variables by project success (Dataset 1)

	Successful project	Unsuccessful project
Goal (CZK)	111,747.08	128,402.02
Total amount pledged (CZK)	135,187.12	12,862.65
Percent of goal reached	119.73	11.22
Reward categories	15.72	11.53
Total contributions	173.24	17.39
Average contribution (CZK)	999.33	679.78

Table 6.4 shows the relationships between *Video*/*Length* and *Success*. As expected, projects having a video are more likely to succeed. There were 832 successful and 795 unsuccessful projects with videos, which gives us a success rate of 51.14%. On the other hand, projects without a video had a success rate of only 30.3% (120 successful and 276 unsuccessful campaigns). What is more interesting is that shorter campaigns (lasting 30 days) were more successful than longer campaigns (lasting 45 days). The success rate is 59.14% for campaigns with a shorter duration and only 45.30% for campaigns with a longer duration. This is in line with previous research.

Figure 6.1 illustrates the distribution of projects' outcomes in terms of the

Table 6.4: Summary statistics of binary variables by project success (Dataset 1)

	Successful projects		**Unsuccessful projects**	
Video:	**Yes**	**No**	**Yes**	**No**
	832	120	795	276
Length:	**30 days**	**45 days**	**30 days**	**45 days**
	152	800	105	966

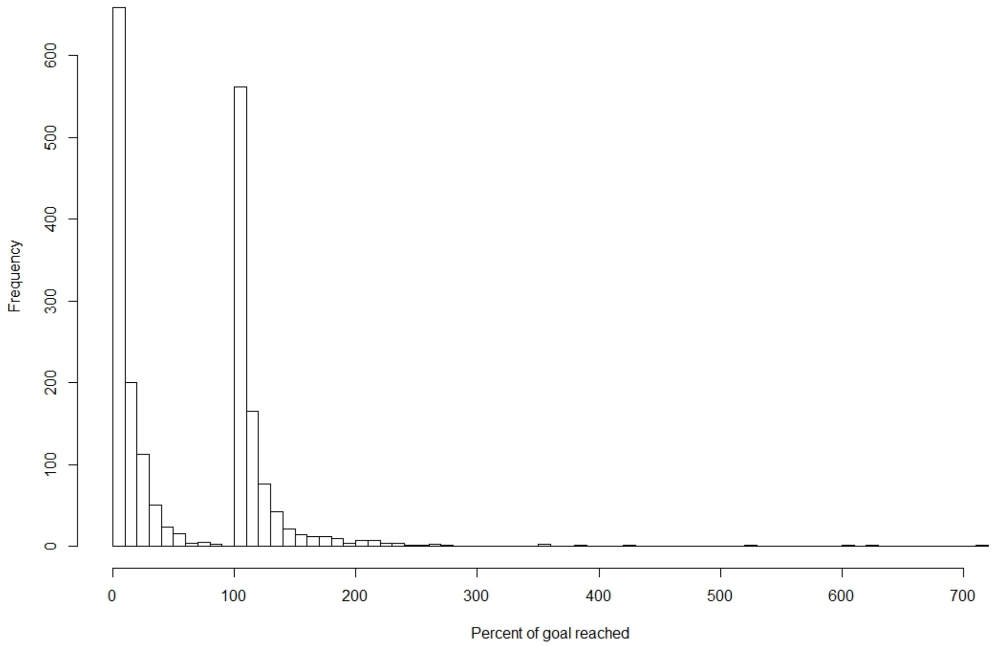
percentage of the goal reached. We can see that the outcomes of crowdfunding projects are highly skewed. As observed by Mollick (2014) and others regarding data from other crowdfunding platforms, the distribution reaches two peaks, at zero and 100% of the goal or slightly more. This is a result of the all-or-nothing crowdfunding mechanism. The majority of unsuccessful projects reached only 20% or less of their funding goal; it is very unlikely that a project reaches more than 60% of its goal and is eventually not funded (even though there are few exceptions in our sample). This distribution is similar for successful projects—most of them reached between 100% and 120% of their funding goal, and only a small number of projects collected more than 200% of goal.

Descriptive statistics by project category is provided in Table 6.5. The category with the highest proportion of successful projects is *Theater*, with a success rate of 55.56%, followed by the categories *Music* (54.85%) and *Literature* (51.08%). On the other hand, the least successful category is *Dance*, with only 24.49% successful projects, followed by *Food* (30.95%) and *Games* (30.95%). On average, the projects with the highest amount of money pledged were in categories *Technology* (approximately 89,200 CZK), *Film* (88,800 CZK), and *Theater* (87,000 CZK). Categories with the lowest average amount of money collected per project were *Photography* (approximately 48,300 CZK), *Sport* (54,000 CZK), and *Art* (55,500 CZK). The category in which an average project collected the highest percentage of its goal is *Fashion* (74.95% of goal), followed by categories *Literature* (68.37%) and *Music* (67.94%). On the other hand, categories with the lowest average percentage of their goal reached are *Dance* (31.84% of goal), *Food* (45.35%), and *Games* (48.63%).

Table 6.5: Summary statistics by project category (Dataset 1)

	Number of projects	**Success rate**	**Avg. total amount pledged (CZK)**	**Average percent of goal reached**
Music	454	54.85%	64,962.54	67.94
Community	391	47.57%	84,500.01	61.60
Art	385	48.57%	55,465,01	62.46
Literature	370	51.08%	66,859.27	68.37
Education	254	43.31%	83,449.74	59.41
Film	227	49.78%	88,786.01	63.55
Sport	181	38.67%	54,005.01	50.68
Design	129	34.11%	60,134.74	63.12
Food	126	30.95%	69,348.15	45.35
Technology	118	37.29%	89,155.02	49.93
Theater	117	55.56%	86,976.26	67.18
Photography	74	39.19%	48,258.09	50.50
Fashion	65	33.85%	71,809.80	74.95
Dance	49	24.49%	72,025.51	31.84
Games	42	30.95%	65,774.02	48.63

Figure 6.1: Outcomes of crowdfunding campaigns (Dataset 1)



6.2 Dataset 2

The second dataset comprises 56 projects on Hithit during the period from September 2018 to January 2019. The most represented category is again *Music* (12 projects), followed by *Education*, *Literature*, and *Community*. On the other hand, three categories with zero projects are not represented in this dataset: *Theater*, *Photography*, and *Dance*. The number of projects assigned to each category can be seen below:

Music	12
Education	11
Community	9
Literature	9
Art	8
Fashion	8
Design	7
Film	6
Food	6
Games	4
Sport	3
Technology	3
Theater	0
Photography	0
Dance	0

Table 6.6 presents the summary statistics at the project level for all the projects in the dataset. We report the mean, median, minimum, and maximum values of the key variables, along with their standard deviations and standard errors. The average project has a goal of approximately 171,000 CZK, which is around 50,000 CZK more than the average goal for projects in the first dataset. The median value of the goal is 115,000 CZK (compared to 75,000 CZK from the first dataset). The highest goal was 500,000 CZK, and the highest amount of money collected was approximately 678,900 CZK. On average, projects collected around 154,500 CZK, which is more than twice that in the first dataset. The median value of money received per project is slightly more than 100,000 CZK.

An average project reached 93.26% of its funding goal (compared to 62.29% in the first dataset). The difference between the medians in both datasets is even larger, 106.42% versus 37.30%. The best outcome attained was 341.2% of the goal and the worst outcome was 0.44%. On average, projects received approximately 158 contributions (compared to 91 in the previous dataset). The median is 102.5 contributions and the maximum number of contributions received was 768. The average value of a contribution is approximately 980 CZK—150 CZK more than the average contribution in the first dataset. Projects offered, on average, almost 18 different rewards, and the maximum number of reward categories was 41.

