THE DETERMINANTS FOR SUCCESSFUL CROWDFUNDING IN MALAYSIA

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.
(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.
(3) Equal contribution has been made by each group member in completing the research project.
(4) The word count of this research report is 19631.

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DEDICATION

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PREFACE

Arises from financial crisis 2008, small and medium enterprises faced difficulties in raising capital. A good credit rating is usually requiring by bank for loan approval. Even though the entrepreneur is eligible for the bank loan, higher interest rates charges by bank creates an additional profitability burden to them. Therefore, crowdfunding is an alternative way to the entrepreneurs to raise funds for their business from the general public. The importance of crowdfunding makes us keen to know what factors, i.e., funding target, duration, target per capita, density, virality, minimum reward, and description, will affect the probability of crowdfunding success in Malaysia. Through understanding these objectives, it can provide insight to all parties on the determinants of crowdfunding success in Malaysia.

ABSTRACT

This research attempts to investigate the impact of funding target, duration, target per capita, density, virality, minimum reward, and description on the probability of crowdfunding in Malaysia. In the research, secondary data from 2012 to 2018 was collected from Mystartr official website and logistic and probit regression analysis were employed to carry out the research. Diagnostic Checking such as expectation-prediction table and goodness-of-fit tests also employed in order to observe the performance of estimated binary model. The results showed that higher funding target and target per capita negatively associated with probability of crowdfunding success. However, higher number of supporters, virality, and minimum reward positively associated with probability of crowdfunding success. Duration unexpectedly do not have any effect on probability of crowdfunding success. In examining the effect of virality components, images significantly affect probability of crowdfunding success. Furthermore, through observing the effect of project description components, the result showed that including info (images and videos) and budget plan in a project description will lead to reduce in the probability of crowdfunding success. Through combine the components of virality and project description and distinct it into different models, Model 7 (Table 4.8) from logit regression is the most accurate and best fit with our study. Although this research has its own limitations, this study is still applicable for entrepreneurs, firms, crowdfunding platforms operator and academician on the determinants for crowdfunding success in Malaysia.

CHAPTER 1: RESEARCH OVERVIEW

1.0 INTRODUCTION

This research examines the determinants for successful crowdfunding in Malaysia. Firstly, this chapter will give an overview of crowdfunding and background of Malaysia crowdfunding. Based on the research background, research problem for the study is identified and all of the research questions, research objectives and hypotheses are mapped out. Lastly, significance of study will be discussed in this chapter too.

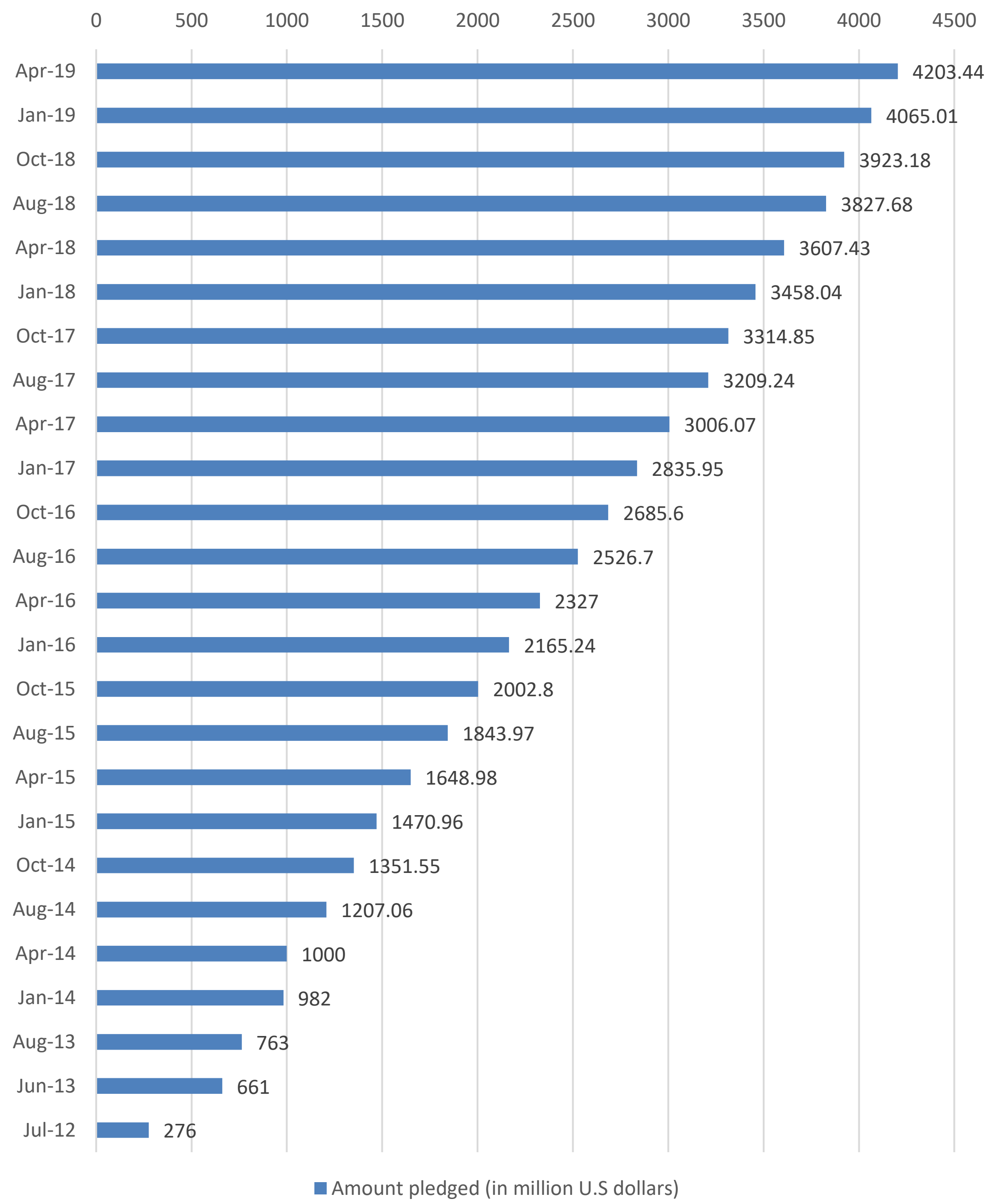
1.1 RESEARCH BACKGROUND

Crowdfunding is defined as an online distributed funding model to raise funds for their businesses from general public whether in form of donation or in exchange for a reward (Belleflamme, Lambert & Schwienbacher, 2010). Crowdfunding is recognized globally for its impressive growth rates. Based on the data presented in The Statistics Portal, Kickstarter had pledged more than 4.2 billion U.S. dollars as from July 2012 to April 2019 (Figure 1.1). More than 439,000 projects had been launched in Kickstarter and 344 projects have managed to raise in excess of 1 million U.S. dollars each.

Moreover, other countries are started to show interest and commitment on crowdfunding. For example, European Commission had issued an action plan in year 2011 in order to improve entry to finance Small and Medium Enterprises (SMEs). Since some specific provisions did not include into the action plan, several policy discussions had been addressed (Buysere, Gajda & Kleverlaan, 2012). In addition, Indonesia also shows interest towards crowdfunding. Ibrahim and Verliyantina (2012) stated that Indonesia had proposed a crowdfunding model to backing Small and Medium Enterprises.

Crowdfunding had been developed in a systematized way arises from financial crisis 2008, which caused SMEs faced difficulties in raising capital. Crowdfunding did not have credit rating requirements to the project founders (Xu, Guo, Xiao & Zhang, 2018). However, a good credit rating is usually requiring by bank for loan approval. Although the entrepreneur is eligible for the bank loan, higher interest rates charges by bank creates an additional profitability burden to them. Thus, crowdfunding is an alternative way to the entrepreneurs to raise funds in having access to people all around the world (Bradford, 2012). A crowdfunding project can be financial support by a group of investors directly without going through an intermediary.

Figure 1.1: Total Amount of Funding Pledged to Kickstarter Projects 2012-2019

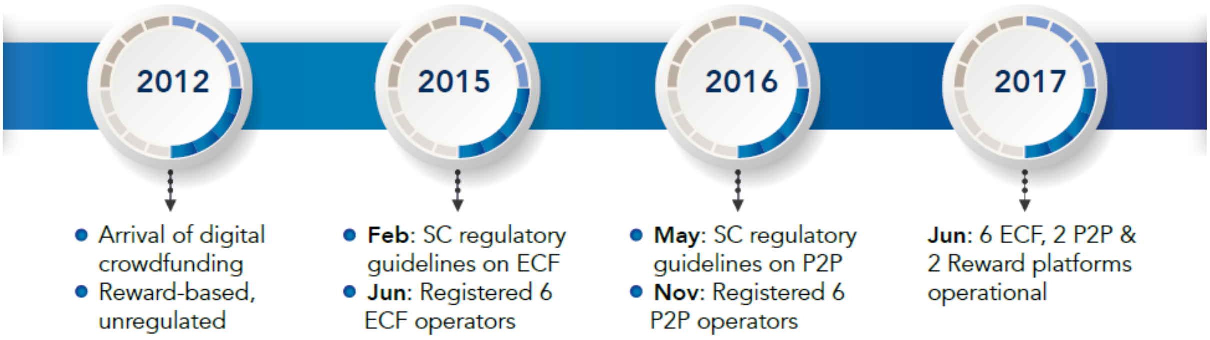


Source: Statista 2019

In general, there are four main types of crowdfunding which are equity-based crowdfunding, lending-based crowdfunding, reward-based crowdfunding, and donation-based crowdfunding. Equity-based crowdfunding is where investors invest into a company in exchange for its shares. Lending-based crowdfunding is where investors will receive interest payments as a return by provide loans to support Start-ups or SMEs (Marsan, Asutay & Boseli, 2014). Reward-based crowdfunding is where supporters will receive a reward for supporting that project such as small gift or products developed. Donation-based crowdfunding typically is the supporters did not have any expectation to receive compensation by funding a project.

Malaysia involved in community-based crowdfunding started from early year of 1980 (Asian Institute of Finance, 2017). Digital crowdfunding arrived at Malaysia in year 2012 (Figure 1.2). Reward-based crowdfunding only focused on community, social causes and arts categories in the first three years. Started from year 2015, investment-based crowdfunding was introduced into Malaysia. Securities Commission had imposed some guidelines on investment-based crowdfunding which involve sale of equity and debt.

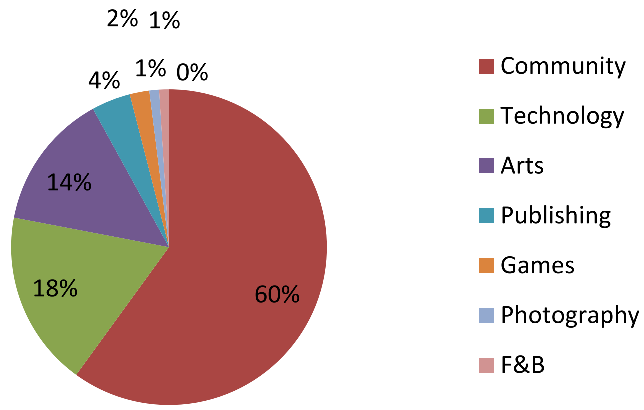
Figure 1.2: Malaysia Crowdfunding Milestones



Source: Asian Institute of Finance (2017)

There are numerous crowdfunding platforms in Malaysia that can help entrepreneurs to raise capital for their businesses (Table 1.2). Among all of these crowdfunding platforms, Mystartr is the most popular reward-based crowdfunding platform in Malaysia that many people will choose to raise funds with. Figure 1.3 shows all of the reward-based crowdfunding project categories such as community, technology, arts, publishing, games, photography, and food & beverage. More than half of the reward-based projects are community-based follow by technology-based and arts-based.

Figure 1.3: Breakdown of Reward Projects



Source: Asian Institute of Finance (2017)

Table 1.1: Top 10 Crowdfunding Platforms in Malaysia

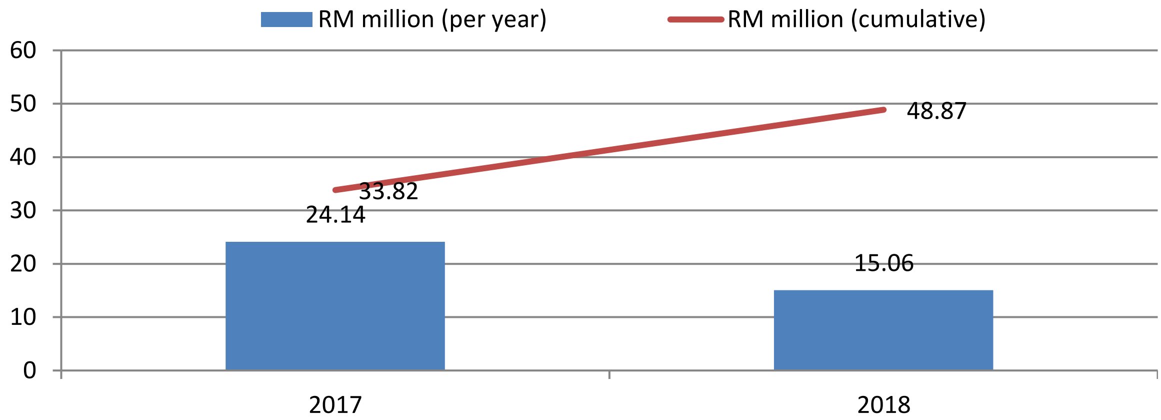
Top 10 Crowdfunding Platforms in Malaysia
MystartrSdnBhd
pitchINSdnBhd
SkolaFundSdnBhd
PeoplenderSdnBhd
ATA PLUSSdnBhd
Netrove Ventures Groups
Alix GlobalSdnBhd
EthisKapitalSdnBhd
EdSpace Projects SdnBhd
GIVE.MY

Source: Asian Institute of Finance (2017)

PitchIN is the famous equity-based crowdfunding platform in Malaysia. CEO of PitchIN revealed that their company has uphold its position as the top equity crowdfunding operator by maintain 100% success rate as until year 2018 (Pikri, 2019). Other than that, P2P financing was accounted a huge success in Malaysia in year 2018 due to it had been driven largely by young generation who have fewer biases in investing and they mostly using electronic devices when invests.

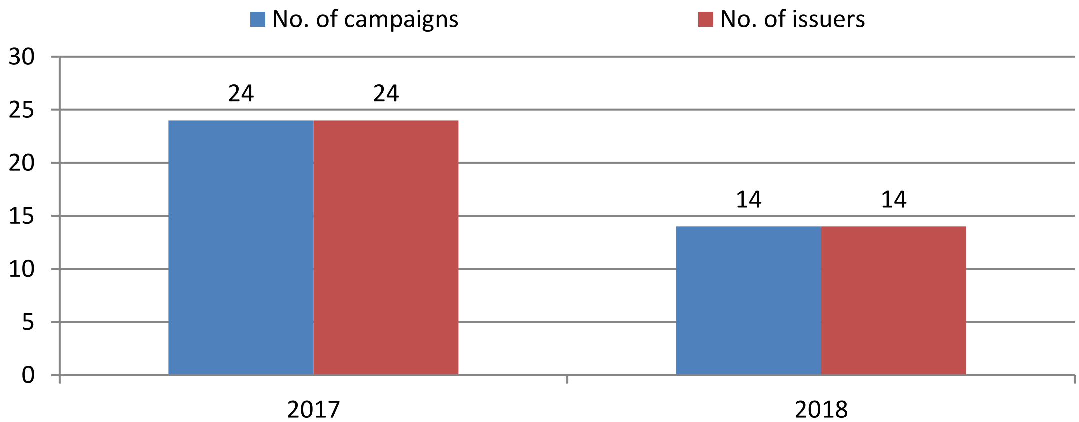
According to the data presented by Securities Commission Malaysia, equity-based crowdfunding (ECF) has pledged RM48.87 million capitals (Figure 1.4) through 51 projects as until year 2018. In year 2018, RM15.06 million was raised through 14 projects (Figure 1.5). Besides that, there have 2,505 successful peer-to-peer (P2P) financing projects transverse over 643 founders, which had raised a total of RM212.65 million as from year 2015 until year 2018 (Figure 1.6). In year 2018, P2P financing had raised RM180.05 million which reflecting 452% development compared to year 2017 (Figure 1.7).

Figure 1.4: Capital Raised (Equity crowdfunding)



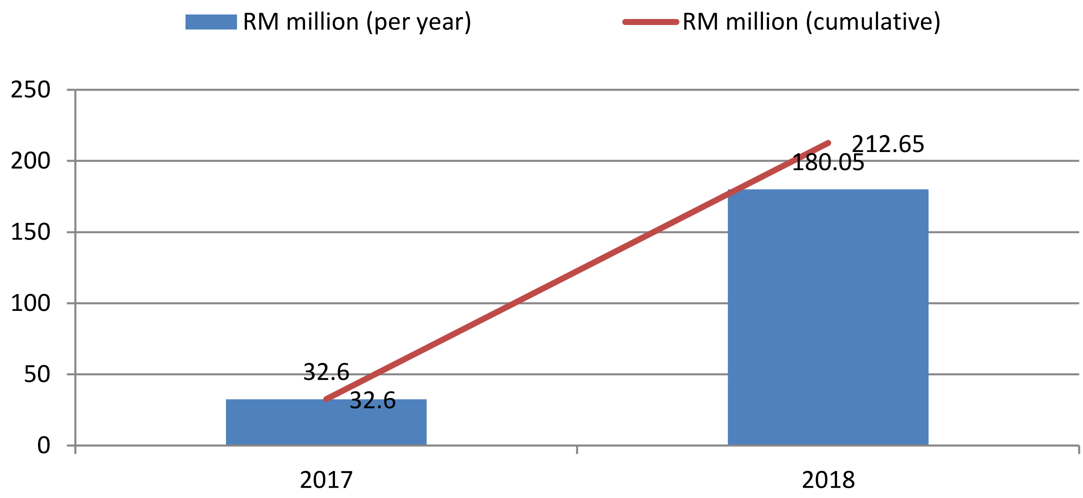
Source: Annual report of Securities Commission Malaysia (2018)

Figure 1.5: Number of Successful Campaigns and Issuers by Year (Equity Crowdfunding)



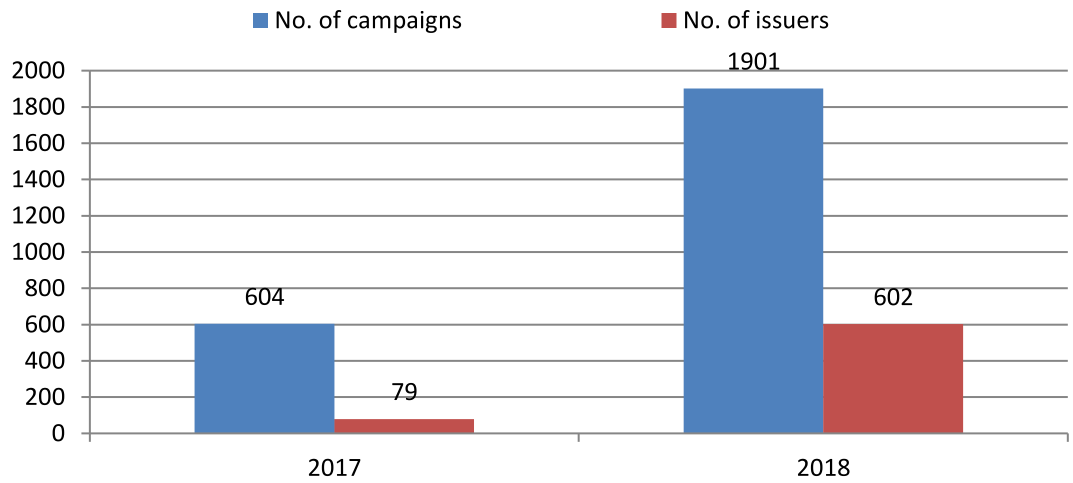
Source: Annual report of Securities Commission Malaysia (2018)

Figure 1.6: Capital Raised (P2P Financing)



Source: Annual report of Securities Commission Malaysia (2018)

Figure 1.7: Number of Successful Campaigns and Issuers by Year (P2P Financing)



Source: Annual report of Securities Commission Malaysia (2018)

In conclusion, the acceptance level of publics on crowdfunding in Malaysia is still low (Asian Institute of Finance, 2014). Some important matters that require attention are factors that will contributing to successful crowdfunding. Therefore, this study aims to discover the problems related to crowdfunding and to determine the important factors that need to be considered by the entrepreneurs in order for their projects to be success.