An originator of an average project posted 14 times on the Facebook page of his or her project during the entire funding cycle, or 0.4 posts per day. Each project included in the dataset has at least one post on its Facebook page (a criterion for our selection of projects). The maximum number of posts during the campaign was 40. On average, each project received 45.6 reactions (likes, comments and shares) below each Facebook post. The most popular campaign on Facebook had 202 reactions per post, while the least popular campaign only 0.5.

Table 6.6: Summary statistics of key variables (Dataset 2)

	Mean	Median	Minimum	Maximum	Std. dev.	Std. error
Goal (CZK)	171,302.36	115,000.00	50,000.00	500,000.00	124,758.56	16,671.56
Total amount pledged (CZK)	154,317.16	102,023.50	900.00	678,897.00	158,838.40	21,225.67
Percent of goal reached	93.26	106.42	0.44	341.20	62.69	8.38
Reward categories	17.79	17.00	6.00	41.00	7.97	1.06
Total contributions	158.45	102.50	4.00	768.00	156.95	20.97
Average contribution (CZK)	979.31	897.03	225.00	3,532.94	546.62	73.05
Private prizes value (CZK)	57,058.82	44,750	900,00	189,800	50,959.73	6,809.78
Private prizes coefficient	0.47	0.44	0.13	1.00	0.21	0.03
Total Facebook posts	14.16	12.00	1.00	40.00	10.28	1.37
Posts per day	0.40	0.33	0.02	1.10	0.28	0.04
Total Facebook reactions	653.39	301.50	1.00	3,415.00	797.39	106.56
Reactions per post	45.64	36.47	0.5	202	42.28	5.65

Table 6.7 summarizes the binary variables. Almost 70% of projects (39 of 56) were successfully funded, which is much more than the 47% in the first dataset. This improvement in the measure of success occurred for several reasons. First, our sample of 56 projects is rather small and its success rate is not directly comparable with that of over 2,000 projects from an earlier period—the two periods do not overlap. Second, since the data were collected only in a part of the year (from September to January), many of the projects finished before Christmas. We argue that there exists a seasonal effect—willingness to contribute may increase before Christmas because of a surge in altruism, but

also because of greater interest in the rewards, which can be used as Christmas presents.

Table 6.7: Summary statistics of binary variables (Dataset 2)

	Yes	**No**
Success	39	17
Video	53	3
	30 days	**45 days**
Length	27	24

Third, we must keep in mind that the sample consists only of projects that were active on Facebook (an originator of a project published at least one post mentioning the Hithit campaign during the funding cycle). Projects that did not have an active Facebook page were not included in our sample. In contrast to Beier & Wagner (2015), who found no correlation between the simple use of social media channels and success, we note that Hithit projects that have a Facebook page are on average more successful. Therefore, the 70% success rate cannot be interpreted as the overall success rate for this period. However, as Table 6.8 shows, the success rate of all projects on Hithit has been increasing since 2013 with the development of the crowdfunding market in the Czech Republic (statistics for 2012 are not reported because Hithit was founded in that year and only 17 projects were launched). The success rate of crowdfunding projects on Hithit rose steadily from 2013 to 2018, from 44.75% to 54.85%, with the exception of 2014, when it dropped to 39.15%. This increase may have been due to the rising popularity of crowdfunding and a higher number of potential contributors but may be also a result of a booming economy. We also argue that authors of projects are now able to set more realistic goals.

Going back to Table 6.7, we see that only three projects in our sample (or slightly more than 5% of the projects) did not include a video on the campaign's page on the Hithit website. Compared to the previous dataset, we observe a much higher proportion of campaigns with a shorter duration (30 days)—48.2% of campaigns lasted 30 days and 42.9% of campaigns lasted 45 days. The remaining five projects had different durations, which were set a few days shorter or longer for different reasons by Hithit. We change the values of *Length* for these five projects to missing (NA) for the purpose of further analysis. The large proportion of projects with a shorter duration in this sample may

Table 6.8: Success rate of projects on Hithit by year

	2013	2014	2015	2016	2017	2018
All projects	181	355	421	465	504	412
Successful project	81	139	201	224	257	226
Unsuccessful project	100	216	220	241	247	186
Success rate (%)	44.75	39.15	47.74	48.17	50.99	54.85
Total amount collected (CZK)	6,619,125	14,513,930	25,412,842	35,413,891	44,690,692	37,862,450

Source: Hithit (2019).

simply be a matter of chance, given the small size of our sample. Alternatively, authors of projects may rush to finish the campaigns early because of a seasonal Christmas effect—either because they want the project to be funded before the holidays (as the funding activity of potential contributors may be lower during holidays), or because they promised contributors that rewards would be delivered before Christmas. However, this cannot be the only explanation as the proportion of projects with a shorter duration has been increasing since the foundation of Hithit in 2012. With increasing experience with crowdfunding in the Czech Republic, originators of projects may choose a shorter duration for campaigns more often because they have learnt that shorter campaigns signal confidence and create a sense of urgency, which is favorable to the project's final outcome.

Now we again report on correlations between success and project characteristics. Mean values dependent on the success of a project are reported in Table 6.9. In line with the previous dataset, unsuccessful projects have higher goals—the difference is again slightly more than 17,000 CZK (or 10.5%). This is much smaller difference than reported by Kuppuswamy & Bayus (2017) who found that unsuccessful campaigns on Kickstarter have funding goals more than three times larger than successful projects. An average successful project collected approximately 207,900 CZK, 127% of its goal. This is around 70,000 CZK more than the average amount collected for a successful project in our previous dataset, while the percentage of the goal reached does not differ much. Projects that failed reached, on average, 16% of their goal and collected approximately 31,400 CZK. Successful projects offered more reward categories (19, compared to 15 for unsuccessful projects). They also received more contributions and the average value of each contribution is higher—approximately 1,020 CZK for successful projects, compared to 880 CZK for projects that eventually fail.

Quite surprisingly, successful projects have, on average, a lower coefficient for private prizes (0.42 compared to 0.60), which means that contributors to these projects receive rewards of lower market value than the market value of the rewards for unsuccessful projects (which are not delivered to the contributors, who receive all of their money back). This evidence suggests that the crowding-out effect on intrinsic motivation is present and relatively more important than the prize effect. Rewards of high market value are typical for preselling campaigns, and therefore signal the low public value of the project. On average, successful projects have greater marketing activity on their Facebook page than do unsuccessful ones (0.48 posts per day, compared to 0.21). As expected, projects that succeed also receive more likes, shares, and comments than projects that fail (48.4 reactions per post, compared to 39.3).

Table 6.9: Mean values of key variables by project success (Dataset 2)

	Successful project	**Unsuccessful project**
Goal (CZK)	166,026.10	183,406.71
Total amount pledged (CZK)	207,886.64	31,422.47
Percent of goal reached	126.80	16.31
Reward categories	19.03	14.94
Total contributions	214.38	30.12
Average contribution (CZK)	1,022.41	880.41
Private prizes value (CZK)	74,819.69	16,313.29
Private prizes coefficient	0.42	0.60
Total Facebook posts	17.36	6.82
Posts per day	0.48	0.21
Total Facebook reactions	838.13	229.59
Reactions per post	48.41	39.29

The relationship between the binary variables *Length* and *Success* is provided in Table 6.10. The success rate is 62.96% for campaigns with a 30-day duration and 70.83% for campaigns with a 45-day duration, which suggests that the relationship is exactly the opposite of that in the previous dataset. However, this pattern may be simply caused by the small size of our sample—the difference is not statistically significant. It is also possible that originators of projects with a longer duration, who may be less confident about the success of their projects, achieved to set more realistic funding goals. Interestingly, even though the success rate of projects with a shorter length is lower, these projects were more successful in terms of the percentage of the goal reached. An average successful campaign with a 30-day duration reached 142.75% of its goal, while a project with a length of 45 days reached only 110.83% of its goal. In addition, unsuccessful campaigns lasting 30 days collected a higher percentage of their goal than campaigns lasting 45 days—22.07%, compared to 8.08%. The relationship between *Video* and *Success* is not reported as only three out of 56 projects did not have a video.