1.2 PROBLEM STATEMENT

It is important to examine factors that will affect successful rate of crowdfunding in Malaysia. The number of projects launched in Malaysia crowdfunding platforms was relatively less when compare to other countries such as United States and China. The success rate of crowdfunding projects in Malaysia also lower, such as the success rate of projects launched at Mystartr accounted only 29.40% since 2012. Therefore, some issues need to be considered by the entrepreneurs before engage into crowdfunding.

One of the problems associated with crowdfunding is target per capita. Does the amount of fund each backer need in order to finances that project will have significant effect on probability of success? Funds that can be raised by a project through crowdfunding not just depend on the number of backers but it also need to consider amount of funds each backer pledged to the project. A project will be more likely to reaches it funding goal when it has higher number of supporters. It is because each supporter only needs to contribute a small amount of funds in order for that project to success. The lower the target per capita, the higher the probability of crowdfunding success.

In addition, will the project description will enhance investors confident to the crowdfunding projects? Moreover, does virality of the project will influence the probability of success? Cheung, Lee & Rabjohn (2008) stated that deeper project description can help investors in the process of making decision. The more the information uploaded by the project founder, it will increase project transparency and thus attract more supporters to support it (Thanh Tu, Anh & Ha Thu, 2018). After that, it will lead to virality of the project. Kuppuswamy and Bayus (2013) indicate that probability of crowdfunding success will be significantly affected by social information. Virality means frequent social spread of emotionally charged content where it can signal quality of the project. Hence, it will affect the project probability of success.

In conclusion, it was the issues associated with crowdfunding. It is important for us to identify and determine factors that will significantly affect the probability of crowdfunding success in order to improve successful rate of crowdfunding in Malaysia.

1.3 RESEARCH OBJECTIVES

1.3.1 GENERAL OBJECTIVE

The purpose of this study is to observe the determinants for successful crowdfunding in Malaysia.

1.3.2 SPECIFIC OBJECTIVES

It is important to identify the factors that will affect the probability of crowdfunding success in Malaysia. Hence, the specific objectives of this study are

1. To identify the impact of higher funding target on probability of crowdfunding success in Malaysia.
2. To examine the impact of longer duration on probability of crowdfunding success in Malaysia.
3. To identify the impact of higher minimum rewards on probability of crowdfunding success in Malaysia.
4. To examine the impact of higher number of supporters on probability of crowdfunding success in Malaysia.
5. To identify the impact of higher virality on probability of crowdfunding success in Malaysia.
6. To examine the impact of deeper project description on probability of crowdfunding success in Malaysia.
7. To identify the impact of lower target per capita on probability of crowdfunding success in Malaysia.

1.4 RESEARCH QUESTIONS

Based on the general and specific research objectives, research question is a guide for research and investigation of problem statement. Hence, the research questions of this study are

1. What is the impact of funding target on probability of crowdfunding success in Malaysia?
2. What is the impact of duration on probability of crowdfunding success in Malaysia?
3. What is the impact of minimum rewards on probability of crowdfunding success in Malaysia?
4. What is the impact of number of supporters on probability of crowdfunding success in Malaysia?
5. What is the impact of virality on probability of crowdfunding success in Malaysia?
6. What is the impact of project description on probability of crowdfunding success in Malaysia?
7. What is the impact of target per capita on probability of crowdfunding success in Malaysia?

1.5 HYPOTHESIS OF STUDY

This proposed research provides seven hypotheses to test factors that will affect the successful rate of crowdfunding in Malaysia. Hence, the hypotheses of this study are

1.5.1 Funding target

H_0: Higher funding target will not lead to higher probability of crowdfunding success.

H_1: Higher funding target will lead to higher probability of crowdfunding success.

1.5.2 Duration

H_0: Longer duration of the project will not lead to higher probability of crowdfunding success.

H_1: Longer duration of the project will lead to higher probability of crowdfunding success.

1.5.3 Minimum reward

H_0: Higher minimum reward will not lead to higher probability of crowdfunding success.

H_1: Higher minimum reward will lead to higher probability of crowdfunding success.

1.5.4 Density

H_0: Higher number of supporters will not lead to higher probability of crowdfunding success.

H_1: Higher number of supporters will lead to higher probability of crowdfunding success.

1.5.5 Virality

H_0: Lower virality will not lead to higher probability of crowdfunding success.

H_1: Lower virality will lead to higher probability of crowdfunding success.

1.5.6 Description

H_0: Deeper project description will not lead to higher probability of crowdfunding success.

H_1: Deeper project description will lead to higher probability of crowdfunding success.

1.5.7 Target per capita

H_0: Lower target per capita will not lead to higher probability of crowdfunding success.

H_1: Lower target per capita will lead to higher probability of crowdfunding success.

1.6 SIGNIFICANCE OF STUDY

Factors that will affect the probability of crowdfunding success has been an attractive issue to entrepreneurs and crowdfunding platform operators for a long period. This research is capable to explain whether the independent variables (funding target, duration, density, target per capita, virality, minimum reward, and description) will affect the dependent variable (probability of crowdfunding success).

In this study, we intend to recognize determinants for successful crowdfunding and distinguish which factors will significantly affect probability of crowdfunding success in Malaysia, where there are no similar studies had been done before. This study has discovered some new variables that will influence the probability of crowdfunding success such as virality, description, and target per capita. By using regression analysis, we attempt to explain whether all of the variables include in this study have significant effect on probability of crowdfunding success in Malaysia.

Other than that, the contribution of this study could assist community to know which factor will significantly affect the probability of crowdfunding success in Malaysia. They can have a clear picture of how the factors affect probability of success and distinguish which variables affect the most. For example, project duration negatively associated with probability of crowdfunding success, which means longer project duration could led the project to success. Moreover, societies also can identify the challenges at the beginning of the campaign via this study. The common challenge that every entrepreneur will face at the initial stage of their campaign is they did not make enough impression to the investors.

In short, this study enables entrepreneurs have a better understanding on the determinants of successful crowdfunding. It also can help to promote crowdfunding as an alternative funding platform that enables the development of SMEs because the acceptance level of publics on crowdfunding in Malaysia is still low.

1.7 CHAPTER LAYOUT

The remaining chapters of the research are organized as follow. Chapter 2 will provide a literature reviews based on the previous studies which related to our research, and provide a summary table of the study. This chapter will end by describing the gap for research. Chapter 3 demonstrates the research methodology that shows the methods and techniques that will focus and use. This chapter will also further describe the model specification, data collection method, and data analysis. Chapter 4 focuses on describes the results and findings by using model and techniques in the previous chapter. Chapter 5 is the last chapter that concludes or summarize the results of the research. This chapter conclude with policy implication, limitation of study, and contribution of the study.

CHAPTER 2: REVIEW OF THE LITERATURE

2.0 INTRODUCTION

This chapter will give an introduction about concept of crowdfunding and types of crowdfunding. A literature review of crowdfunding will be discussed in this chapter too. Under literature review, previous researchers had determined some factors that will affecting crowdfunding success which are shown in Table 2.1. Based on the literature review, gap for our research is identified.

2.1 CONCEPT AND FOUNDATION OF CROWDFUNDING

Kickstarter was the first crowdfunding platform launched in year 2009. Nowadays, Kickstarter is the most popular and actively used crowdfunding platform in US. Kickstarter projects had been supported by more than 10 million people and pledged more than $3.2 billion (Zhou, 2018). In this technological era, crowdfunding becoming an alternative platform to entrepreneurs and SMEs as they can use this platform to raise capital for their projects or businesses. However, a project will be considered as unsuccessful when it unable to reach its funding target (Yuan, Lau & Xu, 2016).

Moisseyey (2013) stated that crowdfunding is a way for individual or businesses requests the community to perform certain work without any initial payment. More specifically, entrepreneurs and SMEs can raise capital for their project from the general public through crowdfunding platform. Funds pledged by each crowdfunding projects can be range from hundred dollars to million dollars based on their project size. An online space-trading-and-combat video game “Star Citizen” had successfully raised around $91.35 million through crowdfunding, where it is the highest pledged crowdfunding project (Chen, Thomas & Kohli, 2016).

Chen, Thomas & Kohli (2016) stated that Pebble smart watch is the first successful crowdfunding project in Kickstarter. In earlier, Pebble smart watch was named as “in Pulse”. “in Pulse” had raised $375,000 in the beginning but failed to get additional funding until the end of the funding period, so the funds pledged had been returned to the investors. In year 2012, project founder renamed his concept as “Pebble” and startup a business called “Pebble Technology”. Later, “Pebble” launched at Kickstarter and successfully raised more than $10 million within 30 days. After one year, Pebble smart watch were manufactured and had been hand over to investors and retailers.

Colombo, Franzoni, and Rossi–Lamastra (2015) stated that no matter how good the project it is, if the project was lack of supporters at the beginning, it would unable to attract more supporters. Other than that, there are some issues needs to be pay attention in the early stage of crowdfunding. The researcher pointed that greater level of contribution reached in the early stage of crowdfunding will reduce uncertainty. In addition, funding a project that is expected to be unsuccessful is consider as wasting time. This is because supporters need to register on that platform and follow all of the instructions in order to supporting a project. Furthermore, the transactions will not proceed immediately and the money will be on hold.

Crowdfunding also is a way to raise fund through online by requesting general public to pledge those projects usually for a relatively short period, such as few months. Project founders can easily share their projects through social media in order to attract more investors. Crowdfunding can be used for various types of project, such as charitable cause, creative project, and business startup. “Fundraisers” launched by Facebook in year 2017 allow its users to raise funds for nonprofits, which further expand the crowdfunding boundaries to 2.2 billion active Facebook users worldwide (Statista, 2017).

According to Diogo, Nogueira & Moutinho (2014), crowdfunding gives companies the right in communication. By launching a project at crowdfunding platform, the companies able to gain access to information such as preferences, reservation prices and market penetration. Crowdfunding platform act as an intermediary and help to promoting the project directly to the publics. Hence, company and entrepreneurs can collect and give information to the market at the same time.

Crowdfunding consists of three types, which are equity-based, reward-based, and donation-based crowdfunding (Belleflamme & Lambert, 2014). The supporters of equity-based and reward-based projects will receive financial or non-financial incentives as an appreciation. On the contrary, donation-based project supporters will not receive any incentives from the project founder. Wash and Solomon (2014) stated that donation-based projects almost under education and community category, thus providing financial and social support to individuals and communities whose faced difficulties.

2.2 TYPES OF CROWDFUNDING

2.2.1 Donation-Based Crowdfunding

Donation-based crowdfunding is where investors have no expectation to receive any compensation such as products, gifts, or rewards by funding a project. The founders of donation-based crowdfunding project will be appreciative to the investor's donation of fund.

In donation-based crowdfunding, the backers funded with "no return". However, the project founders often promised return is the products that will be developed or a "Thank you" card. Examples of donation-based crowdfunding platforms are GoFundMe, YouCaring.com, GiveForward, FirstGiving, Crowdfunder and Rocket hub. Lee, Yen and Fu (2016) stated that donation-based crowdfunding raise funds from the general public through social media and the crowdfunding website, thus it has the potential to democratize capital raising. In addition, donation-based crowdfunding platforms function as unregulated open market where there is less intervention in the process of raising funds.

2.2.2 Investment-Based Crowdfunding

Investment-based crowdfunding is that the investors pledged that project whether in form of debt or equity in return for a capital ownership. Investment-based crowdfunding differ from donation-based crowdfunding in terms of return. By investing in investment-based crowdfunding project, project founder will provide an incentive in the form of company shares to the investors. Investment-based crowdfunding consists of P2P lending and equity-based crowdfunding, where the investors wish to get an interest, principal or dividends as a return from funding those projects (Borello, De Crescenzo & Pichler, 2015).

Kirby and Worner (2014) showed that P2P lending platform is primarily consist of three categories, such as guaranteed return model, client segregated account model, and notary model. The guaranteed return model is where investors will receive the amount that has been promised by the founder as a return. Client segregated account model is where it uses by platform operator to distinct investors' money from the firm's money. The funds raised was collected in the bank account of the project founder, because the platform does not have the right to access the bank account. Moreover, notary model act as an intermediary by matching the project founder and investors together. Bank will issue a loan promissory note to investors to prove that the project founder had collected the money.

For equity-based crowdfunding, it usually is for start-ups business to raise capital by providing equity stake as a return to the investors who pledged the business.

2.2.3 Reward-based Crowdfunding

Reward-based crowdfunding is where investors will receive a reward as an appreciation from funding the project (Zoeli, 2014). In other words, reward-based crowdfunding aims for small businesses. Project founder launched their project on the crowdfunding platform and setting a funding target that they wish to achieve. As a return to the contribution of the investors, the project founder will give some incentives such as product that will be developed, album, tickets and more (Miller, 2019).

Reward-based crowdfunding is also known as "perks-based" crowdfunding which functions as pre-sale of products or services. An opportunity to pre-purchase the product at relatively attractive prices can be enjoy by the supporters by pledged that project. Additionally, reward-based project founder only needs to deliver the promised reward to the supporters when the campaign ends (Outlaw, 2013).

The two most popular worldwide reward-based crowdfunding platforms are Kickstarter and Indiegogo. According to the Miller (2019), Kickstarter had pledged more than $4 billion which backed by 15.6 million of people. Besides that, 5.1 million of people have support more than one project. Reward-based crowdfunding has been an attractive fundraising option for entrepreneurs and SMEs due to it is easy to launch and manage compare to traditional business finance.

Vissers (2017) stated that reward-based crowdfunding is the most popular and common crowdfunding for entrepreneurs and investors. First, it suitable for start-ups business to raise capital by offering some rewards to the public. Second, project founder can set different level of reward depending the amount of funds pledged by the investors. Third, it is available for general publics to support the project since it has no equity dilution. Last of all, it is easy to launch and manage (Okhrimenko, 2018).

2.3 COMMON FACTORS THAT AFFECT THE PROBABILITY OF CROWDFUNDING SUCCESS

2.3.1 Funding Target

Every crowdfunding projects will set a funding target that the project founder wish to achieve at the end of the crowdfunding period. There are two basic models that can be run by crowdfunding platform, which are “all or nothing” model and “keep-it-all” model. In “all or nothing” model, entrepreneurs will set a relatively lower funding goals, and only can obtained the pledge funds when it successfully reached the funding goals. In “keep-it-all” model, entrepreneurs can obtain all the pledged funds without need to consider whether the project is successful or failed (Cumming, Leboeuf & Schwienbacher, 2014). For “all or nothing” model, the project will have high probability to fail if any insufficient movement happen.

There are many researches had conducted research on the effect of funding target on probability of crowdfunding success. Cumming, Günther and Schweizer (2014) found that there is no significant relationship between funding target and the number of supporters, thus does not have effect on crowdfunding success. Higher funding targets can provide insurance to equity-based crowdfunding investors, because there will have greater number of investors invest to those projects in order to make it success (Hakenes & Schlegel, 2014). Cumming (2014), Mollick (2014) and Zheng et al. (2014) indicates that higher funding targets are negatively correlated with reward-based crowdfunding success. Funding target will have different impact on probability of crowdfunding success in different types of crowdfunding. Belleflamme et al. (2014) stated that higher funding target is preferred in equity-based crowdfunding, in contrast, reward-based crowdfunding more prefer lower funding target.

A project will be classified as successful if reached the funding goals before the deadline, whereas failed in the opposite. In the study of Levin (2015), funding target is positively correlated with crowdfunding success. In addition, the total number of images, the number of videos, the number of investment grades, and the information of the project founder will affect the funding goals (Thanh Tu, Anh, & Ha Thu, 2018). However, these variables will not affect the probability of success of the project.

According to Evers, Lourenco and Beijie (2012), funding goal will most influence probability of crowdfunding success. However, the result obtain for this study is not accurate since the data is collected from one platform only. Every crowdfunding platform have different among each other's. For example, some crowdfunding platforms allow project founders to collect pledged amount once reach their funding goal, but some platforms will give company shares as a return to the investors. Moreover, different proxy used by the researches in their studies, different results will be provided.

2.3.2 Duration

The duration of crowdfunding project is usually set before launching at the platform. Cumming, Günther, & Schweizer (2015) and Mollick (2014) found that longer duration has a negative relationship with rewards-based crowdfunding success. It might due to investors think that longer funding duration indicates founders' lack of confidence to their project. The researchers also stated that longer funding duration will brings some disadvantages to the project founder. This is because it will be leaving a relatively calm period in the middle of funding period. Additionally, investors will spend more time in the process of making investment decision and they may even overlook the project. In contract, in the study of Zheng, Li, Wu and Xu (2014), longer project funding period was positively related to the crowdfunding success in China, while no significant relationship to the crowdfunding success in United States. Furthermore, Burtch, Ghose, and Wattal (2013) found that longer durations have significant effect on donation-based crowdfunding projects due to it indicates higher project visibility.

2.3.3 Social Media Networks

There are few researches shows that there is positive relationship between social media networks and probability of crowdfunding success. As Etter, Grossglauser and Thiran (2013) found that the number of social media posts will affects crowdfunding success. According to Mollick (2014), any updates posted by the founders on the social media would let the backers know more about the progress of the projects. Based on Zheng, Li, Wu, and Xu (2014), the successful rate of a reward-based crowdfunding significantly affected by the size of social media network.

Besides that, Kaur & Gera (2017) found out that there is a positive relationship between social media and successful rate of crowdfunding. Social media such as Facebook and Twitter are the good platforms that can coordinate the interaction between creators and backers. Hence, backers can know well about the progress of the crowdfunding project and build trust towards the creator. Creators can easily promote their project through social media such as Facebook, Twitter or other social media platform by posting videos, images, and update their profile or information.

There is some research had been made on how social media affect crowdfunding success. According to Hekman & Brussee (2013), online social networks will positively affect crowdfunding success. For example, a crowdfunding project with infrequent updates of progress of the project and diverse network can lead to lower success rate. To increase the probability of crowdfunding successful, project backers must update their progress through the social media frequently.

Colombo, Franzoni and Rossi-Lamastra (2015) stated that there is no relationship between social media network and successful of crowdfunding. This research also stated that crowdfunding project will be more likely to be success if the project creator builds up relationship with others project founders by supporting each other’s project. This could increase the interaction among the project creators in the same crowdfunding platform.

2.3.4 Interaction of Backer and Creator

According to Wang, Li, Liang, Ye & Ge (2018), interaction between backer and creator will lead to increase in the probability of crowdfunding success. The review of the project is an important indicator to the crowdfunding success. If the project receives a lot of positive comment, it would enhance investors' confidence towards that project. Investors might not want to take risk to support that project if there are many negative comments about that project. Besides that, the length and quantity of review is also important to the investors in making decision. If the comments described how good it is the project in details, thus, it will attract more investors to support the project. Consequently, it will increase the probability of crowdfunding project success. In addition, the project founder patiently and responsively when reply all of the questions asking by investors can enhance investors' confidence and attract more investors to support which will lead the project success.

2.3.5 Project Updates

Project updates will positively affect probability of crowdfunding success (Borst, Moser & Ferguson, 2018). If project founder frequently updates progress of their project, it can attract more investors. This is due to investors can follow up the progress of the project and potential investors also can make investment decision based on the relevant information provided by the founder. Furthermore, the numbers of updates posted by project creators in the social media have positive relationship to crowdfunding success. Many researchers claimed that the more frequent the project founder updates the progress of the project, the higher the probability of crowdfunding success.

2.4 GAP FOR RESEARCH

After going through the past studies done by the researchers, there are some new perspectives on the determinants of crowdfunding success. Most of the researchers had examines the effect of number of shares, number of images, number of videos, and number of updates on probability of crowdfunding success separately. In our study, these variables will be combined together and calculated on the basis of value-weighted index. The combination of these variables will be name as "virality". Virality in our study means how these components (shares, images, videos, and updates) can help the crowdfunding projects goes viral.

Other than that, some researchers used the total number of words as a proxy for project description. The project description may consist of thousands of words, but it may not sufficiently deliver all the relevant information related to the project. Hence, project description in our study consists of a few components such as founder profile, purpose, risk and challenges, images and videos, budget plan, and bilingual. These components will be calculated according to the percentages classified by us based on different conditions.

In summary, virality and project description will have impact on the probability of crowdfunding success. Further research will be done on both variables.

Table 2.1: Summary Table

Author	Title	Sample	Source	Method	Findings
Douglas J. Cumming; Gael Leboeuf; Armin Schwienbacher (2015)	Crowdfunding Models: Keep-it-All vs. All-or-Nothing	47,139 fundraising campaigns 2008 - 2013	IndieGoGo	Probit regression, Hypotheses Testing	Negative relationship between funding target and crowdfunding success. Campaign duration is negatively related to success in rewards-based crowdfunding. No relationship between social media networking and success of crowdfunding.
Schlegel Friederike; Hakenes Hendrik (2014)	Exploiting the financial wisdom of the crowd: Crowdfunding as a tool to aggregate vague information	Barack Obama collect about 750 million USD for his presidential campaign in 2008.	US	Binomial distribution, Comparative statics	Funding targets may provide security to funders in equity- and debt-based Crowdfunding, as their investments will only go through if sufficiently many other people also view the campaign sufficiently positively to invest in it.
Ethan Mollick (2014)	The dynamics of crowdfunding: An exploratory study	48,500 projects 2009 to 2012	Kickstarter	Descriptive pattern	Negative relationship between funding target and crowdfunding success. Campaign duration is negatively related to success in

					rewards-based crowdfunding. Positive relationship with social media networking and success of crowdfunding.
Haichao Zheng; Dahui Li; Jing Wu; Yun Xu (2014)	The role of multidimensional social capital in crowdfunding: A comparative study in China and US	$900 million to fund 13 million projects	Kickstarter	Descriptive statistics, Regression model	Negative relationship between funding target and crowdfunding success. Campaign duration is positively related to success in rewards-based campaigns. size of an Founder's social media network is a significant predictor of campaign success in rewards-based crowdfunding.
Gordon Burtch; Anindya Ghose; Sunil Wattal (2013)	An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets	All projects from the both platforms	Kickstarter IndieGoGo	Antecedents model, Consequences model	Longer campaign durations are associated with higher project visibility and thereby better performance in donation-based crowdfunding.
Massimo G. Colombo; Chiara Franzoni; Cristina Rossi-	Internal social capital and the attraction of early contributions	669 projects started during the fall of 2012	Kickstarter	Descriptive statistics, Probit regression	No relationship between social media networking and success of crowdfunding.

Lamastra (2015)	in crowdfundin g.				
Vincent Etter; Matthias Grossglause r; Patrick Thiran (2013)	Launch hard or go home! Predicting the success of Kickstarter campaigns.	16042 projects	Kickstarter	Dataset description	Number of social media posts about rewards-based crowdfunding campaigns will predicts their success of the crowdfunding.
Erik Hekman; Rogier Brussee (2013)	Crowdfundin g and Online Social Network	31,371 projects	Kickstarter Facebook	Statistical analysis, Scatterplot	Positive relationship between the success of crowdfunding and online social networks.
Fedor Levin (2015)	Success Determinants of Crowdfundin g Project	More than thousand project from Kickstarte r server; Conduct survey	Kickstarter, Facebook, LinkedIn and Vkontakte	OLS regression, Survey	Positive relationship between project category, amount funding, amount pledge and a number of backers. The duration and location are insignificance
Alexey Moisseyev (2013)	Crowdinvesti ng News-Effect Of Social Media On Crowdfundin g	All the “Ending Project” from the platform	Kickstarter	Hypotheses, Statistical method	Social media would positively affect the success of the crowdfunding projects. The potential backers can make a positive decision of whether to support the project or check which friends of the project

					creator have supported the project.
Mart Evers; Dr. Carlos Lourenço; Dr. Paul Beije	Main drivers of crowdfunding success: A conceptual framework and empirical analysis	All the “Finished Project” still accessible on IndieGoGo	IndieGoGo	Regression model	Positively affect the success of crowdfunding are image, cause of needs, picture appeal, perspective advocated, social comparison, and labelling Otherwise, decisional control, the number of words for comments have a negative relationship. The request size is insignificance.
Tran Thi Thanh Tu; Dinh Phuong Anh; Tang Thi Ha Thu;	Exploring Factors Influencing the Success of Crowdfunding Campaigns of Startups in Vietnam	124 projects	Betado.com; Comicola.com; Firststep.vn; Fundstart.vn; Funding.vn	Binary logistic regression, Multiple Linear Regression Model	The number of images, video and email information of the project founder have a positive relationship. Target amount of capital and number of investment level have a negative relationship.
Harmeet Kaur; Jaya Gera	Effect of Social Media Connectivity on Success of Crowdfunding Campaigns	4,121 projects (1,899 are successful and 2,232 are not)	Kickstarter	Logistic regression	Positive relationship between social media and successful of crowdfunding.

Nianxin Wang; Qingxiang Li; Huigang Liang; Taofeng Ye; Shilun Ge;	Understanding the importance of interaction between creators a and backers in crowdfunding success	959 projects (393 are successful while 566 are not)	Dreamore	Descriptive statistic, Binary logistic regression	A positive comment it would give the confidence for the backer to support the project. Positive relationship between the interaction of backer and creator and successful of crowdfunding.
Irma Borst; Christine Moser; Julie Ferguson;	From friendfunding to crowdfunding: Relevance of relationships, social media, and platform activities to crowdfunding performance	271 projects (204 projects were successful and 67 were not)	Voorde-kunst	Descriptive statistic, Linear regression	Positive relationship between project updates and the successful of crowdfunding. The project may attract more funders as project updating the latest information or progress

CHAPTER 3: METHODOLOGY

3.0 INTRODUCTION

In this chapter, research design, model specification, data collection method, and estimation will be discussed. We have selected funding target, duration, target per capita, density, virality, minimum rewards, and description as our independent variables while probability of crowdfunding success as our dependent variable. Total data employed is 433 observations which collected from Mystartr as from year 2012 to year 2018.

3.1 RESEARCH DESIGN

This study is to examine determinants for successful crowdfunding in Malaysia. This study using quantitative data in which it is cross-sectional data and all these secondary data is collected from Mystartr official website. These data are used to investigate the impact of independent variables (funding target, duration, target per capita, density, virality, minimum rewards, and description) on the dependent variable (probability of crowdfunding success; 1, successful while 0, unsuccessful), which is the objective of this study.

3.2 MODEL SPECIFICATION

This model include probability of crowdfunding success (1, successful while 0, unsuccessful) as dependent variable, while funding target (TAR_i), duration (DUR_i), target per capita (MIN_i), density (DEN_i), virality (VIR_i), minimum rewards (MINR_i), and description (DES_i) as independent variables.The estimated regression model in this study are

$$probability\ of\ success = f(TAR_i, DUR_i, MIN_i, DEN_i, VIR_i, MINR_i, DES_i) \qquad (3.1)$$

Where the following notation has been used:

3.2.1 Probability of Crowdfunding Success

If the amount of funds raised by the crowdfunding project is higher or equal to its funding target, it will be considered as successful. If the amount of funds raised is lower than the funding target, this project is a failed campaign. In our study, the probability of crowdfunding project is either 0 or 1. The value 1 indicates it is a successful project and 0 indicates the project is unsuccessful.

3.2.2 Funding Target ($\mathbf{TAR}_i$)

Funding target is the amount of capitals project founder wants to raises via crowdfunding for its business. The funds raised can help project founders to develop a product or service that they wish to produce. If the funding target was set too high, it will be difficult to accomplish. Hence, the probability of crowdfunding success will be higher if the project founder set a lower funding target (Mollick, 2014). However, the funding target set need to be high enough to cover all the expenses of the project (Ahler, Cumming, Günther, & Schweizer, 2015).

3.2.3 Duration ($\mathbf{DUR}_i$)

Duration is the amount of days the project used to raise fund. Burtch et al (2013) stated that the project will be successful reached its funding goals if the duration used to raise fund by the project is longer. However, Mollick (2014) and Muller, Geyer, Soule, Daniels & Cheng (2013) claimed that longer duration negatively associated with the probability of success since it does not guarantee that the project will be success. Muller et al. (2013) indicated that many projects did not make enough impression to the investors which caused it does not reach their funding goals.

3.2.4 Target per Capita ($\mathbf{MIN}_i$)

Target per capita is a calculation of funding target divided by the number of supporters. Funds that can be raised by a project through crowdfunding not just depend on the number of backers but it also need to consider amount of funds each backer pledged to the project. A project will be more likely to reaches it funding goal when it has higher number of supporters. This is because each supporter only needs to contribute a small amount of funds in order for that project to success. The lower the target per capita, the higher the probability of crowdfunding success. In contrast, lower number of supporters will cause each supporter to invest more funds. It will lead to investor's low willingness to invest more funds in order to make the project success.

3.2.5 Density ($\mathbf{DEN}_{\boldsymbol{i}}$)

Density is the number of backers supporting the project. The higher the number of supporters, the greater the probability of success (Ahler et al, 2015). Molick (2014) stated that the number of backers will positively affect the probability of project's success. The project will be easier to reach their funding goal if it has higher number of supporters compared to the project that has fewer supporters.

3.2.6 Virality ($\mathbf{VIR}_{\boldsymbol{i}}$)

Virality means frequent social spread of emotionally charged content whether it can be positive or negative content (Berger & Milkman, 2011).

Using pictures to promote a project can attract people to view the project. It easier for funders to share it to their family and friends and thus attracts more investors. Other than that, founder can use videos to present the idea of their project. Video can help delivers information more effectively since it delivers to people through their eyes, their ears, and their brains. If the project founder frequently updates the relevant information of the project, it may increase investor confidence towards the project (Koch and Siering, 2015). Crowdfunders can also get the project information through the social media such as Facebook. Lin, Prabhala & Viswanathan (2013) stated that factors that can lead to successful crowdfunding includes information about contributions, choices and interactions between founder and investors.

In our study, virality is the value-weighted index calculation of number of shares, number of updates, number of videos, and number of images that abstract directly from Mystartr.

Virality = $w_1 picture + w_2 video + w_3 share + w_4 update$ (3.2)

Where w_{1}, w_2, w_3, w_4 = the weightage of factors for each project
$picture$ = the number of pictures in each project
$video$ = the number of videos in each project
$share$ = the number of shares in each project
$update$ = the number of updates in each project

Equation 3.2 shows that w_1, w_2, w_3, w_4 is the weightage of factors for each project. The weightage of the factors for each project in our study is calculate based on the percentage that classify by ourselves which is 10 (0% to 100%, with 10 as the default). For example, if a project from the crowdfunding platform consist 10 pictures, it will be divided by 48 (the largest number of pictures among all of the projects) and then multiple it by 10. The number of pictures for each project is subsequently normalized against the base value of 48. It is due to some projects consist less than 48 pictures but successfully funded their funding target. In addition, the values on different scales will be converted into common scale for the purpose of comparison among all of the observations.

3.2.7 Minimum Reward($\mathbf{MINR}_{\boldsymbol{i}}$)

Minimum reward is one of factors that can affect the probability of crowdfunding success if chosen wisely (Drabløs, 2015). According to the Frydrych, Bock and Kinder (2015), the project founder set different levels of rewards in order to attract more investors to fund their project. Minimum reward in our study is the price of the incentive that supporter will receive when they funded the project and the price is estimate according to the product market price. The proxy used in our study was totally different with other researches. Table 3.1 shows the market price of common types of rewards will be receives by the supporters.

Table 3.1: Market Price of Common Types of Rewards

Types of rewards	RM
Bookmarks	2.00
Calendars	3.00
"Thank you" card	3.00
Badge	4.00
Key chain	5.00

3.2.8 Description ($\mathbf{DES}_i$)

Description is the relevant project information which consist of founder profile, purpose, risk and challenges, images and videos, budget plan, and bilingual. Detail project description can influence investors in making decision (Cheung et al, 2008).

In this study, all of the components of project description had been allocated based on our own ideas. First, founder profile includes their education or working background which can evaluate their dependability. Next, purpose of the project was necessary since it shows the objectives of the founder launched this project. Third, risk and challenge can better inform investors about difficulties faced by the founder. Image and video can deliver message more effectively compared with words. Furthermore, budget plan will let investors know how the funds invested will be use. Lastly, include different languages of project description can attracts other cultures supporters and thus raising more funds.

Table 3.2 shows the calculation on description in our study which calculated based on the percentages that classified by ourselves. The percentage for each category of the description assigned based on different conditions. For example, the category of owner's profile which has more than or equal 50 words will distribute 20%; owner's profile which has less than 50 words will distribute 10%; while owner's profile which do not has any word will distribute 0%.

Table 3.2: Calculation on Description

Categories	Percentages
Owner's Profile (About me) i. More than or equal 50 words ii. Less than 50 words iii. No words	 20% 10% 0%
Purpose of the Project	20%
Risk and Challenge	20%
Info of the Project i. Include images and videos ii. Only image, no video; if • More than or equal to 5 images • Less than 5 images • No image iii. No image but have video	 20% 10% 5% 0% 5%
Budget Plan	10%
Languages (include English and Chinese description)	10%

3.3 DATA COLLECTION METHOD

3.3.1 Data Sources

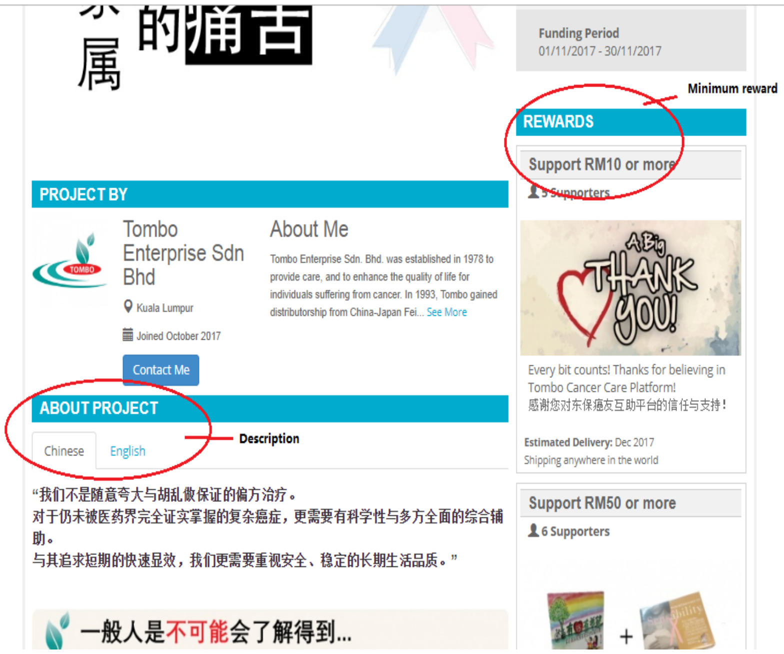
This study is using secondary data collected from Mystartr as from year 2012 to year 2018. Variables included are funding target, duration, target per capita, density, virality, minimum rewards, and description which involve a total of 433 observations.

Figure 3.1 to 3.3 shows how data extract from Mystartr official website. Funding target and density (number of supporters) can abstract directly from the website. Next, duration is calculated based on the number of days founder use to raise funds. Target per capita is the ratio of funding target divided by the number of supporters where both data can get from website directly. Moreover, virality is the value-weighted index calculation of the number of shares, number of updates, number of videos, and number of images that can be viewed in the website. Minimum reward is the prices of the incentive that will be receive by the supporter and it is estimate according to the product market prices. Lastly, description is relevant project information which consist of founder profile, purpose, images and video, budget plan, and bilingual which can be view at Mystartr.

Figure 3.1: Mystartr Official Website

Figure 3.2: Mystartr Official Website

Figure 3.3: Mystartr Official Website



3.4 ESTIMATION

3.4.1 Logistic Model and Probit Model

Logistic regression (logit) is an analytical analysis which use to explain the relationship between binary dependent variable and independent variables, which only consists of two values.

An explanation of logistic regression started with log-odds function value. It is defined as

$$Z_i = \beta_1 + \beta_2 X_2 + \varepsilon_i \qquad (3.3)$$

In a univariate regression model, Z_i act as linear function. Therefore, logistic regression change to

$$P_i = \frac{1}{1+e^{z}i} \qquad (3.4)$$

After simplification, Eq. (3.4) will become as

$$P_i = \frac{e^{z_i}}{1+e^{z_i}} \tag{3.5}$$

Eq. (3.5) becomes a logistic model as below after natural logarithms transformation.

$$\ln\left(\frac{P_i}{1-P_i}\right) = Z_i \tag{3.6}$$

Logistic analysis prediction of probability will be either equal to 1 or 0. 1 indicates that the event will happens while 0 indicates it will not happen. In the natural logarithms transformation, the probability of dependent variable will close to zero if the independent variable value is relatively low. In contrast, the probability of the dependent variable will be close to one (Klieštik, Kočišová & Mišanková, 2015).

Probit model explain a binary dependent variable by using normal cumulative density function.