Table 6.10: Summary statistics of binary variables by project success (Dataset 2)

	Successful projects		**Unsuccessful projects**	
Length:	**30 days**	**45 days**	**30 days**	**45 days**
	17	17	10	7

Figure 6.2 shows the distribution of project outcomes in terms of the percentage of the goal reached. It illustrates the same pattern of funding outcomes as the one observed in the first, larger dataset. Projects that meet their target reach mostly between 100% and 130% of their funding goal and only few successful projects raised much more than their goal. On the other hand, unsuccessful projects failed to collect any substantial proportion of their goal. No failed project in our sample reached more than 50% of its target.

Using the data on contributions over time, we now explore the dynamics of projects' funding. We first normalize the length of all projects to make their funding duration comparable. Campaign duration is thus between 0 (start date) and 1 (end date) for all projects. The accumulation of funding in terms of the percentage of each project's goal over its funding cycle is depicted in Figure 6.3. The first graph illustrates the funding dynamics of all projects in our sample; the other two graphs show the dynamics separately for successful and unsuccessful projects. We add a LOESS (locally estimated scatterplot smoothing) curve with a confidence region to all scatter plots (the curve is obtained by conducting a weighted least squares regression in localized subsets).

A typical project receives a relatively large proportion of its goal in the first 15-25% of the funding cycle (about a week). Successful projects collect more than 40% of their goal in the first quarter of the funding cycle, while

Figure 6.2: Outcomes of crowdfunding campaigns (Dataset 2)

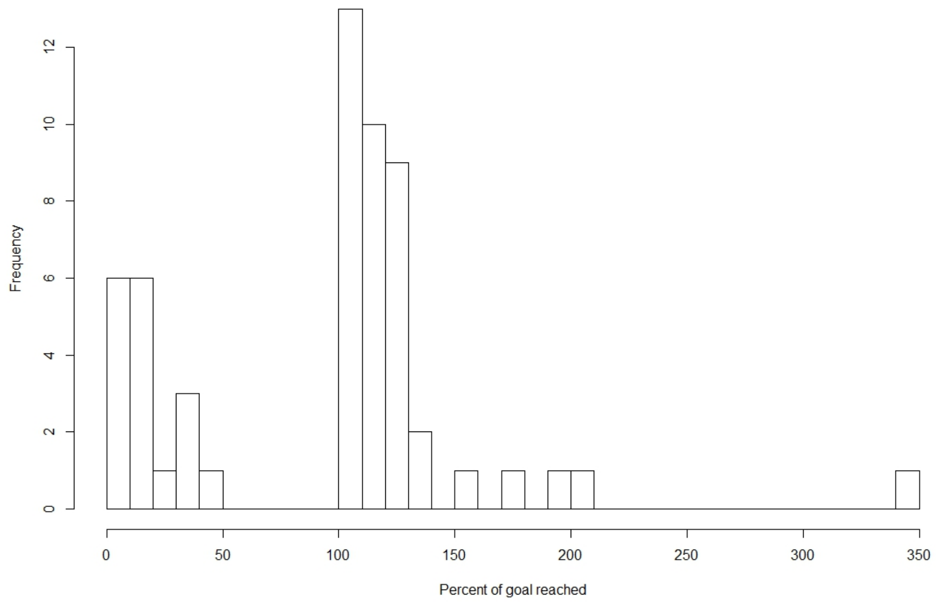
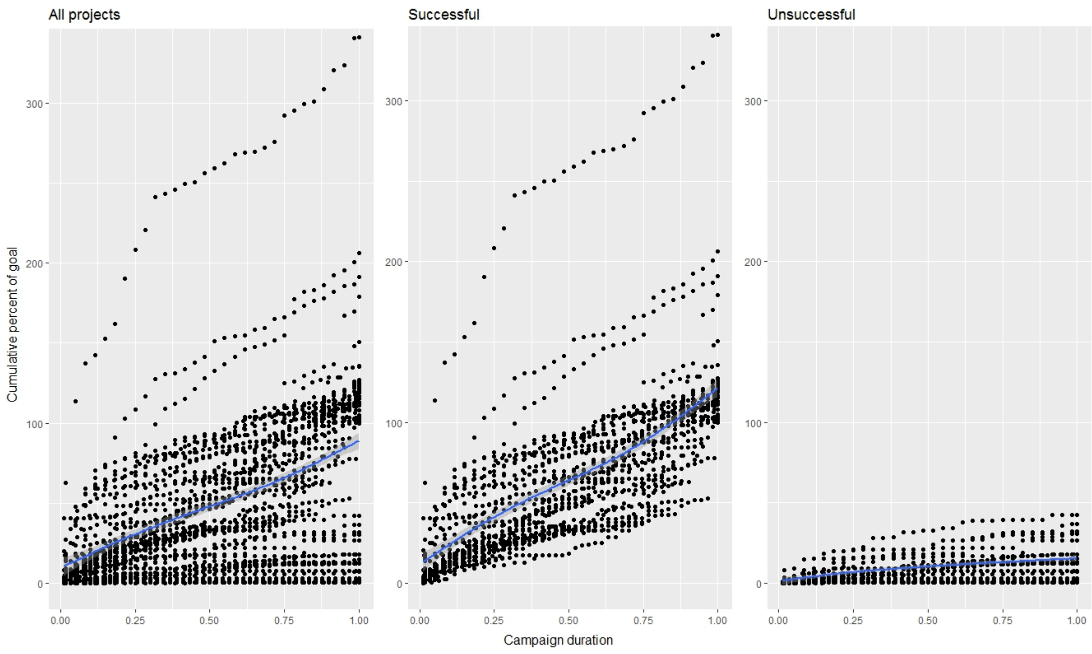


Figure 6.3: Dynamics of project funding (1)



unsuccessful projects achieve only around 7%. We can also see that contributions to projects continued even after they had reached their funding goal. In reward-based crowdfunding, this behavior of contributors can be explained by their interest in the rewards. However, it is also possible that people want to be part of a successful project, as has been argued by Crosetto & Regner (2014).

Figure 6.4 and Figure 6.5 present the separation of successful and unsuccessful projects during the funding cycle for campaigns lasting 30 and 45 days, respectively. To eliminate outliers, we use the 90th percentile of the cumulative percent of the goal reached for unsuccessful projects and the 10th percentile for successful projects on each day. For projects with a duration of 30 days, we observe the separation point on day 9 (30% of the campaign length), while for projects with a duration of 45 days, it had already occurred on day 2 (4.4% of the campaign length). The success of a project is therefore determined quite early in the funding cycle. If we instead look at the maximum values for unsuccessful projects and the minimum values for successful projects over time, we observe full separation on day 22 for campaigns lasting 30 days and already on day 3 for campaigns lasting 45 days. Thereafter, the best-performing unsuccessful project never surpassed the worst-performing successful project.

Figure 6.4: Separation of successful and unsuccessful projects during the funding cycle (30-day duration)

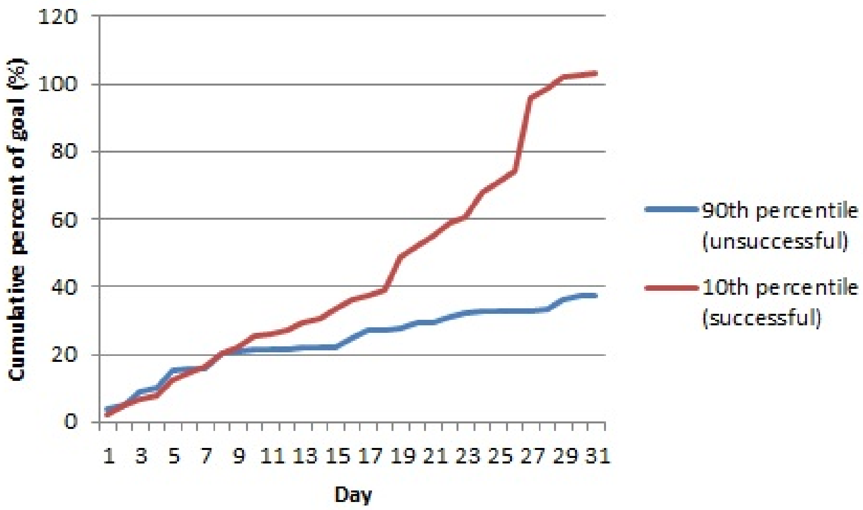
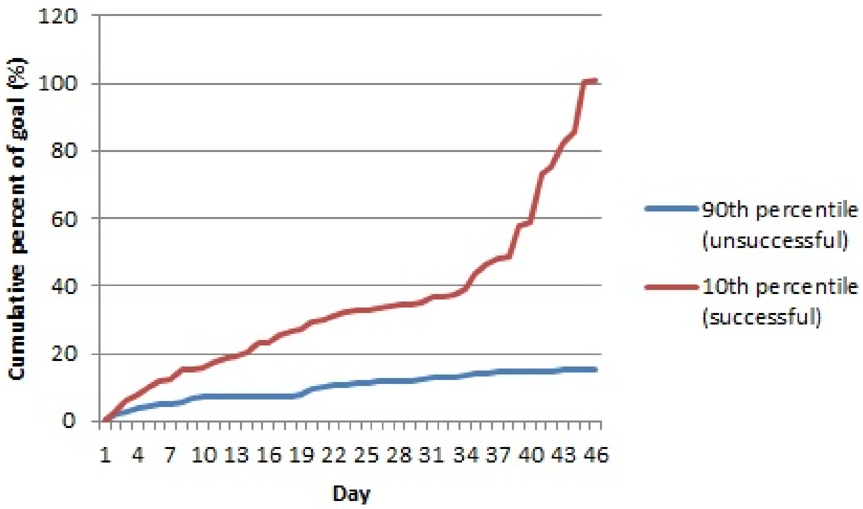


Figure 6.6 shows the amount of money (relative to the funding goal) raised by each project over time. The first two scatter plots (for all projects, and for successful projects only) illustrate the bathtub-shaped pattern of support for

Figure 6.5: Separation of successful and unsuccessful projects during the funding cycle (45-day duration)



crowdfunding projects. After the first week, the support for a project decreases and remains relatively low for most of its funding cycle. As the end date of the campaign approaches, we again observe an acceleration in contributions. This happens approximately one week before the end of the campaign. However, only successful projects tend to receive an increasing amount of contributions in the last week. The funding dynamics of unsuccessful projects are different. Contributions to a project that will eventually fail constantly decrease over its whole funding cycle and almost disappear as it becomes more obvious to potential contributors that the project will not make it.

The number of contributions added to a project over its funding cycle is provided in Figure 6.7. The funding dynamics for both successful and unsuccessful projects is similar regardless of whether we look at the percentage of the goal received on each day or the actual number of contributions. Again, only successful projects are likely to receive an increase in contributions in the final phase of the campaign. These patterns of contributions over time are in line with Crosetto & Regner (2014) and Kuppuswamy & Bayus (2017).

The distribution of Facebook posts on each project's page over the funding cycle is provided in Figure 6.8. Interestingly, the dynamics of marketing activity on social media is very similar to the dynamics of contributions. We investigate the relationship between Facebook posts and contributions in our further analysis. Authors of projects are most active on Facebook in the first

Figure 6.6: Dynamics of project funding (2)

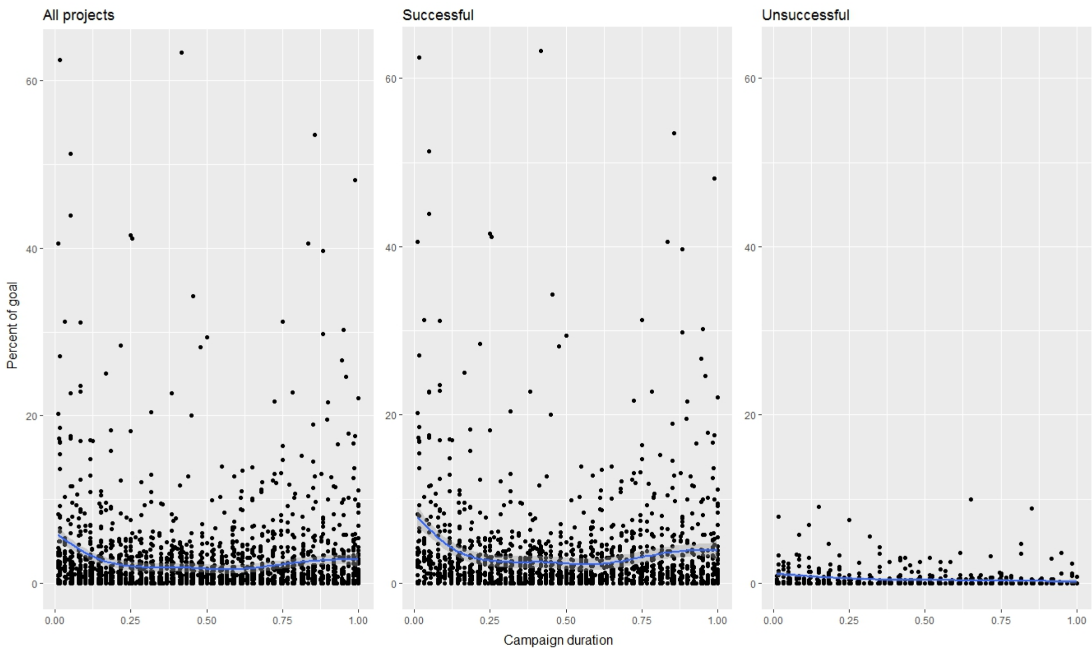
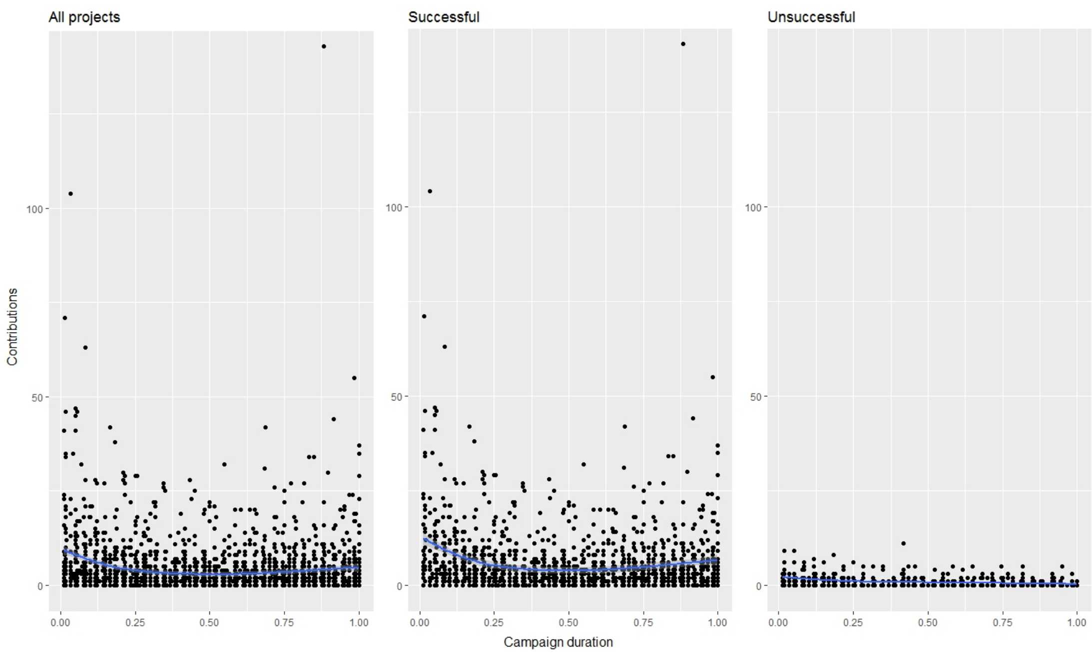