An explanation of probit regression started with generalized linear models. It is defined as

$$\text{Zi} = \beta_1 + \beta_2 X_{2i} + \varepsilon_i \tag{3.7}$$

Based on the normality assumption, the probability of $I_i * \leq I_i$, will be computed as

Pi = P (Y= 1| X_i)

=P ($I_i* \leq I_i$)

= P (Z$\leq \beta_1 + \beta_2 X_{2i}$)

= F ($\beta_1 + \beta_2 X_{2i}$) (3.8)

Where P (Y= 1|X) is the probability that an event will happen given the value(s) of X.

F is the standard normal Cumulative Distribution Function, which written as

$$F(I_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{I_i} \frac{-z^2}{e^2}\, dz \tag{3.9}$$

Klieštik, Kočišová and Mišanková (2015) stated that the mains difference between probit and logistic is where probit assumes normal distribution of the independent variables and logistic function has a fatter tail. However, there is no significant differences between logit and probit in practice. It will only have different between them if the sample contains large number of observations.

3.4.2 Dependent Variable Frequencies

Dependent variable frequencies indicate the frequency and cumulative frequency table for dependent variable in binary model. Two tests were include under the dependent variable frequencies, which are categories regressor statistic and expectation-prediction (classification) table. Firstly, categories regressor statistic indicates the descriptive statistics which are mean and standard deviation for each regressor. The descriptive statistics are calculated for entire sample.

Next, expectation-prediction (classification) table indicates a table of correct and incorrect classification derived from user particular prediction rule and expected value calculations. Each study will be separated as having a predicted probability that lies above or below the cut-off. Correct classifications are attained during predicted probability is less than or equal to the cut-off, and show the observed y is equal to 0. Besides, observed y is equal to 1 when the predicted probability is larger than the cut-off.

3.4.3 Goodness-of-Fit Tests

Goodness-of-Fit Tests perform Pearson x^2 type tests of goodness-of-fit and it also evaluated fitted expected values to the actual values by group. If the differences are huge, the model will be reject since it given an inadequate fit to the data.

"Quantiles of Risk" in the EViews result signify the higher and lower value of the predicted probability for each decile. It also describes the actual and estimated amount of observations in each group with the contribution of each group. Large values show large differences between actual and estimated values. The result for Andrews test statistic and HL test is report as the basis of fitted values which fall between the structures of Andrews test. A mixed evidence of troubles may occur if the value for the Andrews test statistic is small while the *p* value for HL test is big.

CHAPTER 4: DATA ANALYSIS

4.0 INTRODUCTION

This chapter is going to analyze the data collected from Mystartr official website and a comprehensive discussion will be provided based on the results of descriptive analysis and regression analysis.

4.1 DESCRIPTIVE ANALYSIS

In explaining the general pattern, trend and basic features of data collected, descriptive statistics which included the mean, median, maximum, minimum, standard deviation, skewness and kurtosis is used in the analysis. The analysis included the dependent variable and independent variables from 2012 to 2018 as shown in Table 4.1.

Table 4.1 shows the descriptive statistics for all dependent and independent variables. The sample dataset used contain 433 crowdfunding projects launched at Mystartr between year 2012 and year 2018. Out of 433 projects, 127 projects had successfully funded their funding target, accounting for a 29.4% success rate. On average, each project has an average funding target of RM22599. The higher funding target among all the projects is RM750000. The average duration per projects was 46 days, funded by on average 44 backers per projects where each backer funded around RM364. The average virality shows that 79% of the projects can effectively social spread of emotionally charged content to people whether it is positive or negative content. It can be through shares, updates, videos, or images. In addition, the average minimum reward that supporters will be received was RM69. Some projects even did not provide any rewards, which only send a thank you card to their supporters. The highest minimum reward provided by the project founder worth RM5000. Within the project description, more than half of the successful projects have includes founder profile, purpose, videos and images, risk and challenges, or budget plan in their proposal and is translated into two languages, whereas English is the common language followed by Chinese.

Table 4.1. Descriptive Statistics

	Probability	Funding Target (RM)	Duration (Days)	Target per Capita (RM)	Density (Number of supporters)	Virality (Index)	Minimum Reward (RM)	Description (%)
Mean	0.2940	22599.84	46	3415.69	44	0.7953	69.84	59.1088
Median	0.0000	8000.00	43	364.30	10	0.6096	20.00	60.0000
Maximum	1.0000	750000.00	793	240000.00	2388	4.6378	5000.00	100.0000
Minimum	0.0000	0.00	1	0.00	0	0.0521	0.00	5.0000
Std. Dev.	0.4561	60159.23	42	14267.78	159	0.6651	327.60	17.6313
Skewness	0.9044	7.56	13	11.96	10	2.0896	11.36	-0.1471
Kurtosis	1.8180	73.03	230	183.06	123	9.1759	148.16	2.5730

4.2 REGRESSION ANALYSIS

In order to investigate factors that will influence crowdfunding success, two regressions analysis are run. Two regressions analysis which are probit regression and logistic regression model. Some diagnostic checking also has been run which are expectation-prediction table and goodness-of-fit tests in order to observe the performance of estimated binary model.

4.2.1 Baseline Result

According to Table 4.2, funding target is negatively associated with probability of crowdfunding success. When the funding target set by project founder is relatively high, it will reduce the probability of success since it might be difficult to achieve. Unexpectedly, duration has no significant effect on probability of crowdfunding success. Based on probit regression analysis, the result shows that target per capita is negatively correlated with probability of success. The higher the number of supporters funded that project, the lesser the funding amount each supporter has to invest in order for that project to success. Result shows that density is positively correlated at 1% significant level. Loeoey and Schwienbacher (2015) stated that the project will be more easily to reach their funding target if it has higher number of supporters.

Probability of crowdfunding success is positively affected by virality. By using pictures, videos, updates, and shares, project founder can frequent social spread of emotionally charged content whether it is positive or negative content (Berger & Milkman, 2011). The result shows that minimum reward also positively associated with probability of success. According to Drabløs (2015), if the project founders chosen wisely the reward, it can influence the successful rate of their projects. However, description does not have significant effect on probability of success. It possibly because the project description presented may not signal the preparedness and professionalism of project founders, thus decrease supporters' interest to support those projects.

In probit regression model, it can predict 86.34% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 15.74 percentage points. In logit regression model, it can predict 87.27% of the total observations. The estimated model predicted ability will improve by 16.67 percentage points if the model only predicts successful projects.

Table 4.2: Results from Probit and Logit Regression

Variables	Probit	Logit
Funding Target	-0.0001***	-0.0002***
	(0.0000)	(0.0000)
Duration	-0.0004	-0.0024
	(0.0019)	(0.0032)
Target per Capita	-0.0003**	-0.0004
	(0.0001)	(0.0003)
Density	0.0241***	0.0652***
	(0.0032)	(0.0095)
Virality	0.2066*	0.4259*
	(0.1248)	(0.2338)
Minimum Reward	0.0022**	0.0035*
	(0.0009)	(0.0019)
Description	0.0044	0.0049
	(0.0045)	(0.0081)
C	-0.8965	-1.5600
	(0.2944)	(0.5371)
McFadden R-squared	0.4330	0.4718
% of Correct Prediction	86.3400	87.2700
Total Gain	15.7400	16.6700
Prob. Chi-Sq	0.0276	0.0735

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.
Where target per capita = funding target / number of supporters; density represent number of supporters; virality = shares index + updates index + videos index + images index

4.2.2 Closer Look at Virality

According to Table 4.3 and Table 4.4, higher funding target negatively associated with the probability of success. The result shows that density positively associated with the probability of success. The more the supporters each project has, the higher the probability of the project can success. In addition, the results indicate that higher minimum reward will lead to higher probability of success since it can attract more investors to fund those projects. Based on the result shows in Table 4.3, higher target per capita will reduce probability of success. Each supporter needs to invest more funds into the project in order for that project to success. By examine the effects of virality components on probability of crowdfunding success, the result indicates that images index is positively correlated at 5% and 1% significant level, respectively. It possibly because images can promote a project more effectively by attract people to view the project and thus attracts more investors.

Based on the result from probit regression, Model 1, Model 2, and Model 3 can predict 85.88% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 15.28 percentage points. Model 4 can predict 87.04% of the total observation. If the estimated model only predicts successful projects, the predicted ability will improve by 16.44 percentage points. Based on the result shows in Table 4.4, all of the models can predict 87.73% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 17.13 percentage points.

Table 4.3: The Effects of Virality Components on Probability of Success – Results from Probit Regression

Variables	Model 1	Model 2	Model 3	Model 4
Funding Target	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration	-0.0001	-0.0001	-0.0002	-0.0002
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Target per Capita	-0.0003**	-0.0003**	-0.0003**	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Density	0.0247***	0.0248***	0.0248***	0.0234***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Minimum Reward	0.0022**	0.0021**	0.0021**	0.0021**
	(0.0009)	(0.0010)	(0.0009)	(0.0010)
Description	0.0052	0.0054	0.0050	0.0053
	(0.0045)	(0.0045)	(0.0045)	(0.0045)
C	-0.8371	-0.8242	-0.8268	-0.9829
	(0.2904)	(0.2894)	(0.2895)	(0.3005)
Virality				
Shares Index	0.2546			
	(0.2902)			
Updates Index		-0.0244		
		(0.0754)		
Videos Index			0.0224	
			(0.0499)	
Images Index				0.1319**
				(0.0560)
McFadden R-squared	0.4292	0.4280	0.4282	0.4389
% of Correct Prediction	85.8800	85.8800	85.8800	87.0400
Total Gain	15.2800	15.2800	15.2800	16.4400
Prob. Chi-Sq	0.0046	0.0154	0.0052	0.0142

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.
Where target per capita = funding target / number of supporters; density represent number of supporters; Shares Index, Updates Index, Videos Index, and Images Index are total number of shares, updates, videos, and images in each project, respectively.

Table 4.4: The Effects of Virality Components on Probability of Success – Results from Logit Regression

Variables	Model 1	Model 2	Model 3	Model 4
Funding Target	-0.0001***	-0.0002***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration	-0.0019	-0.0017	-0.0020	-0.0022
	(0.0031)	(0.0032)	(0.0031)	(0.0032)
Target per Capita	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Density	0.0657***	0.0671***	0.0660***	0.0653***
	(0.0095)	(0.0097)	(0.0095)	(0.0096)
Minimum Reward	0.0034*	0.0032*	0.0034*	0.0033*
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Description	0.0057	0.0062	0.0054	0.0065
	(0.0080)	(0.0080)	(0.0080)	(0.0082)
C	-1.3607	-1.3518	-1.3669	-1.7474
	(0.5171)	(0.5171)	(0.5173)	(0.5523)
Virality				
Shares Index	0.3435			
	(0.5458)			
Updates Index		-0.1158		
		(0.1573)		
Videos Index			0.0485	
			(0.0862)	
Images Index				0.2852***
				(0.1070)
McFadden R-squared	0.4662	0.4665	0.4660	0.4802
% of Correct Prediction	87.7300	87.7300	87.7300	87.7300
Total Gain	17.1300	17.1300	17.1300	17.1300
Prob. Chi-Sq	0.0517	0.0602	0.0343	0.0184

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.
Where target per capita = funding target / number of supporters; density represent number of supporters; Shares Index, Updates Index, Videos Index, and Images Index are total number of shares, updates, videos, and images in each project, respectively.

4.2.3 Decomposing Project Description

According to Table 4.5 and Table 4.6, probability of crowdfunding success highly affected by funding target and density. If the funding goals was set too high by project founder, it will be difficult to achieve. However, higher number of supporters will lead to successful crowdfunding. The result indicates that virality positively associated with crowdfunding success. It might be due to social spread of project information can effectively attract more investors. The result also indicates that higher minimum reward positively associated with probability of success. However, only Model 1, Model 2, Model 3, and Model 6 from logit regression shows that higher minimum reward has significant effect on probability of success. Based on the result shows in Table 4.5, probability of crowdfunding success will be affected by higher target per capita.

By examine the effects of project description components on probability of crowdfunding success, the result indicates that budget plan and info are negatively correlated with the probability of success. There might be some investors that have no interest to reviews the projects information that include budget plan and both the images and videos in project description. It might due to some investors only interested on the preparedness and professionalism of the project founders towards the project and they think that words can express things more clearly and directly.

Based on the result from probit regression, Model 2, Model 3, and Model 6 can predict 86.57% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 15.97 percentage points. Model 1, Model 4 and Model 5 can predict 86.11%, 87.04% and 86.81% of the total observation respectively. If the estimated model only predicts successful projects, the predicted ability will improve by 15.51, 16.20, and 16.44 percentage points respectively.

Based on the result shows in Table 4.6, Model 2 and Model 6 can predict 87.50% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 16.90 percentage points. Model 1, Model 3, Model 4 and Model 5 can predict 87.27%, 88.66%, 87.73% and 88.19% of the total observation respectively. If the estimated model only predicts successful projects, the predicted ability will improve by 16.67, 18.06, 17.13, and 17.59 percentage points respectively.

Table 4.5: The Effects of Project Description Components on Probability of Success – Results from Probit Regression

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Funding Target	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration	-0.0002	-0.0002	-0.0002	-0.0005	-0.0004	-0.0003
	(0.0019)	(0.0019)	(0.0019)	(0.0020)	(0.0019)	(0.0019)
Target per Capita	-0.0003**	-0.0003**	-0.0003**	-0.0003**	-0.0004***	-0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Density	0.0242***	0.0243***	0.0243***	0.0252***	0.0235***	0.0241***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Virality	0.2170*	0.2220*	0.2223*	0.2528**	0.2143*	0.2188*
	(0.1240)	(0.1240)	(0.1241)	(0.1246)	(0.1262)	(0.1238)
Minimum Reward	0.0021**	0.0021**	0.0022**	0.0020**	0.0018*	0.0022**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
C	-0.6869	-0.6950	-0.6906	-0.3492	-0.4657	-0.6929
	(0.1842)	(0.2114)	(0.1803)	(0.1944)	(0.1766)	(0.1673)
Description						
Profile	0.0609					
	(0.1667)					
Purpose		0.0574				
		(0.1873)				
Risk and Challenge			0.0785			
			(0.1729)			
Info				-0.5040**		
				(0.1744)		
Budget Plan					-0.5715***	
					(0.2039)	
Languages						0.1089
						(0.1009)
McFadden R-squared	0.4314	0.4313	0.4315	0.4472	0.4469	0.4332
% of Correct Prediction	86.1100	86.5700	86.5700	86.8100	87.0400	86.5700
Total Gain	15.5100	15.9700	15.9700	16.2000	16.4400	15.9700
Prob. Chi-Sq	0.0042	0.0011	0.0042	0.0031	0.0012	0.0006

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.

Where target per capita = funding target / number of supporters; density represent number of supporters; virality = shares index + updates index + videos index + images index; info means that description have include both the images and videos.

Table 4.6: The Effects of Project Description Components on Probability of Success – Results from Logit Regression

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Funding Target	-0.0002***	-0.0002***	-0.0002**	-0.0001***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration	-0.0023	-0.0024	-0.0022	-0.0030	-0.0027	-0.0024
	(0.0032)	(0.0032)	(0.0032)	(0.0035)	(0.0032)	(0.0032)
Target per Capita	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Density	0.0659***	0.0659***	0.0657***	0.0682***	0.0063***	0.0657***
	(0.0096)	(0.0096)	(0.0095)	(0.0098)	(0.0099)	(0.0096)
Virality	0.4375*	0.4468*	0.4384*	0.5163**	0.4525*	0.4351*
	(0.2334)	(0.2346)	(0.2338)	(0.2454)	(0.2357)	(0.2324)
Minimum Reward	0.0034*	0.0034*	0.0035*	0.0032	0.0028	0.0036*
	(0.0019)	(0.0019)	(0.0019)	(0.0020)	(0.0019)	(0.0020)
C	-1.2514	-1.4220	-1.3324	-0.7206	-0.9691	-1.3632
	(0.3319)	(0.3912)	(0.3286)	(0.3482)	(0.3166)	(0.3069)
Description						
Profile	-0.0811					
	(0.3058)					
Purpose		0.2233				
		(0.3424)				
Risk and Challenge			0.0970			
			(0.3161)			
Info				-0.9575***		
				(0.3248)		
Budget Plan					-1.0979***	
					(0.3837)	
Languages						0.2032
						(0.1844)
McFadden R-squared	0.4712	0.4716	0.4712	0.4881	0.4884	0.4735
% of Correct Prediction	87.2700	87.5000	87.7300	88.1900	88.6600	87.5000
Total Gain	16.6700	16.9000	17.1300	17.5900	18.0600	16.9000
Prob. Chi-Sq	0.0592	0.1145	0.0472	0.0388	0.0044	0.0544

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.
Where target per capita = funding target / number of supporters; density represent number of supporters; virality = shares index + updates index + videos index + images index; info means that description have include both the images and videos.

4.2.4 Finding the Winning Formula

According to Table 4.7 and Table 4.8, probability of crowdfunding success highly affected by funding target and density. When the funding target set by project founder is relatively high, it will reduce the probability of success since it might be difficult to achieve. However, higher number of supporters will lead to successful crowdfunding. The result indicates that higher minimum reward positively associated with probability of success. However, only Model 2, Model 4, Model 6, and Model 8 from logit regression shows that higher minimum reward has significant effect on probability of success. Based on the result shows in Table 4.5, probability of crowdfunding success will be negatively affected by target per capita. If each supporter needs to invest more funds into the project in order for that project to success, it will causes investors refuse to invest it.

By examine the effects of virality and project description components on probability of crowdfunding success, the result indicates that images index positively associated with probability of success. In contrast, budget plan and info are negatively correlated with the probability of success. There might be some investors that have no interest to reviews the projects information that include budget plan and both the images and videos in project description. It possibly because images can promote a project more effectively by attract people to view the project and thus attracts more investors. In addition, some investors only interested on the preparedness and professionalism of the project founders towards the project. Moreover, they might think that words can express things more clearly and directly.

Based on the result from probit regression, Model 1 and Model 3 can predict 87.73% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 17.13 percentage points. Model 2 and Model 4 can predict 86.11% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 15.51 percentage points. Model 5, Model 6, Model 7 and Model 8 in Table 4.7 can predict 87.50%, 86.34%, 89.12% and 86.57% of the total observation respectively. If the estimated model only predicts successful projects, the predicted ability will improve by 16.90, 15.74, 18.52 and 15.97 percentage points respectively.

Based on the result shows in Table 4.8, Model 2 and Model 6 can predict 87.50% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 16.90 percentage points. Model 1 and Model 7 can predict 90.74% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 20.14 percentage points. Model 3, Model 4, Model 5, and Model 8 can predict 90.51%, 87.96%, 90.28% and 87.73% of the total observation respectively. If the estimated model only predicts successful projects, the predicted ability will improve by 19.91, 17.36, 19.68, and 17.13 percentage points respectively.