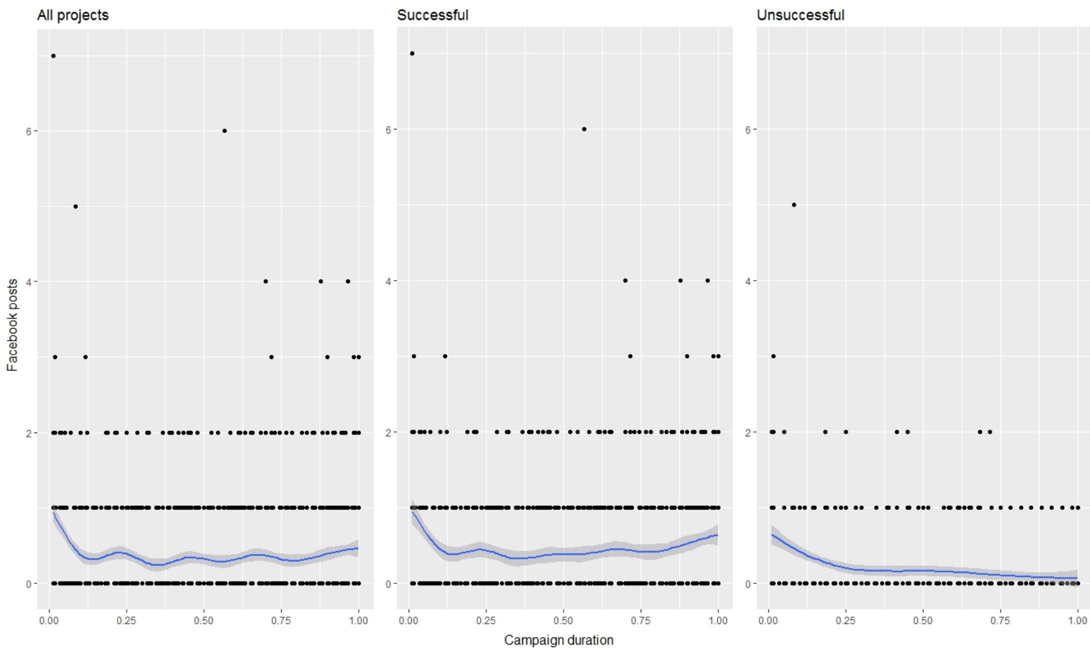
Figure 6.7: Dynamics of project funding (3)



days of the campaign when they try to introduce their projects to crowds and convince as many potential contributors as possible to contribute. After the initial phase of the campaign, the number of Facebook posts per project stays at more or less the same level. As the end date approaches, there is noticeably greater marketing activity from originators of projects that eventually succeed.

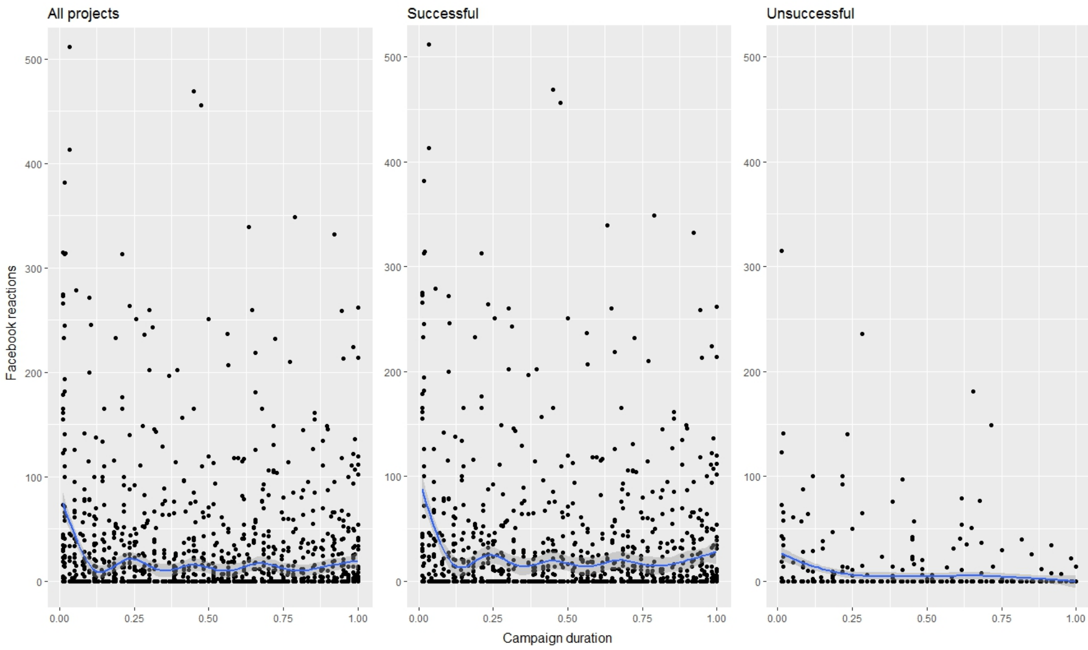
There is no increase in Facebook posts in the final phase for projects which eventually fail. This supports our observation that the success of a project is determined much sooner in the funding cycle, as has also been argued by Etter *et al.* (2013). Even the originators of these projects do not believe that there is still chance to get their not-yet-funded projects over the target. Therefore, the marketing effort steadily declines over time and almost disappears towards the end date as it becomes increasingly clear that the project will not be successful.

Figure 6.8: Dynamics of marketing activity on Facebook



The scatter plots in Figure 6.9 show the number of reactions (likes, comments, and shares) to Facebook posts published by the project originators during the funding cycle (for all projects and then separately depending on the success of the project). The response to new posts is highest at the beginning of a campaign. Subsequently, the number of reactions stays relatively low because the marketing activity of project authors also decreases. For projects that will eventually succeed, Facebook reactions rise again when the end date approaches. However, this increase does not fully reflect the surge in marketing activity—the number of reactions per post is now lower than in the initial phase of a campaign. For unsuccessful projects, the response to posts on a project's Facebook page is relatively high in the first days of the funding cycle and then decreases and never rises again.

Figure 6.9: Dynamics of Facebook reactions



Chapter 7

Cross-sectional Analysis: Determinants of Success

Our econometric analysis consists of two parts. In this chapter, we begin with the investigation of what determines the success of a project (for both datasets). We focus on the following success determinants: *Length*, *Video*, *Goal*, and *Reward categories*. All of these variables were found to be correlated with success in previously conducted empirical studies. Moreover, we examine which categories of projects on Hithit are more likely to lead to success. For the second dataset, we also analyze the impact of activity on Facebook (the variable *Posts per day*) and the value of rewards (the variable *Private prizes coefficient*).

7.1 Methodology

Our baseline model has the following form:

$$Success_i = \beta_0 + \beta_1 Length_i + \beta_2 Video_i + \beta_3 Goal_i + \beta_4 RewardCategories_i + \varepsilon_i \tag{7.1}$$

where i represents the i-th project. All the variables are defined in Chapter 5.

Since our dependent variable is binary and our goal is to estimate the effects of explanatory variables on the probability of success, we estimate the equation as a probit model. The probit model solves the two limitations of a linear probability model—it ensures that the fitted probabilities lie strictly between zero and one (by using the standard normal cumulative distribution function), and it deals with the heteroskedasticity of the error term, which is present in the linear probability model.

The disadvantage of using the probit model is that the estimated coefficients cannot be easily interpreted because the partial effects are not constant, as they are in the linear probability model—they depend on the values of explanatory variables. However, the signs of the estimated coefficients are the same in both models and are sufficient to determine whether the explanatory variable has a negative or positive effect. For roughly continuous variables, we can obtain a partial effect for different values of interest. The most common is *partial effect at the average*, which finds the partial effect of an explanatory variable for the average project in the sample. Alternatively, we can calculate *average partial effect* by averaging the individual partial effects across the sample (Wooldridge 2015). For binary independent variables, we can directly estimate the change in the probability of success when the explanatory variable is equal to 0 or 1.

7.2 Results

We begin with the analysis of the first dataset, which consists of 2,023 projects on Hithit in the period from November 2012 to June 2018. Table 7.1 presents results of our basic probit model regression. The dependent variable is whether a project has been successful or not. As the values of *Goal* are highly skewed, we use a logarithmic transformation of the variable. We find a negative correlation between the *Length* of a project and its success—shorter campaigns are more likely to be successful. *Video* appears to have a positive effect on success. As expected, the *Goal* of a project is negatively correlated with its success. The coefficient estimate for the number of *Reward categories* is positive. All of the variables are significant at the 1% level.

Table 7.1: Success determinants: Probit regression 1

	Coefficient	***p*-value**	
Intercept	1.1513	0.0032	**
Length45	-0.2592	0.0031	**
Video1	0.3851	0.0000	***
log (Goal)	-0.1826	0.0000	***
Reward categories	0.0566	0.0000	***
Observations	2023		

Next, we include dummies for *Project category*. The categories are not mutually exclusive because each project can be assigned to two categories. Therefore, the project categories are added separately to our basic model. As a result, we run 15 models one-by-one, each with a one category dummy. We report only the coefficient estimates and the significance of project category. The coefficients for all the other variables (*Length*, *Video*, *Goal*, and *Reward categories*) remain significant, have the same sign and are of a similar magnitude.

The dummy for the category *Music* is positive and significant at the 5% level (coefficient: 0.1723, *p*-value: 0.0140). The dummy for *Literature* is positive and significant at the 1% level (coefficient: 0.3644, *p*-value: 0.0000). The coefficient estimate for *Education* is negative and significant at the 10% level (coefficient: -0.1726, *p*-value: 0.0506). The project categories *Sport* (coefficient: -0.2276, *p*-value: 0.0275) and *Fashion* (coefficient: -0.3738, *p*-value: 0.0260) are also negatively correlated with success (at the 5% level). The following categories are negatively correlated with success and significant at the 1% level: *Design* (coefficient: -0.3541, *p*-value: 0.0037), *Food* (coefficient: -0.3835, *p*-value: 0.0022), and *Dance* (coefficient: -0.6839, *p*-value: 0.0008). Dummies for all the remaining categories (*Technology*, *Games*, *Community*, *Theater*, *Photography*, *Film*, and *Art*) are not significant at the 10% level.

The estimation results of the probit regression on the second dataset (the sample of 56 projects from the period from September 2018 to January 2019) can be seen in Table 7.2. We excluded the variable *Video* because only three projects did not contain a video. Only the coefficient estimate for *Reward categories* is positive and significant at the 5% level. *Goal* seems to be negatively correlated with success, but its statistical significance is slightly above the 10% level. The variable *Length* is not statistically significant (*p*-value: 0.39).

Table 7.2: Success determinants: Probit regression 2

	Coefficient	**p-value**
Intercept	5.0480	0.1479
Length45	0.3348	0.3887
log (Goal)	-0.4937	0.1054
Reward categories	0.0621	0.0231 *
Observations	56	

As a next step, we include variable *Private prizes coefficient* into our baseline model. The results of this regression are reported in 7.3. The variable

Length remains insignificant, while the *Goal* of a project becomes statistically significant at the 5% level, and it is again negatively correlated with success. The coefficient estimate for *Reward categories* remains positive, now statistically significant at the 10% level. *Private prizes coefficient* is negatively correlated with success (at the 5% level)—projects with higher market value rewards appear to have a lower probability of success.

Table 7.3: Success determinants: Probit regression 3

	Coefficient	**p-value**	
Intercept	8.7167	0.0289	$*$
Length45	0.2820	0.4926	
log (Goal)	-0.6809	0.0392	$*$
Reward categories	0.0538	0.0533	•
Private prizes coefficient	-2.6919	0.0107	$*$
Observations	56		

Now we add to our model the measure of marketing activity on Facebook—the variable *Posts per day*. Since the values of this variable are highly skewed, we apply a log transformation. The regression coefficients and their corresponding *p*-values are provided in Table 7.4. As expected, the variable *Posts per day* has a positive impact on project success and the coefficient estimate is significant at the 1% level. Surprisingly, *Length* becomes statistically significant at the 10% level and seems to be positively correlated with success. *Goal* remains statistically significant at the 5% level and its coefficient estimate is negative. The variable *Reward categories* becomes insignificant (*p*-value: 0.52). The coefficient estimate for *Private prizes coefficient* remains negative and is statistically significant at the 5% level.

Table 7.4: Success determinants: Probit regression 4

	Coefficient	p-value	
Intercept	18.5082	0.0017	∗∗
Length45	1.0911	0.0597	•
log (Goal)	-1.3428	0.0038	∗∗
Reward categories	0.0215	0.5217	
Private prizes coefficient	-2.6587	0.0267	∗
log (Posts per day)	1.1897	0.0015	∗∗
Observations	56		

Chapter 8

Panel Data Analysis: Funding Dynamics

In this part of our econometric analysis, we explore the funding dynamics of projects in our second dataset, for which we have data on contributions over time and also data on the marketing activity. We test Hypotheses 4 and 5 by investigating the relationship between the amount of contributions a project receives and its past level of funding, and the change of this relationship in the final phase of the funding cycle. The data on marketing activity allows us to test Hypothesis 3—that is, whether the amount of contributions is positively related to the authors' recent activity on Facebook.

8.1 Methodology

The analysis of funding dynamics is conducted in the form of panel data regressions. We begin with the following baseline model:

$$\begin{aligned} PercentOfGoal_{it} &= \beta_1 lagCumulativePercentOfGoal_{it} + \beta_2 FirstWeek_{it} \\ &+\beta_3 LastWeek_{it} + \beta_4 PostFunded_{it} + \beta_5 lagContributions_{it} + \beta_6 NewPost_{it} \\ &+\beta_7 lagNewPost_{it} + \alpha_1 Goal_i + \alpha_2 Length_i + \alpha_3 RewardCategories_i \\ &+\alpha_4 PrivatePrizesCoefficient_i + \beta_8 DayOfWeek_{it} + a_i + u_{it} \end{aligned} \tag{8.1}$$

where i represents the i-th project, and t is the t-th day of a project's funding cycle. All the variables are defined in Chapter 5. Variables with coefficients β_1 – β_8 vary across projects and over time, while variables with coefficients α_1 – α_4

are control variables that describe individual projects but do not change over time. If β_1 is negative and significant, Hypothesis 4 (the relationship between the amount of contributions a project receives and its past level of funding is negative) is confirmed. As a next step, we add interaction terms involving *lagCumulative percent of goal* and the dummy variables *FirstWeek*/*LastWeek* to examine Hypothesis 5 (whether this negative relationship is moderated by time as the risk of a breakdown increases).

Since we suppose that contributions can be concentrated on certain days, we account for this possibility by including dummy variables for the day of the week. The error term comprises two components—a_i is the unobserved effect, and u_{it} is the idiosyncratic error. In all of the following regressions, we use cluster-robust standard errors because the assumption of homoskedastic and serially uncorrelated idiosyncratic errors is found to be violated—there is dependence among the errors over time within a project.