Table 4.7: The Effects of Virality and Project Description Components on Probability of Success – Results from Probit Regression

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Funding Target	-0.0001*** (0.0001)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Duration	-0.0003 (0.0021)	-0.0000 (0.0019)	-0.0003 (0.0021)	0.0000 (0.0019)	-0.0005 (0.0020)	-0.0001 (0.0019)	-0.0003 (0.0021)	-0.0000 (0.0020)
Target per Capita	-0.0004*** (0.0001)	-0.0003** (0.0001)	-0.0004*** (0.0001)	-0.0003** (0.0001)	-0.0004*** (0.0001)	-0.0003** (0.0001)	-0.0004*** (0.0001)	-0.0004** (0.0001)
Density	0.0253*** (0.0032)	0.0248*** (0.0032)	0.0255*** (0.0033)	0.0249*** (0.0032)	0.0255*** (0.0032)	0.0249*** (0.0032)	0.0239*** (0.0032)	0.0234*** (0.0032)
Minimum Reward	0.0016* (0.0009)	0.0021** (0.0009)	0.0015* (0.0009)	0.0021** (0.0009)	0.0016* (0.0009)	0.0021** (0.0009)	0.0016* (0.0009)	0.0021** (0.0009)
C	-0.0480 (0.1975)	-0.7195 (0.2378)	-0.0272 (0.1973)	-0.6653 (0.2293)	-0.0636 (0.1982)	-0.6993 (0.2359)	-0.1971 (0.2091)	-0.8457 (0.2454)
Virality								
Shares Index	0.4442 (0.3127)	0.2988 (0.3052)						
Updates Index			-0.0431 (0.0784)	-0.0216 (0.0754)				
Videos Index					0.0566 (0.0485)	0.0321 (0.0490)		
Images Index							0.1273** (0.0576)	0.1317** (0.0560)
Description								
Profile		0.0749 (0.1668)		0.0706 (0.1667)		0.0658 (0.1664)		0.0545 (0.1676)
Purpose		0.0995 (0.1947)		0.0525 (0.1871)		0.0533 (0.1870)		0.0876 (0.1907)
Risk and Challenges		0.0536 (0.1731)		0.0675 (0.1719)		0.0749 (0.1726)		0.0733 (0.1737)
Info	-0.4866*** (0.1765)		-0.5760*** (0.2049)		-0.5053*** (0.1780)		-0.4761*** (0.1764)	
Budget Plan	-0.6020*** (0.2067)		-0.4787*** (0.1762)		-0.5795*** (0.2055)		-0.5413*** (0.2054)	
Languages		0.1165 (0.1030)		0.1154 (0.1030)		0.1172 (0.1029)		0.1092 (0.1024)
McFadden R-squared	0.4553	0.4280	0.4558	0.4282	0.4577	0.4288	0.4651	0.4391
% of Correct Prediction	87.7300	86.1100	87.7300	86.1100	87.5000	86.3400	89.1200	86.5700
Total Gain	17.1300	15.5100	17.1300	15.5100	16.9000	15.7400	18.5200	15.9700
Prob. Chi-Sq	0.0008	0.0193	0.0070	0.0049	0.0003	0.0024	0.0046	0.0044

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.

Where target per capita = funding target / number of supporters; density represent number of supporters; Shares Index, Updates Index, Videos Index, and Images Index are total number of shares, updates, videos, and images in each project respectively; info means that description have include both the images and videos.

Table 4.8: The Effects of Virality and Project Description Components on Probability of Success – Results from Logit Regression

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Funding Target	-0.0002*** (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)
Duration	-0.0027 (0.0035)	-0.0019 (0.0032)	-0.0025 (0.0035)	-0.0017 (0.0032)	-0.0031 (0.0034)	-0.0021 (0.0031)	-0.0030 (0.0036)	-0.0022 (0.0033)
Target per Capita	-0.0004* (0.0003)	-0.0004 (0.0003)	-0.0004* (0.0003)	-0.0004 (0.0002)	-0.0004* (0.0003)	-0.0004 (0.0003)	-0.0004* (0.0003)	-0.0004 (0.0003)
Density	0.0691*** (0.0100)	0.0667*** (0.0096)	0.0715*** (0.0104)	0.0682*** (0.0099)	0.0702*** (0.0101)	0.0671*** (0.0096)	0.0691*** (0.0102)	0.0664*** (0.0097)
Minimum Reward	0.0025 (0.0018)	0.0034* (0.0019)	0.0022 (0.0016)	0.0032* (0.0019)	0.0024 (0.0017)	0.0034* (0.0019)	0.0023 (0.0016)	0.0032* (0.0019)
C	-0.1332 (0.3431)	-1.2728 (0.4196)	-0.0772 (0.3399)	-1.2008 (0.4053)	-0.1820 (0.3465)	-1.2772 (0.4196)	-0.4633 (0.3658)	-1.6355 (0.4491)
Virality								
Shares Index	0.7473 (0.5587)	0.4446 (0.5617)						
Updates Index			-0.1684 (0.1557)	-0.1200 (0.1539)				
Videos Index					0.1108 (0.0844)	0.0658 (0.0848)		
Images Index							0.2905*** (0.1116)	0.2895*** (0.1068)
Description								
Profile		-0.0698 (0.3059)		-0.0595 (0.3067)		-0.0818 (0.3062)		-0.1058 (0.3109)
Purpose		0.2171 (0.3482)		0.1586 (0.3363)		0.1607 (0.3364)		0.2563 (0.3479)
Risk and Challenge		0.0726 (0.3150)		0.0973 (0.3140)		0.1034 (0.3155)		0.1185 (0.3190)
Info	-0.9263*** (0.3254)		-0.9346*** (0.3263)		-0.9600*** (0.3284)		-0.9491*** (0.3293)	
Budget Plan	-1.1611*** (0.3943)		-1.1060*** (0.3889)		-1.1406*** (0.3935)		-1.0368*** (0.3917)	
Languages		0.2220 (0.1834)		0.2266 (0.1822)		0.2277 (0.1848)		0.2122 (0.1891)
McFadden R-squared	0.4994	0.4687	0.4984	0.4686	0.4993	0.4686	0.5105	0.4826
% of Correct Prediction	90.7400	87.5000	90.5100	87.9600	90.2800	87.5000	90.7400	87.7300
Total Gain	20.1400	16.9000	19.9100	17.3600	19.6800	16.9000	20.1400	17.1300
Prob. Chi-Sq	0.0124	0.0234	0.0358	0.1045	0.0718	0.3275	0.1827	0.4748

Note: Standard errors are presented in parentheses. ***, **, * represent statistical significance at 1%, 5% and 10%.

Where target per capita = funding target / number of supporters; density represent number of supporters; Shares Index, Updates Index, Videos Index, and Images Index are total number of shares, updates, videos, and images in each project respectively; info means that description have include both the images and videos.

4.3 SUMMARY

Based on the regression analysis, we found that Model 7 in Table 4.8 is the best model among all the models presented. Hosmer-Lemeshow test has been performed to statistical goodness of fit of all of the models. The result shows that the probability of chi-square of Model 7 is 0.1827 which is greater than the significant level. It indicates that Model 7 is the most accurate and best fit with our study. Model 7 can predict 90.74% of the total observations. If the estimated model only predicts the successful projects, the predicted ability will improve by 20.14 percentage points. In addition, McFadden R-squared of Model 7 indicates that 51.05% of the predicted probability is correct.

Each variable plays an important role in estimating probability of crowdfunding success.

1. Higher funding target was hard to achieve since it requires investors to funded more in order to make that project success. Thus, a lower funding target can increase probability of crowdfunding success since it will become easier to reach.
2. The longer the duration set by project founders to reached funding target, it will decrease probability of crowdfunding success. Longer duration indicates that the project founders lack of confidence to their project.
3. If each project only has few supporters, each supporter needs to invest more in order to make the project successful. Therefore, higher number of supporters in each project can lead to each supporter to invest less amount of funds.
4. Greater number of supporters in each of the project can lead a project successfully achieve it funding target.
5. Higher minimum reward can attract more investors and lead to crowdfunding success. Investors can receive greater incentive when invest into that project.
6. Images can express information more effectively since it can easily capture people attention and make an impression on them.
7. By including both the images and videos into a project description, it does not show the preparedness and professionalism of the project founder.
8. Project description that include budget plan does not increase probability of crowdfunding success. Investors may not concern about how their money will be use, they only concern whether the project is worth to invest.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATION

5.0 INTRODUCTION

Chapter 4 had analysed the significance between dependent variable and independent variables by carry out descriptive analysis, regression analysis, and diagnostic checking. The result shows us that there are some independent variables may affect the probability of crowdfunding success. Therefore, a summary result of the descriptive analysis, regression analysis, and diagnostic checking in the previous chapter will be discussed in chapter 5. Moreover, limitation of the study and policy recommendation will also discuss thoroughly in this chapter, as well as the contribution of the study.

5.1 SUMMARY OF RESULT

The main purpose of carry out this research is to identify factors that will affect the probability of crowdfunding success in Malaysia for both entrepreneurs and investors during considering launched or investing a crowdfunding project. Hence, it is importance to do this research and encourage more research on this topic in Malaysia. The independent variables that involve in this research are funding target, duration, target per capita, density, virality, minimum rewards, and description.

5.1.1 Descriptive Analysis

Based on the result from the previous chapter, only 127 projects out of the whole sample dataset (433 crowdfunding projects) successfully meet their funding target, which means that there is only 29.4% of success rate. Besides that, the average virality shows that 79% of the projects can effectively social spread of emotionally charged content to people through shares, updates, videos, and images. If a project founder frequently keeps update information of the project, this may help the founder to attract more investors and increase the investor’s confidence towards the project (Koch and Siering, 2015). Others than that, the independent variable of description showed more than half of the crowdfunding projects which includes founder profile, purpose, videos and images, risk and challenges, or budget plan in their proposal and contain of two languages (English and Chinese) success reached their funding goals. The more detailed the description, the more useful for investors in making a decision (Cheung et al, 2008).

5.1.2 Regression Analysis

Based on Table 4.2 which shows the Baseline Result, the probability of crowdfunding success is positively affected by virality, minimum reward, and density; while funding target, and target per capita show negatively affected the probability of crowdfunding success in probit regression model. If funding target set by a project founder is relatively high, it will cause the crowdfunding project unsuccessful to fund the target crowdfunding amount. Besides, if more supporters funded in a crowdfunding project, the amount of funds need to invest by each supporter will decrease and thus lead the crowdfunding project successful rate rise.

On the other hand, the probability of crowdfunding success is positively affected by virality, minimum reward, and density; while negatively affected by funding target in logistic regression model. Other independent variables such as duration and description showed do not significantly affect the probability of crowdfunding success in Malaysia, this might because of the project description and duration existing at the crowdfunding platform does not show preliminary and professionalism of the project founders, and hence it does not attract supporters to support those projects.

5.1.3 Diagnostic Checking

The diagnostic checking tests that involved in this research are Dependent Variable Frequencies and Goodness-of-Fit Tests in order to observe the performance of estimated binary model. All the models in Table 4.2 until Table 4.8 can predict more than 85% of the total observations. The forecast capability will improve if the estimated model only predicts the successful projects. In opposite, the forecast capability does more badly if estimated model only predicts unsuccessful projects. Therefore, the forecast capability in overall can be improves in all the models in Table 4.2 until Table 4.8.

Besides, Model 7 in Table 4.8 might be our best model among all of the models in Table 4.2 until Table 4.8. The probability of chi-square of Model 7 is 0.1827 which is greater than the significant level and it indicates that it is the most perfect in this research. The McFadden R-squared of Model 7 indicates that 51.05% of the predicted probability is correct. Other than that, the model also can predict 90.74% of the total observations and it predicted ability will improve by 20.14 percentage points if only predicts the successful projects.

5.2 LIMITATION OF STUDY

There are certain limitations throughout the study. First, this study mainly focuses on crowdfunding in Malaysia but ignoring other countries such as Canada, United Kingdom, Italy, and New Zealand. There might have different impact between funding target, duration, target per capita, density, virality, minimum rewards, and description on the probability of crowdfunding success due to different culture and location. The result also will differ across different countries as it may also affected by other factors such as economic condition, population, number of companies.

As crowdfunding is still a new phenomenon in Malaysia, thus there is only 7 years of data available for this study which is collected from year 2012 to year 2018. Quantitative data is used in this study in which they are cross-sectional data and these secondary data is taken from Mystartr official website. Consequently, the result from the analysis is dependent. This is because the accuracy of the result is relying on the secondary data. It means that if the secondary data is inaccurate, it would affect the impact of funding target, duration, target per capita, density, virality (total shares, video, images, and updates), minimum rewards, and description on the probability of crowdfunding success.

5.3 POLICY RECOMMENDATIONS

As crowdfunding becomes more popular in Malaysia, it will only become harder and harder to make the projects to be success in a short period. Our selected crowdfunding platform, Mystart has 127 successful projects, and the number of successful projects still increasing. However, it is not easy to be part of this statistic. Although the project founders have to follow a specific crowdfunding agreement, the founders have to put more efforts at any time to stand out from the competition with others projects. As competition continues to increase, staying at the forefront is crucial. There are a few of recommendations will be discussed.

5.3.1 Create Attractive Images to Convince the Backers

Images can express information more effectively and it can easily capture people attention and make an impression on them. Our brain will prioritize visual information, which makes the image become a quick connection that all marketers are looking for. Images is one of the faster ways where project founders can communicate with outsiders and convincing them to support the projects. This will increase the trustworthiness between project founders and backers and enhancing the credibility of those campaigns. Create attractive images and post it on the crowdfunding page can keep project backers and potential backers in the loop.

5.3.2 Appreciate the Supporters or Backers with Special Actions

All the project creators have to appreciate their supporters or backers with something special to let them feel loved and important. The founders have to react to each comment or question as fast as possible. All those replies should be honest and give the backers a clear answer for their enquiries. If the founder promises the backers can get a free gift such as t-shirts, stickers, or handwritten thank you notes by invest certain amount, they should deliver all those gifts on time. The backers feedback also a best way to let the crowdfunding projects to be success. Project founder should accept all those feedbacks given with thanks, no matter it is a good or negative feedback. Furthermore, the creators may take it as suggestions to improve their projects.

5.3.3 Make the Reward Financially Worthwhile for the Backers

Although some supporters do not need to be rewarded for their investments or donation, but providing some rewards to funders can enhance successful rate. The project founders have to make sure rewards offered are financially worth it. Even though handwritten thank-you letter is decent, but it is unable to motivate people to invest. Rewards are important to crowdfunding activities because it can encourage general publics to invest into the projects. Rewards show the appreciation of the project founders to the supporter's contributions. Furthermore, it also had created important incentives for new supporters. Rewards can be anything, as long as the founders can provide somethings that worth for the supporter's contributions. On the other hand, project founder can bundle the gifts to accumulate higher rewards to the supporters that invest more funds. The owners also can try to personalize the rewards. It may not only show more gratitude, but also increases project founder connection with supporters.

5.4 CONTRIBUTION OF THE STUDY

Crowdfunding is an alternative way for entrepreneurs to raise fund in other countries, but it is not famous in Malaysia. People that are considering launch a crowdfunding project should realize that it is not an easy task and not easy to success. The crowdfunding platform that chooses to observe in our study is Mystartr, which is the most popular reward-based crowdfunding platform in Malaysia. It consists of 433 projects from year 2012 until year 2018. In order to make the crowdfunding project success, the project has to be carefully designed and the information about the project must be clear.

Based on our research, it showed that fundraiser will not easily achieve their goal if they set higher funding target. Hence, they should set a reasonable funding target that able to cover all the expenses of the project. In case any unpredictable problem happens, fundraiser still able to cover it without incurring any insufficient amount. Besides, the longer the duration used by project creators to raise fund, this might decrease the successful rate of crowdfunding and show unprofessional and lack of confidence of the project creator to their project. Thus, the project creators have to shorten their funding period without giving the funder a relatively calm period.

Next, a project with higher number of supporters will be more likely to achieve the funding goal where each supporter only needs contributing less amount of money. Lower number of supporters can cause the crowdfunding unsuccessful and these supporters have to contribute more funds in order to make that project success. Furthermore, the project founder can set different levels of rewards to attract more investors to invest into the crowdfunding project.

In addition, images can lead to crowdfunding projects go viral. Fundraisers can attract investors to fund into the project through sharing their projects' images such as poster and photo of the event. This is because images can easily convey the important information of the projects to the investors in an interesting way. Most of the investors seek for short and simple information to save their time from reading thousands of words in the projects. However, some of the investors would not focus on the images or videos prepared by the project creator since the information in words is more clearly and direct stated. It will decrease the misconceptions of the information. The investors might concern only the content of the information which clearly show the preparedness and professionalism of the project.

Budget plan in the project description show it does not increase probability of crowdfunding success because most of the investors may not concern about how their money will be use by the project founder to run their projects or businesses. Moreover, they are more likely to support the meaningful projects such as the community projects and business start-up that can capture investors' attention and lead them to making decision to invest into those projects.

In short, images and budget plan which consist in our research showed significant effect on the probability successful crowdfunding in Malaysia and the project creators must manage their crowdfunding project wisely and carefully before the project mature.

REFERENCES

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice, 39* (4), 955–980.

Asian Institute of Finance. (2017). Annual report. KL Sentral, Kuala Lumpur.

Barnett, C. (2013). Top 10 crowdfunding sites for fundraising. *New York: Forbes*. Retrieved from http://www.tradecraftfilms.com/TCFDocuments/Top_10_crowdfunding_sites_May_2013.pdf

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2010). "Crowdfunding: An Industrial Organization Perspective". Prepared for the workshop Digital Business Models: Understanding Strategies', held in Paris, pp. 25–26.

Belleflamme, P., & Lambert, T. (2014). SSRN Electronic Journal. *Crowdfunding: Some Empirical Findings and Microeconomic Underpinnings*. ,1-15. doi:10.2139/ssrn.2437786

Berger, J., & Milkman, K. L., (2011). Social Transmission, Emotion, and the Virality of Online Content. *University of Pennsylvania*, 38 (2), 1-52. Retrieved from http://opim.wharton.upenn.edu/~kmilkman/Virality.pdf

Bradford, S. (2012). Crowdfunding and the federal securities laws. Columbia Business Law Review. Retrieved 11 October 2013, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1916184

Borello, G., De Crescenzo, V., & Pichler, F. (2015). The funding gap and the role of financial return crowdfunding: some evidence from European platforms. The Journal of Internet Banking and Commerce, 20 (1), 1-20.

Borst, I., Moser, C., & Ferguson, J. (2018). From friendfunding to crowdfunding: Relevance of relationships, social media, and platform activities to crowdfunding performance. New media & society, 20 (4), 1396-1414.

Burtch, G., Ghose, A., & Wattal, S. (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Information Systems Research, 24* (3), 499–519.

Buysere, K.D., Gajda, O., Kleverlaan, R., & Marom, D. (2012). A framework for European crowdfunding, European Crowdfunding Network. Retrieved from http://www.europecrowdfunding.org

Chen, S., Thomas, S., & Kohli, C. (2016). What Really Makes a Promotional Campaign Succeed on a Crowdfunding Platform? Guilt, Utilitarian Products, Emotional Messaging, and Fewer but Meaningful Rewards Drive Donations. Journal of Advertising Research, 56 (1), 81-94.

Cheung, C. M., Lee, M. K., & Rabjohn, N. (2008). "The impact of electronic word of mouth." Inter-net Research 18 (3), 229 – 247.

Colombo, M. G., Franzoni, C., & Rossi-Lamastra, C. (2015). Internal social capital and the attraction of early contributions in crowdfunding. *Entrepreneurship Theory and Practice, 39* (1), 75–100.

Cumming, D. J., Leboeuf, G., & Schwienbacher, A. (2014). Crowdfunding models: Keep-it-all vs. all-or-nothing, Retrieved from http://ssrn.com/abstract=2447567.