The fixed effects and random effects models are the two main methods of panel data estimation that are widely used in empirical research. In our estimation of Equation 8.1, we prefer the fixed effects approach over random effects on our data. The reason for this is that the unobserved effects at project level a_i are allowed to be correlated with the explanatory variables. As we assume that there exists such a correlation in our data, the use of the random effects model would result in inconsistent estimates. The random effects model is preferred due to its greater efficiency, but since the assumption that the unobserved effect is uncorrelated with each explanatory variable in all time periods holds rather exceptionally, the use of the fixed effects approach is generally more appropriate as it provides a better estimation of *ceteris paribus* effects (Wooldridge 2015).

As a supporting argument for the choice of the fixed effects model, we apply the Hausman test which selects between the two models by testing for statistically significant differences in the coefficients for the time-varying independent variables. In all of our following regressions, the Hausman test strongly rejects the null hypothesis of no correlation between the explanatory variables and a_i in any time period, which supports our choice of the fixed effects estimator. Importantly, the obvious disadvantage of the fixed effects model is that we cannot estimate the effect of explanatory variables that are constant over time as the fixed effects estimation removes all of them as well as unobserved time-invariant heterogeneity across projects.

8.2 Results

The estimation results of our baseline model (without the interaction terms) from Equation 8.1 are provided in Table 8.1. The dependent variable is the amount of money collected on a given day, expressed as a percentage of the project's goal. We control for all of the time-invariant characteristics of projects—*Goal*, *Length*, *Reward categories*, and *Private prizes coefficient*—but since we follow the fixed effects approach, we do not obtain estimates for these variables. We do not include project categories, because of the small number of projects belonging to each category. Since the values for the variables *Goal* and *Contributions* are highly skewed, we use log transformations.

We find a negative association between the amount of contributions a crowdfunding project receives on a given day and the level of funding it has already received. The coefficient estimate for *lagCumulative percent of goal* is negative and statistically significant at the 10% level. Even though the significance level is higher than 5%, we find support for Hypothesis 4. The dummy variable for *Last week* is strongly positively associated with the amount of contributions and highly significant (at the 1% level)—reflecting the accelaration in contributions in the last days of a project's funding cycle.

Surprisingly, the observed higher level of contributions in the first week of a campaign is not captured in the coefficient estimate for *First week*. It is probable that this early large number of contributions is accounted for by the marketing activity on Facebook (variable *New post*)—as there is a greater chance of new posts appearing at the start of a campain—and also by the variable *lagContributions*, which controls for immediate word-of-mouth and inertia effects. Moreover, as t starts on day 2, we cannot reflect the high percentage of goal contributed to a project on the first day in the analysis.

As expected, the dummy *Post funded* is negative and significant at the 1% level—the amount of contributions declines once the project reaches its goal. We find a positive association between the amount of contributions and the dummies *New post* and *lagNew post*. This supports Hypothesis 3: contributions are positively related to previous marketing activity on Facebook on the given day and the day before. Both coefficient estimates are significant at the 1% level.

The coefficient estimate of the variable *lagContributions* is positive and highly significant (at the 1% level)—the number of contributors on the previous day has a positive impact. In general, projects receive higher amounts of contributions on weekdays and fewer on weekends. The reference (baseline) day in our model is Friday. The funding peak occurs on Thursday, while the lowest levels of contributions are reported on Saturday. The dummy for Thursday is significant at the 10% level and the dummy for Saturday is at the 1% level.

Table 8.1: Funding dynamics: Fixed effects regression 1

	Coefficient	**p-value**	
lagCumulativePercentOfGoal	-0.0299	0.0919	•
FirstWeek	-0.4896	0.2283	
LastWeek	1.9931	0.0001	***
PostFunded	-1.7404	0.0088	**
NewPost	1.2672	0.0000	***
lagNewPost	0.8354	0.0018	**
log (lagContributions)	1.1800	0.0000	***
DayOfWeekMon	0.3300	0.3575	
DayOfWeekTue	0.3366	0.3785	
DayOfWeekWed	0.1749	0.6001	
DayOfWeekThu	0.6452	0.0578	•
DayOfWeekSat	-0.7102	0.0071	**
DayOfWeekSun	-0.0705	0.8320	
Adjusted R^2	0.080		
Observations	1890		
Projects	56		

Next, we add to our baseline model interaction terms involving *lagCumulative percent of goal* and the dummy variables *First week/Last week* and *Post funded.* The results are displayed in Table 8.2. The coefficient estimate for the interaction between *lagCumulative percent of goal* and *Last week* is positive and significant at the 1% level, thereby providing strong support for Hypothesis 5. On the other hand, the coefficient estimate for the interaction between *lagCumulative percent of goal* and *First week* is not significant.

The significant negative coefficient estimate for *lagCumulative percent of goal* and *Post funded* shows that the relationship between the level of funding already achieved and the amount of contributions is even more negative after a project reaches its goal. Moreover, as the risk of breakdown is no longer present, we can see that the negative effect of past contributions on the decision to contribute is not reduced in the last week to the same extent found in projects which have not yet met their funding goal. This is captured by the negative coefficient estimate for the interaction between *lagCumulative percent of goal*, *Last week*, and *Post funded*, though not statistically significant.

Table 8.2: Funding dynamics: Fixed effects regression 2

	Coefficient	**p-value**	
lagCumulativePercentOfGoal	-0.0177	0.1914	
lagCumulativePercentOfGoal * FirstWeek	-0.0118	0.5332	
lagCumulativePercentOfGoal * LastWeek	0.0432	0.0020	**
lagCumulativePercentOfGoal * PostFunded	-0.0957	0.0022	**
lagCumulativePercentOfGoal * LastWeek * PostFunded	-0.0161	0.3173	
FirstWeek	-0.1404	0.7729	
LastWeek	0.1911	0.5507	
LastWeek * PostFunded	-1.0764	0.2801	
PostFunded	8.2306	0.0020	**
NewPost	1.1249	0.0001	***
lagNewPost	0.7463	0.0056	**
log (lagContributions)	1.0383	0.0000	***
DayOfWeekMon	0.3157	0.3788	
DayOfWeekTue	0.3466	0.3643	
DayOfWeekWed	0.1949	0.5633	
DayOfWeekThu	0.6394	0.0541	•
DayOfWeekSat	-0.7391	0.0054	**
DayOfWeekSun	-0.1251	0.7080	
Adjusted R^2	0.108		
Observations	1890		
Projects	56		

As a final step, we present an alternative model examining the dynamics of contribution-giving in the final stage of a campaign. The model is applied to all projects in our second dataset for the last 10 days of their funding cycles only. Given the need to separate the time effect and the effect of past contributions, we introduce two key explanatory variables: *Days to end* and *Percent of goal missing*. The variable *Days to end* is chosen to better reflect the accelaration of contributions as the end date approaches. This was not possible in the previous model, where the variable *Last week* assumes higher but stable level of contributions in the last week.

The dependent variable is again *Percent of goal*—the amount of money collected on a given day as a percentage of the project's goal. We again control for time-invariant project characteristics (*Goal*, *Length*, *Reward categories*, and *Private prizes coefficient*), as well as for recent marketing activity on Facebook and the number of contributions on the day before (the variables *New post*, *lagNew post*, and *lagContributions*). The results are provided in Table 8.3.

Now we interpret the results. As expected, the coefficient estimate of the variable *Days to end* is negative and significant at the 1% level. This means that the amount of contributions is positively determined by the proximity of the closing date. However, the time effect is reduced for those projects which are already funded, as is demonstrated by the positive and highly significant coefficient for the interaction between *Days to end* and *Post funded*.