Davies, R. (2015). *Three provocations for civic crowdfunding*. Information Commun. Soc. 18, 342–355.

Drabløs, C. (2015). What influences crowdfunding campaign success (Master's thesis, Universiteteti Agder; University of Agder).

Etter, V., Grossglauser, M., & Thiran, P. (2013). *Launch hard or go home! Predicting the success of Kickstarter campaigns*. Presented at COSN'13: Conference on Online Social Networks (2013), Northeastern University, and Boston, MA. Retrieved From http://vincent.etter.io/publications/etter2013cosn.pdf.

Evers, M., Lourenço, C., & Beije, P. (2012). Mart-Evers_Concept-thesis_Main-drivers-of-crowdfunding-success_RSM_Marketing-Management_9-2012_PDF, (September). Retrieved from https://www.cultuurmarketing.nl/wp-content/uploads/2013/01/Mart-Evers_Master-thesis_Main-drivers-of-crowdfunding-success_RSM_Marketing-Management_9-2012_PDF.pdf

Frydrych, D., Bock, A. J., & Kinder, T. (2015). Creating Project Legitimacy – The Role of Entrepreneurial Narrative in Reward-Based Crowdfunding. ResearchGate, 25.

Gujarati, D. N., & Porter, D. C. (2009). Basic Econometric. (5th ed.). Boston, MA: McGraw-Hill/Irwin.

Hakenes, H., & Schlegel, F. (2014). Exploiting the financial wisdom of the crowd: Crowdfunding as a tool to aggregate vague information, Retrieved from, http://ssrn.com/abstract=2475025.

Hekman, E., & Brussee, R. (2013). Crowdfunding and Online Social networks. Manchester Metropolitan University, (January), 1–22. https://doi.org/10.1016/j.psyneuen.2015.07.552

Hong, A. P. Y. (2016). Equity Crowdfunding in Malaysia: An Implementation of Setting Valuations, 24.

Ibrahim, N., & Verliyantina. (2012). The model of crowdfunding to support small and micro businesses in Indonesia through a web-based platform, Procedia Economics and Finance 4, 390 – 397.

Joern, H. (2016). -Crowdinvesting - New venture financing. *Crowdfunding: A Literature Review and Research Directions,6* (14), 1-30.

Kaur, H., & Gera, J. (2017). Effect of social media connectivity on success of crowdfunding campaigns. Procedia Computer Science, 122, 767-774.

Kirby, E., & Worner, S. (2014). Crowd-funding: An Infant Industry Growing Fast. Retrieved fromhttps://www.ivey.uwo.ca/cmsmedia/3341223/iosco-2014-crowd-funding-an-infant-industry-growing-fast.pdf

Klieštik, T., Kočišová, K. & Mišanková, M. (2015). Logit and Probit Model used For Prediction of Financial Health of Company. Procedia Economics and Finance, 23, 850-855.

Koch, J. A., & Siering, M. (2015). Crowdfunding success factors: The characteristics of successfully funded projects on crowdfunding platform. *European Conference on Information Systems*, 19-23.

Lee, Y. C., Yen, C. H., & Fu, W. T. (2016). Improving Donation Distribution for Crowdfunding. An Agent-Based Model, 6 (12), 3-12.

Levin, F. (2015). Success Determinants of Crowdfunding Projects. Review of Business and Economics Studies, 3 (4), 79–87.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2014). Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending. Management Science, 59 (1), 17–35.

Leboeuf, G., Schwienbacher, A., Cumming, D. (2015). Crowdfunding Models: Keep-It-All vs. All-Or-Nothing. Working paper.

Malaysia, T. (2017). Malaysian Crowdfunding Companies – The Top 10 · Top 10 of Malaysia. Retrieved from http://top10malaysia.com/main/malaysian-crowdfunding-companies-top-10/

Marzban, S., Asutay, M., & Boseli, A. (2014). Shariah-compliant Crowdfunding: An Efficient Framework for Entrepreneurship Development in Islamic Countries. Conference Paper presented in Harvard Islamic Finance Forum, April 2014, United States America.

Miller, Z. (2019). Learn About Rewards-Based Crowdfunding. Small Business. Retrieved from https://www.thebalancesmb.com/what-is-rewards-based-crowdfunding-985103

Moisseyev, A. (2013). Crowdinvesting News- Effect of Social Media on Crowdfunding. Retrieved from http://parabanking.blogspot.de/2013/04/effect-of-social-media-on-crowdfunding.html?utm_source=feedburner&utm_medium=feed&utm_campaign=Feed:+blogspot/RDuLWs+(Crowdinvesting+News)

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. Journal of Business Venturing, 1-16. https://doi.org/10.1016/j.jbusvent.2013.06.005

Muller, M., Geyer, W., Soule, T., Daniels, S., & Cheng, L. T. (2013). “Crowdfunding inside the enterprise: employee-initiatives for innovation and collaboration”. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 503–512, Paris, France.

Okhrimenko, O. (2018). Crowdfunding Business Models: What Is the Best Choice for Your Startup? Justcoded. Retrieved from https://justcoded.com/blog/crowdfunding-business-models-what-is-the-best-choice-for-your-startup/

Outlaw, S. (2013). Which Type of Crowdfunding Is Best for You? Entrepreneur. Retrieved from https://www.entrepreneur.com/article/228524

Peyankov, D. (2013). Social crowdfunding: individual- and project-related determinants of success Empirical investigation on Kickstarter.com. *Economics.* Retrieved fromhttp://hdl.handle.net/2105/15532

P2P financing is booming in Malaysia. (2018, November 28). The Star Online.

Pikri, E. (2019). PitchIN owns 75% of the equity crowdfunding market in 2018. (2019, January 15). Fintech Malaysia.

Securities Commission Malaysia. (2018). Annual report. Bukit Kiara, Kuala Lumpur.

Statista. (2017). *Facebook users worldwide 2017*. Retrieved from https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/

Thanh Tu, T. T., Anh, D. P., & Ha Thu, T. T. (2018). Exploring Factors Influencing the Success of Crowdfunding Campaigns of Startups in Vietnam. Accounting and Finance Research, 7 (2), 19.

The Statistics Portal. (2019). Cumulative amount of funding pledged to Kickstarter projects as of January 2019 (in million U.S. dollars). Retrieved from https://www.statista.com/statistics/310218/total-kickstarter-funding/?fbclid=IwAR2REk3n1XBk_abS5e1AasmZUdeMQR6--ZNxQq7nKFa7JhiPf1gv8RePq58

Xu, F. S., Guo, X. M., Xiao, G., & Zhang, F. Q. (2018). Crowdfunding or Bank Financing: Effects of Market Uncertainty and Word-of-Mouth Communication. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3209835

Vissers, J. (2017). Types of Crowdfunding for Business: Debt, Equity, Or Rewards. Merchant Maverick. Retrieved from https://www.merchantmaverick.com/types-of-crowdfunding-for-business-debt-equity-or-rewards/

Wang, N., Li, Q., Liang, H., Ye, T., & Ge, S. (2018). Understanding the importance of interaction between creators and backers in crowdfunding success. Electronic Commerce Research and Applications, 27, 106-117.

Wash, R. & Solomon, J. (2014). Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing. Coordinating Donors on Crowdfunding Websites,38-58. doi:10.1145/2531602.2531678

World Bank. (2013). Crowdfunding's potential for the developing world. infoDev, Finance and Private Sector Development Department, Washington DC.

Zeoli, A. J. (2014). The four types of crowdfunding. Crowdfunding Legal Hub. Retrieved from https://crowdfundinglegalhub.com/2014/04/27/test-3/

Zheng, H., Li, D., Wu, J., & Xu, Y. (2014). The role of multidimensional social capital in crowdfunding: A comparative study in China and US. Information & Management, 51, 488–496.

APPENDICES

Appendix 1: Descriptive Statistics

	PROB	TARGET	DURATION	MIN	DENSITY	VIRALITY	MINREWARD	DESCRIPTION
Mean	0.293981	22599.84	45.76620	3415.691	44.30787	0.795262	69.83657	59.10880
Median	0.000000	8000.000	43.00000	364.2999	10.00000	0.609600	20.00000	60.00000
Maximum	1.000000	750000.0	793.0000	240000.0	2388.000	4.637800	5000.000	100.0000
Minimum	0.000000	0.000000	1.000000	0.000000	0.000000	0.052100	0.000000	5.000000
Std. Dev.	0.456112	60159.23	42.18172	14267.78	159.3499	0.665103	327.6046	17.63130
Skewness	0.904416	7.557910	13.07044	11.96079	9.757513	2.089639	11.35582	-0.147107
Kurtosis	1.817968	73.03268	229.6435	183.0584	122.6691	9.175937	148.1617	2.572992
Jarque-Bera	84.04330	92395.16	936911.3	593878.6	264627.6	1000.954	388579.2	4.840157
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.088915
Sum	127.0000	9763132.	19771.00	1475579.	19141.00	343.5532	30169.40	25535.00
Sum Sq. Dev.	89.66435	1.56E+12	766877.4	8.77E+10	10944116	190.6581	46256978	133981.9
Observations	432	432	432	432	432	432	432	432

Appendix 2: Probit Regression

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 06/28/19 Time: 00:56
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.17E-05	9.93E-06	-6.214807	0.0000
DURATION	-0.000382	0.001887	-0.202344	0.8396
MIN	-0.000336	0.000135	-2.491763	0.0127
DENSITY	0.024112	0.003155	7.641330	0.0000
VIRALITY	0.206578	0.124787	1.655441	0.0978
MINREWARD	0.002210	0.000941	2.347567	0.0189
DESCRIPTION	0.004436	0.004503	0.985098	0.3246
C	-0.896451	0.294382	-3.045194	0.0023

McFadden R-squared	0.432974	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.319010
Akaike info criterion	0.723908	Sum squared resid	43.14947
Schwarz criterion	0.799249	Log likelihood	-148.3641
Hannan-Quinn criter.	0.753652	Deviance	296.7282
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	226.5778	Avg. log likelihood	-0.343435
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 3: Probit Regression: Expectation-Prediction Table

Expectation-Prediction Evaluation for Binary Specification
Equation: PROBIT
Date: 07/14/19 Time: 10:59
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	295	49	344	305	127	432
P(Dep=1)>C	10	78	88	0	0	0
Total	305	127	432	305	127	432
Correct	295	78	373	305	0	305
% Correct	96.72	61.42	86.34	100.00	0.00	70.60
% Incorrect	3.28	38.58	13.66	0.00	100.00	29.40
Total Gain*	-3.28	61.42	15.74			
Percent Gain**	NA	61.42	53.54			

Appendix 4: Probit Regression: Goodness-of-Fit Tests

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: PROBIT
Date: 07/14/19 Time: 11:00
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	2.E-06	43	43.0000	0	5.0E-06	43	5.0E-06
2	3.E-06	0.0142	43	42.8491	0	0.15093	43	0.15146
3	0.0166	0.0713	41	41.0799	2	1.92012	43	0.00348
4	0.0716	0.1233	41	38.8163	2	4.18365	43	1.26260
5	0.1273	0.2045	39	36.8032	5	7.19676	44	0.80167
6	0.2072	0.2706	37	32.5300	6	10.4700	43	2.52267
7	0.2712	0.3409	31	29.7825	12	13.2175	43	0.16192
8	0.3426	0.5001	20	25.3716	23	17.6284	43	2.77406
9	0.5055	0.8044	6	15.2826	37	27.7174	43	8.74696
10	0.8102	1.0000	4	2.58092	40	41.4191	44	0.82888
		Total	305	308.096	127	123.904	432	17.2537

H-L Statistic	17.2537	Prob. Chi-Sq(8)	0.0276
Andrews Statistic	42.6504	Prob. Chi-Sq(10)	0.0000

Appendix 5: Logistic Regression

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 06/28/19 Time: 00:58
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000154	2.42E-05	-6.351779	0.0000
DURATION	-0.002411	0.003160	-0.763060	0.4454
MIN	-0.000399	0.000252	-1.581743	0.1137
DENSITY	0.065229	0.009541	6.836420	0.0000
VIRALITY	0.425919	0.233804	1.821693	0.0685
MINREWARD	0.003511	0.001940	1.810114	0.0703
DESCRIPTION	0.004928	0.008105	0.608023	0.5432
C	-1.559979	0.537110	-2.904393	0.0037

McFadden R-squared	0.471753	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.304429
Akaike info criterion	0.676933	Sum squared resid	39.29493
Schwarz criterion	0.752274	Log likelihood	-138.2175
Hannan-Quinn criter.	0.706677	Deviance	276.4351
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	246.8710	Avg. log likelihood	-0.319948
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 6: Logistic Regression: Expectation-Prediction Table

Expectation-Prediction Evaluation for Binary Specification
Equation: LOGISTIC
Date: 07/14/19 Time: 11:03
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	291	41	332	305	127	432
P(Dep=1)>C	14	86	100	0	0	0
Total	305	127	432	305	127	432
Correct	291	86	377	305	0	305
% Correct	95.41	67.72	87.27	100.00	0.00	70.60
% Incorrect	4.59	32.28	12.73	0.00	100.00	29.40
Total Gain*	-4.59	67.72	16.67			
Percent Gain**	NA	67.72	56.69			

Appendix 7: Logistic Regression: Goodness-of-Fit Tests

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: LOGISTIC
Date: 07/14/19 Time: 11:04
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-58	0.0001	43	42.9993	0	0.00066	43	0.00066
2	0.0001	0.0200	43	42.7551	0	0.24488	43	0.24628
3	0.0216	0.0558	42	41.3325	1	1.66747	43	0.27796
4	0.0558	0.0903	41	39.9279	2	3.07210	43	0.40293
5	0.0904	0.1636	38	38.5126	6	5.48743	44	0.05470
6	0.1661	0.2384	37	34.0692	6	8.93080	43	1.21392
7	0.2398	0.3353	34	30.6038	9	12.3962	43	1.30738
8	0.3398	0.5941	19	23.9193	24	19.0807	43	2.28003
9	0.5951	0.9162	5	10.0069	38	32.9931	43	3.26500
10	0.9203	1.0000	3	0.87334	41	43.1267	44	5.28346
		Total	305	305.000	127	127.000	432	14.3323

H-L Statistic	14.3323	Prob. Chi-Sq(8)	0.0735
Andrews Statistic	42.2409	Prob. Chi-Sq(10)	0.0000

Appendix 8: Probit Regression: The Effect of Shares Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 11:56
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-5.99E-05	9.70E-06	-6.173268	0.0000
DURATION	-0.000111	0.001897	-0.058516	0.9533
MIN	-0.000332	0.000132	-2.506711	0.0122
DENSITY	0.024747	0.003153	7.848929	0.0000
MINREWARD	0.002178	0.000928	2.348130	0.0189
DESCRIPTION	0.005207	0.004464	1.166532	0.2434
S_INDEX	0.254645	0.290208	0.877459	0.3802
C	-0.837078	0.290379	-2.882707	0.0039

McFadden R-squared	0.429194	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.320633
Akaike info criterion	0.728487	Sum squared resid	43.58954
Schwarz criterion	0.803828	Log likelihood	-149.3532
Hannan-Quinn criter.	0.758231	Deviance	298.7063
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	224.5997	Avg. log likelihood	-0.345725
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 9: Probit Regression: Expectation-Prediction Table for Shares Index

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_V_SHARES
Date: 07/14/19 Time: 11:56
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	295	51	346	305	127	432
P(Dep=1)>C	10	76	86	0	0	0
Total	305	127	432	305	127	432
Correct	295	76	371	305	0	305
% Correct	96.72	59.84	85.88	100.00	0.00	70.60
% Incorrect	3.28	40.16	14.12	0.00	100.00	29.40
Total Gain*	-3.28	59.84	15.28			
Percent Gain**	NA	59.84	51.97			

Appendix 10: Probit Regression: Goodness-of-Fit Tests for Shares Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_V_SHARES
Date: 07/14/19 Time: 11:57
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	3.E-06	43	43.0000	0	7.5E-06	43	7.5E-06
2	3.E-06	0.0180	43	42.8243	0	0.17573	43	0.17645
3	0.0201	0.0657	40	41.0186	3	1.98137	43	0.54897
4	0.0702	0.1354	43	38.7498	0	4.25025	43	4.71643
5	0.1361	0.2082	39	36.6695	5	7.33051	44	0.88903
6	0.2099	0.2750	37	32.5026	6	10.4974	43	2.54915
7	0.2766	0.3426	31	29.8190	12	13.1810	43	0.15258
8	0.3442	0.4890	19	25.4160	24	17.5840	43	3.96072
9	0.4893	0.8023	6	15.1102	37	27.8898	43	8.46859
10	0.8053	1.0000	4	2.67937	40	41.3206	44	0.69313
		Total	305	307.789	127	124.211	432	22.1551

H-L Statistic	22.1551	Prob. Chi-Sq(8)	0.0046
Andrews Statistic	81.6632	Prob. Chi-Sq(10)	0.0000

Appendix 11: Probit Regression: The Effect of Updates Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 11:59
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-5.92E-05	9.48E-06	-6.247528	0.0000
DURATION	-0.000120	0.001890	-0.063497	0.9494
MIN	-0.000329	0.000131	-2.503536	0.0123
DENSITY	0.024839	0.003175	7.824185	0.0000
MINREWARD	0.002113	0.000926	2.280691	0.0226
DESCRIPTION	0.005367	0.004482	1.197360	0.2312
U_INDEX	-0.024372	0.075388	-0.323288	0.7465
C	-0.824233	0.289390	-2.848177	0.0044

McFadden R-squared	0.427994	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.320328
Akaike info criterion	0.729940	Sum squared resid	43.50654
Schwarz criterion	0.805281	Log likelihood	-149.6671
Hannan-Quinn criter.	0.759685	Deviance	299.3342
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	223.9718	Avg. log likelihood	-0.346452
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 12: Probit Regression: Expectation-Prediction Table for Updates Index

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_V_UPDATES
Date: 07/14/19 Time: 11:59
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	52	348	305	127	432
P(Dep=1)>C	9	75	84	0	0	0
Total	305	127	432	305	127	432
Correct	296	75	371	305	0	305
% Correct	97.05	59.06	85.88	100.00	0.00	70.60
% Incorrect	2.95	40.94	14.12	0.00	100.00	29.40
Total Gain*	-2.95	59.06	15.28			
Percent Gain**	NA	59.06	51.97			

Appendix 13: Probit Regression: Goodness-of-Fit Tests for Updates Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_V_UPDATES
Date: 07/14/19 Time: 12:00
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	4.E-06	43	43.0000	0	9.6E-06	43	9.6E-06
2	5.E-06	0.0198	43	42.8119	0	0.18806	43	0.18889
3	0.0220	0.0689	40	41.0174	3	1.98255	43	0.54740
4	0.0693	0.1366	42	38.7486	1	4.25140	43	2.75944
5	0.1382	0.2075	40	36.6164	4	7.38357	44	1.86320
6	0.2162	0.2811	37	32.2475	6	10.7525	43	2.80093
7	0.2824	0.3407	30	29.7192	13	13.2808	43	0.00859
8	0.3409	0.4796	21	25.6599	22	17.3401	43	2.09853
9	0.4834	0.8012	6	15.1910	37	27.8090	43	8.59847
10	0.8119	1.0000	3	2.69302	41	41.3070	44	0.03727
		Total	305	307.705	127	124.295	432	18.9027