The effect of the amount missing is ambiguous. The variable *Percent of goal missing* is positive but not significant in this regression, and the significant positive coefficient for the interaction term between *Days to end* and *Percent of goal missing* actually suggests that the effect of the missing amount on the amount of contributions is greater when the closing day is further away. This result may be driven by the subsample of unsuccessful projects; the willingness to contribute decreases as it becomes obvious that the project will not meet its goal.

Table 8.3: Funding dynamics: Fixed effects regression 3

	Coefficient	p-value	
DaysToEnd	-1.3392	0.0000	$***$
DaysToEnd * PostFunded	1.1719	0.0001	$***$
PercentOfGoalMissing	0.0202	0.6796	
DaysToEnd * PercentOfGoalMissing	0.0135	0.0000	$***$
PostFunded	-10.8532	0.0000	$***$
NewPost	2.0981	0.0024	$**$
lagNewPost	0.1507	0.7999	
log (lagContributions)	0.6606	0.1075	
DayOfWeekMon	0.6035	0.4894	
DayOfWeekTue	0.5456	0.3938	
DayOfWeekWed	-0.0872	0.8882	
DayOfWeekThu	1.6132	0.0267	$*$
DayOfWeekSat	-0.4135	0.3341	
DayOfWeekSun	0.2490	0.7453	
Adjusted R^2	0.063		
Observations	561		
Projects	56		

Chapter 9

Discussion of Results

In our preliminary analysis of projects' funding dynamics, we found evidence of a bathtub-shaped pattern of contributions and marketing activity on social media over the funding cycle. The initial excitement at the launch of a project is followed by relatively low amounts of contributions for most of the remainder of the campaign, with renewed acceleration in contributions and greater marketing efforts on the part of the projects' authors observed towards the end date. However, this pattern does not hold for the subsample of unsuccessful projects.

Contributions to a project that will eventually fail are seen to constinuously decrease across the funding cycle, and we do not observe an increase in marketing activity as the end date approaches. This suggests that the success of a campaign is determined early on. As we demonstrated from the Hithit data, it is possible to separate successful from unsuccessful projects in the initial phase of the funding cycle—on day 2 for projects lasting 45 days and day 9 for projects of 30-day duration. At this stage, the causes of this earlier separation point for longer campaigns can only be surmised. Further analysis of the differences in funding dynamics between the two types of campaign would be needed to better understand this phenomenon.

Our cross-sectional analysis of the determinants of success found many of the same project characteristics associated with success on other crowdfunding platforms. Projects which have a video, offer more reward categories, have smaller goals, and which generate a higher number of posts on Facebook, are more likely to be successful. The same is true for a shorter length of campaign, which provides support for Hypothesis 1. No positive association between shorter length and success was found in our second dataset, but this may have been due to data limitations (the dataset consists of a rather small number of projects, from shorter time period).

It is important to add that the results of our analysis of success determinants do not assess causality. This is because the project characteristics are not selected randomly, but are correlated with the author's confidence or the quality of the project. It is therefore difficult to distinguish treatment effects. However, we were interested in the combined (observable) effect of each characteristic, consisting of the signaling effect and the treatment effect. When the two effects move in opposite directions, useful information about their magnitudes can be obtained. In the case of length of campaign, the signaling effect of the author's confidence outweighs the opportunity effect, as stated in Hypothesis 1.

While we can argue that the short duration of a campaign is mainly a sign of confidence, the use of a video and a higher level of marketing activity on social media can actually help to attract more contributors. Many unsuccessful projects may fail primarily because of unrealistically high goals. However, we did not observe the funding goals of failed projects to be three or four times higher than of successful ones, as was reported by Kuppuswamy & Bayus (2017); the difference was found to be considerably smaller. Furthermore, we observed from yearly success rates on Hihit that the proportion of successful projects steadily increased between 2013 and 2018, from 44.75% to 54.85%.

The novelty in our thesis' contribution is its analysis of the effect of private rewards. Our results suggest that crowdfunding projects which offer private rewards of lower market value are more likely to be successful. This finding refutes Hypothesis 2. It is possible that large private prizes have a negative effect on the funding decision of intrinsically motivated individuals—but again, we cannot argue that offering rewards of lower market value would help to achieve the project's target. It is more likely that potential contributors are more interested in projects with a higher public good component than in pre-selling campaigns, which are characterized by private prizes of higher value. These results are in contrast with the analysis by Crosetto & Regner (2014), who argue that higher presence of pre-selling rewards is positively associated with the success of a project.

Our panel data analysis of funding dynamics provides evidence in support of Hypothesis 3: the amount of contributions a crowdfunding project receives on a given day is positively and strongly related to previous marketing activity on Facebook as contributors respond to calls for contribution. After accounting for unobserved heterogeneity, time-invariant project characteristics, the role of marketing activity, and the number of contributors on the previous day, we found support for Hypothesis 4—there is a negative association between the amount of contributions a crowdfunding project receives and the level of funding it has already achieved. The analysis of the extended model with interaction terms, as shown in Table 8.2, provides evidence for Hypothesis 5. These results are in line with the findings of Kuppuswamy & Bayus (2017): as the end date approaches, potential contributors are more willing to provide funding even when others have contributed too. The overall effect associated with past contributions becomes positive for not-yet-funded projects.

Our alternative model examining the funding dynamics of projects in the last 10 days of a campaign provides strong evidence for a breakdown risk effect—the amount of contributions is positively determined by the proximity to the closing date. The all-or-nothing mechanism with a fixed time horizon dominates on non-equity crowdfunding platforms all around the world. We can argue that having a specific end date helps in achieving the project's goal, as the risk of a breakdown increases, mobilizing project authors and contributors—both of whom are less active in the middle of the funding cycle. We also observed that people are generally less interested in contributing to a project that has already reached its funding goal. We suggest that future research could further investigate the importance of the specific goal and campaign length, and the differences in funding dynamics between pre-selling campaigns and others.

Chapter 10

Conclusion

Crowdfunding is a new method of raising funds from the general public for innovative ideas and new projects. Potential contributors on crowdfunding platforms can observe the level of funding already provided by others before making their own contribution. As has been shown in previous empirical research, this information about past contributions is crucial to the funding decision, and thus to the ultimate success of a project. In our analysis of fudning dynamics, we found evidence for the diffusion of responsibility and free-riding effects, giving rise to a negative association between the amount of contributions and prior levels of funding (as opposed to irrational herding behavior). These effects present a difficult challenge for project authors in working towards fulfilment of their projects' goals.

As the end date approaches, we observe more dynamics in funding and the negative effect of past contributions is reversed as the risk-of-breakdown effect outweighs the free-riding effect. However, with few exceptions, the success of a campaign is determined early in the funding cycle. Our results confirm the importance of marketing activity on Facebook in generating more contributions for a project. We can therefore argue that the marketing efforts of authors are most important in the initial phase of a campaign, when there is a need to attract many contributors via social media and other channels. The finding of a positive and strong relationship between recent posts on Facebook and the amount of contributions is crucial, in that this is something that can be directly influenced by project authors. We suggest that additional research might consider the role of other channels.

Examination of the determinants of success reveals that campaigns of shorter duration are more likely to be successful. The novelty of the thesis lies in part in its analysis of the effect of reward values. We found that rewards of high market value are not the primary motivation for contributors. High private prizes, in fact, appear to have a negative effect on the funding decision. However, these results do not necessarily imply causality, as project's characteristics are correlated with the author's confidence and the quality of the project. Further research using controlled experiments would be needed to assess in detail the determinants of success.

This thesis contributes to the existing body of research from other empirical studies on the determinants of success and the funding dynamics of crowdfunding campaigns. Taken together, our results provide a greater understanding of the funding behaviors of contributors on the Czech crowdfunding platform Hithit, and can be generalized to other platforms with similar features.

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