H-L Statistic	18.9027	Prob. Chi-Sq(8)	0.0154
Andrews Statistic	48.0996	Prob. Chi-Sq(10)	0.0000

Appendix 14: Probit Regression: The Effect of Videos Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 12:01
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.02E-05	9.97E-06	-6.040410	0.0000
DURATION	-0.000221	0.001873	-0.117746	0.9063
MIN	-0.000326	0.000132	-2.478206	0.0132
DENSITY	0.024798	0.003158	7.852723	0.0000
MINREWARD	0.002145	0.000926	2.317032	0.0205
DESCRIPTION	0.004996	0.004483	1.114304	0.2651
V_INDEX	0.022421	0.049937	0.448984	0.6534
C	-0.826755	0.289536	-2.855447	0.0043

McFadden R-squared	0.428168	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.320492
Akaike info criterion	0.729730	Sum squared resid	43.55115
Schwarz criterion	0.805071	Log likelihood	-149.6216
Hannan-Quinn criter.	0.759474	Deviance	299.2433
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	224.0627	Avg. log likelihood	-0.346346
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 15: Probit Regression: Expectation-Prediction Table for Videos Index

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_V_VIDEOS
Date: 07/14/19 Time: 12:03
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	52	348	305	127	432
P(Dep=1)>C	9	75	84	0	0	0
Total	305	127	432	305	127	432
Correct	296	75	371	305	0	305
% Correct	97.05	59.06	85.88	100.00	0.00	70.60
% Incorrect	2.95	40.94	14.12	0.00	100.00	29.40
Total Gain*	-2.95	59.06	15.28			
Percent Gain**	NA	59.06	51.97			

Appendix 16: Probit Regression: Goodness-of-Fit Tests for Videos Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_V_VIDEOS
Date: 07/14/19 Time: 12:04
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	4.E-06	43	43.0000	0	8.9E-06	43	8.9E-06
2	4.E-06	0.0173	43	42.8200	0	0.17996	43	0.18072
3	0.0207	0.0700	40	40.9874	3	2.01255	43	0.50827
4	0.0707	0.1356	42	38.8149	1	4.18506	43	2.68536
5	0.1361	0.2084	40	36.5821	4	7.41788	44	1.89417
6	0.2107	0.2770	36	32.3269	7	10.6731	43	1.68144
7	0.2775	0.3417	32	29.6966	11	13.3034	43	0.57750
8	0.3433	0.4733	20	25.6520	23	17.3480	43	3.08672
9	0.4896	0.7997	5	15.1976	38	27.8024	43	10.5830
10	0.8085	1.0000	4	2.71666	40	41.2833	44	0.64614
		Total	305	307.794	127	124.206	432	21.8433

H-L Statistic	21.8433	Prob. Chi-Sq(8)	0.0052
Andrews Statistic	52.3399	Prob. Chi-Sq(10)	0.0000

Appendix 17: Probit Regression: The effect of Images Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 11:52
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-5.89E-05	9.55E-06	-6.165651	0.0000
DURATION	-0.000174	0.001930	-0.090044	0.9283
MIN	-0.000363	0.000140	-2.585240	0.0097
DENSITY	0.023386	0.003151	7.421639	0.0000
MINREWARD	0.002124	0.000956	2.221541	0.0263
DESCRIPTION	0.005269	0.004503	1.170001	0.2420
I_INDEX	0.131858	0.056021	2.353713	0.0186
C	-0.982919	0.300453	-3.271453	0.0011

McFadden R-squared	0.438913	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.316856
Akaike info criterion	0.716714	Sum squared resid	42.56863
Schwarz criterion	0.792055	Log likelihood	-146.8101
Hannan-Quinn criter.	0.746458	Deviance	293.6203
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	229.6857	Avg. log likelihood	-0.339838
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 18: Probit Regression: Expectation-Prediction Table for Images Index

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_V_IMAGES
Date: 07/14/19 Time: 11:54
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	48	345	305	127	432
P(Dep=1)>C	8	79	87	0	0	0
Total	305	127	432	305	127	432
Correct	297	79	376	305	0	305
% Correct	97.38	62.20	87.04	100.00	0.00	70.60
% Incorrect	2.62	37.80	12.96	0.00	100.00	29.40
Total Gain*	-2.62	62.20	16.44			
Percent Gain**	NA	62.20	55.91			

Appendix 19: Probit Regression: Goodness-of-Fit Tests for Images Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_V_IMAGES
Date: 07/14/19 Time: 11:54
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk Low	High	Dep=0 Actual	Expect	Dep=1 Actual	Expect	Total Obs	H-L Value
1	0.0000	9.E-07	43	43.0000	0	2.0E-06	43	2.0E-06
2	1.E-06	0.0159	43	42.8578	0	0.14216	43	0.14264
3	0.0162	0.0666	42	41.2729	1	1.72710	43	0.31891
4	0.0667	0.1276	41	38.7630	2	4.23701	43	1.31017
5	0.1288	0.2068	37	36.8222	7	7.17777	44	0.00526
6	0.2106	0.2760	39	32.6392	4	10.3608	43	5.14475
7	0.2760	0.3284	31	29.8878	12	13.1122	43	0.13572
8	0.3295	0.4940	21	25.4315	22	17.5685	43	1.89002
9	0.5029	0.8156	5	14.8749	38	28.1251	43	10.0227
10	0.8208	1.0000	3	2.40013	41	41.5999	44	0.15858
		Total	305	307.949	127	124.051	432	19.1288

H-L Statistic	19.1288	Prob. Chi-Sq(8)	0.0142
Andrews Statistic	46.0420	Prob. Chi-Sq(10)	0.0000

Appendix 20: Logistic Regression: The Effect of Shares Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 12:38
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000149	2.29E-05	-6.522474	0.0000
DURATION	-0.001872	0.003133	-0.597470	0.5502
MIN	-0.000402	0.000248	-1.621322	0.1049
DENSITY	0.065657	0.009466	6.935786	0.0000
MINREWARD	0.003420	0.001917	1.783626	0.0745
DESCRIPTION	0.005700	0.008019	0.710848	0.4772
S_INDEX	0.343459	0.545768	0.629313	0.5291
C	-1.360726	0.517056	-2.631679	0.0085

McFadden R-squared	0.466192	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.306843
Akaike info criterion	0.683669	Sum squared resid	39.92065
Schwarz criterion	0.759010	Log likelihood	-139.6724
Hannan-Quinn criter.	0.713413	Deviance	279.3448
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	243.9612	Avg. log likelihood	-0.323316
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 21: Logistic Regression: Expectation-Prediction Table for Shares Index

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_V_SHARES
Date: 07/14/19 Time: 12:39
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	294	42	336	305	127	432
P(Dep=1)>C	11	85	96	0	0	0
Total	305	127	432	305	127	432
Correct	294	85	379	305	0	305
% Correct	96.39	66.93	87.73	100.00	0.00	70.60
% Incorrect	3.61	33.07	12.27	0.00	100.00	29.40
Total Gain*	-3.61	66.93	17.13			
Percent Gain**	NA	66.93	58.27			

Appendix 22: Logistic Regression: Goodness-of-Fit Tests for Shares Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_V_SHARES
Date: 07/14/19 Time: 12:39
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-58	0.0002	43	42.9993	0	0.00073	43	0.00073
2	0.0002	0.0205	43	42.7400	0	0.25999	43	0.26157
3	0.0212	0.0595	40	41.3220	3	1.67800	43	1.08382
4	0.0598	0.0952	43	39.7866	0	3.21340	43	3.47294
5	0.0957	0.1686	39	38.2901	5	5.70985	44	0.10141
6	0.1715	0.2446	37	34.0701	6	8.92990	43	1.21326
7	0.2470	0.3294	32	30.5297	11	12.4703	43	0.24415
8	0.3308	0.6008	18	24.2146	25	18.7854	43	3.65089
9	0.6024	0.9094	7	10.0567	36	32.9433	43	1.21268
10	0.9095	1.0000	3	0.99083	41	43.0092	44	4.16800
		Total	305	305.000	127	127.000	432	15.4095

H-L Statistic	15.4095	Prob. Chi-Sq(8)	0.0517
Andrews Statistic	80.6028	Prob. Chi-Sq(10)	0.0000

Appendix 23: Logistic Regression: The Effect of Updates Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 12:40
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000151	2.28E-05	-6.618888	0.0000
DURATION	-0.001696	0.003159	-0.537023	0.5913
MIN	-0.000392	0.000246	-1.593269	0.1111
DENSITY	0.067053	0.009749	6.877621	0.0000
MINREWARD	0.003235	0.001881	1.720283	0.0854
DESCRIPTION	0.006233	0.008026	0.776561	0.4374
U_INDEX	-0.115768	0.157292	-0.736005	0.4617
C	-1.351797	0.515470	-2.622457	0.0087

McFadden R-squared	0.466466	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.306236
Akaike info criterion	0.683337	Sum squared resid	39.76280
Schwarz criterion	0.758679	Log likelihood	-139.6009
Hannan-Quinn criter.	0.713082	Deviance	279.2017
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	244.1043	Avg. log likelihood	-0.323150
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 24: Logistic Regression: Expectation-Prediction Table for Updates Index

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_V_UPDATES
Date: 07/14/19 Time: 12:41
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	294	42	336	305	127	432
P(Dep=1)>C	11	85	96	0	0	0
Total	305	127	432	305	127	432
Correct	294	85	379	305	0	305
% Correct	96.39	66.93	87.73	100.00	0.00	70.60
% Incorrect	3.61	33.07	12.27	0.00	100.00	29.40
Total Gain*	-3.61	66.93	17.13			
Percent Gain**	NA	66.93	58.27			

Appendix 25: Logistic Regression: Goodness-of-Fit Tests for Updates Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_V_UPDATES
Date: 07/14/19 Time: 12:41
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-57	0.0002	43	42.9992	0	0.00077	43	0.00077
2	0.0002	0.0199	42	42.7380	1	0.26204	43	2.09099
3	0.0206	0.0583	41	41.4088	2	1.59115	43	0.10909
4	0.0590	0.0939	41	39.7917	2	3.20832	43	0.49177
5	0.0944	0.1671	42	38.3353	2	5.66465	44	2.72111
6	0.1678	0.2464	36	33.8494	7	9.15055	43	0.64205
7	0.2473	0.3207	34	30.4948	9	12.5052	43	1.38542
8	0.3267	0.5730	17	24.2877	26	18.7123	43	5.02504
9	0.6002	0.9076	7	10.1493	36	32.8507	43	1.27916
10	0.9126	1.0000	2	0.94564	42	43.0544	44	1.20140
		Total	305	305.000	127	127.000	432	14.9468

H-L Statistic	14.9468	Prob. Chi-Sq(8)	0.0602
Andrews Statistic	23.9421	Prob. Chi-Sq(10)	0.0078

Appendix 26: Logistic Regression: The Effect of Videos Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 12:42
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000151	2.32E-05	-6.488848	0.0000
DURATION	-0.002022	0.003116	-0.648749	0.5165
MIN	-0.000395	0.000248	-1.596453	0.1104
DENSITY	0.066038	0.009508	6.945170	0.0000
MINREWARD	0.003395	0.001910	1.778017	0.0754
DESCRIPTION	0.005368	0.008040	0.667736	0.5043
V_INDEX	0.048459	0.086222	0.562030	0.5741
C	-1.366884	0.517348	-2.642099	0.0082

McFadden R-squared	0.466044	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.306656
Akaike info criterion	0.683848	Sum squared resid	39.87217
Schwarz criterion	0.759190	Log likelihood	-139.7113
Hannan-Quinn criter.	0.713593	Deviance	279.4225
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	243.8835	Avg. log likelihood	-0.323406
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 27: Logistic Regression: Expectation-Prediction Table for Videos Index

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_V_VIDEOS
Date: 07/14/19 Time: 12:42
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	294	42	336	305	127	432
P(Dep=1)>C	11	85	96	0	0	0
Total	305	127	432	305	127	432
Correct	294	85	379	305	0	305
% Correct	96.39	66.93	87.73	100.00	0.00	70.60
% Incorrect	3.61	33.07	12.27	0.00	100.00	29.40
Total Gain*	-3.61	66.93	17.13			
Percent Gain**	NA	66.93	58.27			

Appendix 28: Logistic Regression: Goodness-of-Fit Tests for Videos Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_V_VIDEOS
Date: 07/14/19 Time: 12:43
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	8.E-58	0.0002	43	42.9993	0	0.00074	43	0.00074
2	0.0002	0.0207	43	42.7327	0	0.26727	43	0.26894
3	0.0211	0.0575	40	41.3430	3	1.65701	43	1.13211
4	0.0575	0.0917	42	39.8696	1	3.13039	43	1.56368
5	0.0928	0.1702	40	38.2277	4	5.77233	44	0.62635
6	0.1714	0.2541	38	33.9066	5	9.09338	43	2.33680
7	0.2591	0.3214	32	30.5519	11	12.4481	43	0.23710
8	0.3220	0.5870	17	24.2670	26	18.7330	43	4.99523
9	0.5929	0.9097	7	10.1158	36	32.8842	43	1.25490
10	0.9106	1.0000	3	0.98649	41	43.0135	44	4.20399
		Total	305	305.000	127	127.000	432	16.6198

H-L Statistic	16.6198	Prob. Chi-Sq(8)	0.0343
Andrews Statistic	46.7607	Prob. Chi-Sq(10)	0.0000

Appendix 29: Logistic Regression: The Effect of Images Index on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 12:36
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000153	2.33E-05	-6.579751	0.0000
DURATION	-0.002162	0.003249	-0.665502	0.5057
MIN	-0.000420	0.000257	-1.633974	0.1023
DENSITY	0.065282	0.009615	6.789713	0.0000
MINREWARD	0.003267	0.001893	1.725650	0.0844
DESCRIPTION	0.006520	0.008209	0.794186	0.4271
I_INDEX	0.285170	0.106953	2.666309	0.0077
C	-1.747366	0.552334	-3.163601	0.0016

McFadden R-squared	0.480230	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.301585
Akaike info criterion	0.666664	Sum squared resid	38.56431
Schwarz criterion	0.742005	Log likelihood	-135.9995
Hannan-Quinn criter.	0.696409	Deviance	271.9989
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	251.3071	Avg. log likelihood	-0.314814
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 30: Logistic Regression: Expectation-Prediction Table for Images Index

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_V_IMAGES
Date: 07/14/19 Time: 12:37
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	292	40	332	305	127	432
P(Dep=1)>C	13	87	100	0	0	0
Total	305	127	432	305	127	432
Correct	292	87	379	305	0	305
% Correct	95.74	68.50	87.73	100.00	0.00	70.60
% Incorrect	4.26	31.50	12.27	0.00	100.00	29.40
Total Gain*	-4.26	68.50	17.13			
Percent Gain**	NA	68.50	58.27			

Appendix 31: Logistic Regression: Goodness-of-Fit Tests for Images Index

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_V_IMAGES
Date: 07/14/19 Time: 12:37
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	1.E-60	0.0001	43	42.9994	0	0.00058	43	0.00058
2	0.0002	0.0199	43	42.7665	0	0.23353	43	0.23480
3	0.0200	0.0504	42	41.4726	1	1.52744	43	0.18884
4	0.0511	0.0927	42	39.9477	1	3.05229	43	1.48535
5	0.0939	0.1574	37	38.6162	7	5.38375	44	0.55286
6	0.1586	0.2411	40	34.2468	3	8.75320	43	4.74789
7	0.2441	0.3305	30	30.7632	13	12.2368	43	0.06654
8	0.3341	0.6152	19	23.8973	24	19.1027	43	2.25913
9	0.6190	0.9255	6	9.55952	37	33.4405	43	1.70429
10	0.9295	1.0000	3	0.73074	41	43.2693	44	7.16599
		Total	305	305.000	127	127.000	432	18.4063

H-L Statistic	18.4063	Prob. Chi-Sq(8)	0.0184
Andrews Statistic	48.8598	Prob. Chi-Sq(10)	0.0000

Appendix 32: Probit Regression: The Effect of Profile on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:06
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.19E-05	9.90E-06	-6.249181	0.0000
DURATION	-0.000217	0.001918	-0.113055	0.9100
MIN	-0.000334	0.000136	-2.459715	0.0139
DENSITY	0.024238	0.003156	7.679115	0.0000
MINREWARD	0.002134	0.000931	2.291238	0.0219
VIRALITY	0.216971	0.123974	1.750134	0.0801
PROFILE	0.060898	0.166651	0.365424	0.7148
C	-0.686854	0.184209	-3.728658	0.0002

McFadden R-squared	0.431370	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.319284
Akaike info criterion	0.725851	Sum squared resid	43.22340
Schwarz criterion	0.801192	Log likelihood	-148.7837
Hannan-Quinn criter.	0.755595	Deviance	297.5675
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	225.7385	Avg. log likelihood	-0.344407
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 33: Probit Regression: Expectation-Prediction Table for Profile

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_D_PROFILE
Date: 07/14/19 Time: 15:07
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	51	347	305	127	432
P(Dep=1)>C	9	76	85	0	0	0
Total	305	127	432	305	127	432
Correct	296	76	372	305	0	305
% Correct	97.05	59.84	86.11	100.00	0.00	70.60
% Incorrect	2.95	40.16	13.89	0.00	100.00	29.40
Total Gain*	-2.95	59.84	15.51			
Percent Gain**	NA	59.84	52.76			

Appendix 34: Probit Regression: Goodness-of-Fit Tests for Profile

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_D_PROFILE
Date: 07/14/19 Time: 15:07
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	2.E-06	43	43.0000	0	5.7E-06	43	5.7E-06
2	2.E-06	0.0158	43	42.8519	0	0.14809	43	0.14860
3	0.0161	0.0705	41	41.1308	2	1.86923	43	0.00956
4	0.0724	0.1273	40	38.8276	3	4.17238	43	0.36482
5	0.1293	0.2109	40	36.5536	4	7.44644	44	1.92006
6	0.2143	0.2800	37	32.4298	6	10.5702	43	2.62006
7	0.2837	0.3437	33	29.5778	10	13.4222	43	1.26851
8	0.3453	0.4926	19	25.6879	24	17.3121	43	4.32484
9	0.4942	0.7931	5	15.4065	38	27.5935	43	10.9538
10	0.8004	1.0000	4	2.58270	40	41.4173	44	0.82627
		Total	305	308.048	127	123.952	432	22.4365

H-L Statistic	22.4365	Prob. Chi-Sq(8)	0.0042
Andrews Statistic	48.8074	Prob. Chi-Sq(10)	0.0000

Appendix 35: Probit Regression: The Effect of Purpose on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:08
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.21E-05	9.93E-06	-6.257005	0.0000
DURATION	-0.000247	0.001907	-0.129486	0.8970
MIN	-0.000329	0.000135	-2.432671	0.0150
DENSITY	0.024257	0.003152	7.696696	0.0000
MINREWARD	0.002116	0.000927	2.283192	0.0224
VIRALITY	0.222035	0.124027	1.790214	0.0734
PURPOSE	0.054732	0.187269	0.292266	0.7701
C	-0.694982	0.211359	-3.288166	0.0010

McFadden R-squared	0.431278	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.318962
Akaike info criterion	0.725962	Sum squared resid	43.13633
Schwarz criterion	0.801303	Log likelihood	-148.8078
Hannan-Quinn criter.	0.755706	Deviance	297.6155
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	225.6905	Avg. log likelihood	-0.344462
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 36: Probit Regression: Expectation-Prediction Table for Purpose

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_D_PURPOSE
Date: 07/14/19 Time: 15:08
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	50	347	305	127	432
P(Dep=1)>C	8	77	85	0	0	0
Total	305	127	432	305	127	432
Correct	297	77	374	305	0	305
% Correct	97.38	60.63	86.57	100.00	0.00	70.60
% Incorrect	2.62	39.37	13.43	0.00	100.00	29.40
Total Gain*	-2.62	60.63	15.97			
Percent Gain**	NA	60.63	54.33			

Appendix 37: Probit Regression: Goodness-of-Fit Tests for Purpose

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_D_PURPOSE
Date: 07/14/19 Time: 15:09
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk Low	High	Dep=0 Actual	Expect	Dep=1 Actual	Expect	Total Obs	H-L Value
1	0.0000	2.E-06	43	43.0000	0	5.3E-06	43	5.3E-06
2	2.E-06	0.0158	43	42.8520	0	0.14805	43	0.14856
3	0.0160	0.0697	41	41.1284	2	1.87157	43	0.00921
4	0.0706	0.1263	40	38.7681	3	4.23191	43	0.39776
5	0.1307	0.2170	40	36.6047	4	7.39534	44	1.87380
6	0.2188	0.2795	39	32.3666	4	10.6334	43	5.49755
7	0.2817	0.3444	32	29.6481	11	13.3519	43	0.60085
8	0.3449	0.4717	18	25.6417	25	17.3583	43	5.64157
9	0.4727	0.7898	5	15.4782	38	27.5218	43	11.0826
10	0.7920	1.0000	4	2.64915	40	41.3509	44	0.73296
		Total	305	308.137	127	123.863	432	25.9849

H-L Statistic	25.9849	Prob. Chi-Sq(8)	0.0011
Andrews Statistic	54.7353	Prob. Chi-Sq(10)	0.0000

Appendix 38: Probit Regression: The Effect of Risk and Challenges on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:09
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.18E-05	9.92E-06	-6.230317	0.0000
DURATION	-0.000178	0.001906	-0.093530	0.9255
MIN	-0.000334	0.000135	-2.469137	0.0135
DENSITY	0.024296	0.003157	7.695801	0.0000
MINREWARD	0.002152	0.000931	2.311542	0.0208
VIRALITY	0.222259	0.124053	1.791645	0.0732
R_C	0.078487	0.172853	0.454069	0.6498
C	-0.690598	0.180259	-3.831147	0.0001

McFadden R-squared	0.431508	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.319061
Akaike info criterion	0.725683	Sum squared resid	43.16304
Schwarz criterion	0.801024	Log likelihood	-148.7475
Hannan-Quinn criter.	0.755427	Deviance	297.4950
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	225.8110	Avg. log likelihood	-0.344323
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 39: Probit Regression: Expectation-Prediction Table for Risk and Challenges

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_D_RNC
Date: 07/14/19 Time: 15:10
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	50	347	305	127	432
P(Dep=1)>C	8	77	85	0	0	0
Total	305	127	432	305	127	432
Correct	297	77	374	305	0	305
% Correct	97.38	60.63	86.57	100.00	0.00	70.60
% Incorrect	2.62	39.37	13.43	0.00	100.00	29.40
Total Gain*	-2.62	60.63	15.97			
Percent Gain**	NA	60.63	54.33			

Appendix 40: Probit Regression: Goodness-of-Fit Tests for Risk and Challenges

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_D_RNC
Date: 07/14/19 Time: 15:11
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	2.E-06	43	43.0000	0	5.6E-06	43	5.6E-06
2	3.E-06	0.0152	43	42.8527	0	0.14728	43	0.14778
3	0.0154	0.0721	41	41.1321	2	1.86794	43	0.00976
4	0.0722	0.1277	41	38.7562	2	4.24381	43	1.31627
5	0.1285	0.2141	38	36.6443	6	7.35567	44	0.30001
6	0.2149	0.2797	38	32.3821	5	10.6179	43	3.94707
7	0.2811	0.3402	34	29.6359	9	13.3641	43	2.06778
8	0.3418	0.4852	18	25.6448	25	17.3552	43	5.64645
9	0.4938	0.7923	6	15.3897	37	27.6103	43	8.92211
10	0.7943	1.0000	3	2.63296	41	41.3670	44	0.05442
		Total	305	308.071	127	123.929	432	22.4117

H-L Statistic	22.4117	Prob. Chi-Sq(8)	0.0042
Andrews Statistic	47.7401	Prob. Chi-Sq(10)	0.0000

Appendix 41: Probit Regression: The Effect of Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 14:55
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.49E-05	1.02E-05	-6.375155	0.0000
DURATION	-0.000499	0.002025	-0.246614	0.8052
MIN	-0.000332	0.000133	-2.490542	0.0128
DENSITY	0.025205	0.003197	7.883727	0.0000
MINREWARD	0.001954	0.000913	2.139823	0.0324
VIRALITY	0.252818	0.124644	2.028325	0.0425
INFO	-0.504034	0.174429	-2.889627	0.0039
C	-0.349230	0.194379	-1.796644	0.0724

McFadden R-squared	0.447248	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.312867
Akaike info criterion	0.706617	Sum squared resid	41.50353
Schwarz criterion	0.781958	Log likelihood	-144.6293
Hannan-Quinn criter.	0.736362	Deviance	289.2587
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	234.0474	Avg. log likelihood	-0.334790
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 42: Probit Regression: Expectation-Prediction Table for Info

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_D_INFO
Date: 07/14/19 Time: 14:55
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	48	344	305	127	432
P(Dep=1)>C	9	79	88	0	0	0
Total	305	127	432	305	127	432
Correct	296	79	375	305	0	305
% Correct	97.05	62.20	86.81	100.00	0.00	70.60
% Incorrect	2.95	37.80	13.19	0.00	100.00	29.40
Total Gain*	-2.95	62.20	16.20			
Percent Gain**	NA	62.20	55.12			

Appendix 43: Probit Regression: Goodness-of-Fit Tests for Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_D_INFO
Date: 07/14/19 Time: 14:56
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	4.E-06	43	43.0000	0	7.9E-06	43	7.9E-06
2	5.E-06	0.0148	43	42.8753	0	0.12474	43	0.12510
3	0.0176	0.0690	42	41.3584	1	1.64165	43	0.26075
4	0.0701	0.1181	40	39.0152	3	3.98483	43	0.26826
5	0.1187	0.1978	40	36.9100	4	7.08996	44	1.60535
6	0.1979	0.2617	41	33.0533	2	9.94674	43	8.25945
7	0.2626	0.3549	29	29.9768	14	13.0232	43	0.10510
8	0.3621	0.5007	18	25.2195	25	17.7805	43	4.99805
9	0.5018	0.8302	6	14.3948	37	28.6052	43	7.35940
10	0.8315	1.0000	3	2.33369	41	41.6663	44	0.20090
		Total	305	308.137	127	123.863	432	23.1824

H-L Statistic	23.1824	Prob. Chi-Sq(8)	0.0031
Andrews Statistic	52.6945	Prob. Chi-Sq(10)	0.0000

Appendix 44: Probit Regression: The Effect of Budget Plan on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 14:52
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.06E-05	1.00E-05	-6.043861	0.0000
DURATION	-0.000364	0.001926	-0.189218	0.8499
MIN	-0.000371	0.000144	-2.579334	0.0099
DENSITY	0.023533	0.003191	7.374078	0.0000
MINREWARD	0.001802	0.000926	1.946326	0.0516
VIRALITY	0.214260	0.126155	1.698391	0.0894
BUDGET_PLAN	-0.571521	0.203859	-2.803514	0.0051
C	-0.465743	0.176631	-2.636820	0.0084

McFadden R-squared	0.446942	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.313871
Akaike info criterion	0.706988	Sum squared resid	41.77047
Schwarz criterion	0.782329	Log likelihood	-144.7094
Hannan-Quinn criter.	0.736732	Deviance	289.4188
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	233.8872	Avg. log likelihood	-0.334975
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 45: Probit Regression: Expectation-Prediction Table for Budget Plan

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_D_BUDGETPLAN
Date: 07/14/19 Time: 14:53
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	298	49	347	305	127	432
P(Dep=1)>C	7	78	85	0	0	0
Total	305	127	432	305	127	432
Correct	298	78	376	305	0	305
% Correct	97.70	61.42	87.04	100.00	0.00	70.60
% Incorrect	2.30	38.58	12.96	0.00	100.00	29.40
Total Gain*	-2.30	61.42	16.44			
Percent Gain**	NA	61.42	55.91			

Appendix 46: Probit Regression: Goodness-of-Fit Tests for Budget Plan

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_D_BUDGETPLAN
Date: 07/14/19 Time: 14:54
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	2.E-07	43	43.0000	0	5.5E-07	43	5.5E-07
2	3.E-07	0.0101	43	42.9208	0	0.07923	43	0.07937
3	0.0108	0.0560	42	41.4879	1	1.51208	43	0.17974
4	0.0561	0.1225	40	39.2620	3	3.73802	43	0.15959
5	0.1234	0.1880	41	37.0387	3	6.96134	44	2.67786
6	0.1903	0.2867	34	32.8558	9	10.1442	43	0.16891
7	0.2890	0.3675	35	28.9435	8	14.0565	43	3.87685
8	0.3677	0.4956	20	25.1871	23	17.8129	43	2.57877
9	0.4971	0.8185	3	14.9580	40	28.0420	43	14.6590
10	0.8209	1.0000	4	2.37199	40	41.6280	44	1.18106
		Total	305	308.026	127	123.974	432	25.5611

H-L Statistic	25.5611	Prob. Chi-Sq(8)	0.0012
Andrews Statistic	55.6527	Prob. Chi-Sq(10)	0.0000

Appendix 47: Probit Regression: The Effect of Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:01
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.13E-05	9.93E-06	-6.170743	0.0000
DURATION	-0.000254	0.001925	-0.132018	0.8950
MIN	-0.000339	0.000137	-2.471073	0.0135
DENSITY	0.024062	0.003164	7.604051	0.0000
MINREWARD	0.002184	0.000931	2.344355	0.0191
VIRALITY	0.218767	0.123809	1.766980	0.0772
LANGUAGES	0.108925	0.100919	1.079327	0.2804
C	-0.692942	0.167251	-4.143123	0.0000

McFadden R-squared	0.433194	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.318735
Akaike info criterion	0.723641	Sum squared resid	43.07500
Schwarz criterion	0.798982	Log likelihood	-148.3065
Hannan-Quinn criter.	0.753385	Deviance	296.6129
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	226.6931	Avg. log likelihood	-0.343302
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 48: Probit Regression: Expectation-Prediction Table for Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_D_LANGUANGES
Date: 07/14/19 Time: 15:01
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	50	347	305	127	432
P(Dep=1)>C	8	77	85	0	0	0
Total	305	127	432	305	127	432
Correct	297	77	374	305	0	305
% Correct	97.38	60.63	86.57	100.00	0.00	70.60
% Incorrect	2.62	39.37	13.43	0.00	100.00	29.40
Total Gain*	-2.62	60.63	15.97			
Percent Gain**	NA	60.63	54.33			

Appendix 49: Probit Regression: Goodness-of-Fit Tests for Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_D_LANGUANGES
Date: 07/14/19 Time: 15:02
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk Low	High	Dep=0 Actual	Expect	Dep=1 Actual	Expect	Total Obs	H-L Value
1	0.0000	2.E-06	43	43.0000	0	4.7E-06	43	4.7E-06
2	2.E-06	0.0157	43	42.8632	0	0.13679	43	0.13723
3	0.0168	0.0675	41	41.2008	2	1.79918	43	0.02339
4	0.0701	0.1312	42	38.8365	1	4.16352	43	2.66139
5	0.1334	0.2119	39	36.5930	5	7.40695	44	0.94048
6	0.2137	0.2784	37	32.4638	6	10.5362	43	2.58683
7	0.2793	0.3367	35	29.6245	8	13.3755	43	3.13581
8	0.3418	0.4912	16	25.5378	27	17.4622	43	8.77167
9	0.4939	0.7952	6	15.5243	37	27.4757	43	9.14472
10	0.8051	1.0000	3	2.56141	41	41.4386	44	0.07974
		Total	305	308.205	127	123.795	432	27.4813

H-L Statistic	27.4813	Prob. Chi-Sq(8)	0.0006
Andrews Statistic	55.3062	Prob. Chi-Sq(10)	0.0000

Appendix 50: Logistic Regression: The Effect of Profile on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:29
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000155	2.43E-05	-6.372726	0.0000
DURATION	-0.002263	0.003159	-0.716541	0.4737
MIN	-0.000391	0.000253	-1.543624	0.1227
DENSITY	0.065893	0.009586	6.873967	0.0000
MINREWARD	0.003434	0.001948	1.763259	0.0779
VIRALITY	0.437509	0.233445	1.874143	0.0609
PROFILE	-0.081055	0.305790	-0.265069	0.7910
C	-1.251405	0.331853	-3.770959	0.0002

McFadden R-squared	0.471179	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.304209
Akaike info criterion	0.677628	Sum squared resid	39.23823
Schwarz criterion	0.752969	Log likelihood	-138.3677
Hannan-Quinn criter.	0.707372	Deviance	276.7353
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	246.5707	Avg. log likelihood	-0.320296
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 51: Logistic Regression: Expectation-Prediction Table for Profile

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_D_PROFILE
Date: 07/14/19 Time: 15:30
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	291	41	332	305	127	432
P(Dep=1)>C	14	86	100	0	0	0
Total	305	127	432	305	127	432
Correct	291	86	377	305	0	305
% Correct	95.41	67.72	87.27	100.00	0.00	70.60
% Incorrect	4.59	32.28	12.73	0.00	100.00	29.40
Total Gain*	-4.59	67.72	16.67			
Percent Gain**	NA	67.72	56.69			

Appendix 52: Logistic Regression: Goodness-of-Fit Tests for Profile

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_D_PROFILE
Date: 07/14/19 Time: 15:31
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	7.E-58	0.0002	43	42.9993	0	0.00068	43	0.00068
2	0.0002	0.0180	43	42.7626	0	0.23738	43	0.23870
3	0.0192	0.0549	41	41.3774	2	1.62256	43	0.09124
4	0.0551	0.0921	42	40.0129	1	2.98713	43	1.42059
5	0.0927	0.1660	39	38.4440	5	5.55602	44	0.06369
6	0.1680	0.2440	38	33.9393	5	9.06070	43	2.30572
7	0.2463	0.3430	32	30.5276	11	12.4724	43	0.24483
8	0.3442	0.5636	19	23.9915	24	19.0085	43	2.34922
9	0.5657	0.9139	5	10.0430	38	32.9570	43	3.30399
10	0.9147	1.0000	3	0.90234	41	43.0977	44	4.97848
		Total	305	305.000	127	127.000	432	14.9971

H-L Statistic	14.9971	Prob. Chi-Sq(8)	0.0592
Andrews Statistic	45.8243	Prob. Chi-Sq(10)	0.0000

Appendix 53: Logistic Regression: The Effect of Purpose on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:32
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000155	2.43E-05	-6.381723	0.0000
DURATION	-0.002395	0.003163	-0.757106	0.4490
MIN	-0.000385	0.000252	-1.524501	0.1274
DENSITY	0.065870	0.009566	6.886005	0.0000
MINREWARD	0.003409	0.001943	1.754322	0.0794
VIRALITY	0.446817	0.234622	1.904412	0.0569
PURPOSE	0.177190	0.338204	0.523916	0.6003
C	-1.421993	0.391239	-3.634591	0.0003

McFadden R-squared	0.471574	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.304064
Akaike info criterion	0.677150	Sum squared resid	39.20082
Schwarz criterion	0.752491	Log likelihood	-138.2643
Hannan-Quinn criter.	0.706894	Deviance	276.5287
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	246.7773	Avg. log likelihood	-0.320056
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 54: Logistic Regression: Expectation-Prediction Table for Purpose

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_D_PURPOSE
Date: 07/14/19 Time: 15:32
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	291	40	331	305	127	432
P(Dep=1)>C	14	87	101	0	0	0
Total	305	127	432	305	127	432
Correct	291	87	378	305	0	305
% Correct	95.41	68.50	87.50	100.00	0.00	70.60
% Incorrect	4.59	31.50	12.50	0.00	100.00	29.40
Total Gain*	-4.59	68.50	16.90			
Percent Gain**	NA	68.50	57.48			

Appendix 55: Logistic Regression: Goodness-of-Fit Tests for Purpose

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_D_PURPOSE
Date: 07/14/19 Time: 15:33
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	3.E-57	0.0001	43	42.9993	0	0.00067	43	0.00067
2	0.0002	0.0196	43	42.7556	0	0.24440	43	0.24579
3	0.0207	0.0551	42	41.3733	1	1.62673	43	0.25095
4	0.0555	0.0929	41	39.9252	2	3.07482	43	0.40465
5	0.0934	0.1628	39	38.4511	5	5.54886	44	0.06212
6	0.1656	0.2468	38	34.0053	5	8.99474	43	2.24342
7	0.2495	0.3427	31	30.6266	12	12.3734	43	0.01582
8	0.3436	0.5541	19	23.9596	24	19.0404	43	2.31853
9	0.5579	0.9138	6	10.0295	37	32.9705	43	2.11139
10	0.9157	1.0000	3	0.87446	41	43.1255	44	5.27128
		Total	305	305.000	127	127.000	432	12.9246

H-L Statistic	12.9246	Prob. Chi-Sq(8)	0.1145
Andrews Statistic	40.8080	Prob. Chi-Sq(10)	0.0000

Appendix 56: Logistic Regression: The Effect of Risk and Challenges on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:33
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000154	2.41E-05	-6.402856	0.0000
DURATION	-0.002242	0.003164	-0.708404	0.4787
MIN	-0.000397	0.000253	-1.568782	0.1167
DENSITY	0.065662	0.009530	6.889968	0.0000
MINREWARD	0.003473	0.001948	1.782848	0.0746
VIRALITY	0.438413	0.233758	1.875497	0.0607
R_C	0.097039	0.316126	0.306964	0.7589
C	-1.332438	0.328648	-4.054296	0.0001

McFadden R-squared	0.471224	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.304429
Akaike info criterion	0.677573	Sum squared resid	39.29494
Schwarz criterion	0.752914	Log likelihood	-138.3558
Hannan-Quinn criter.	0.707317	Deviance	276.7115
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	246.5945	Avg. log likelihood	-0.320268
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 57: Logistic Regression: Expectation-Prediction Table for Risk and Challenges

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_D_RNC
Date: 07/14/19 Time: 15:34
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	292	40	332	305	127	432
P(Dep=1)>C	13	87	100	0	0	0
Total	305	127	432	305	127	432
Correct	292	87	379	305	0	305
% Correct	95.74	68.50	87.73	100.00	0.00	70.60
% Incorrect	4.26	31.50	12.27	0.00	100.00	29.40
Total Gain*	-4.26	68.50	17.13			
Percent Gain**	NA	68.50	58.27			

Appendix 58: Logistic Regression: Goodness-of-Fit Tests for Risk and Challenges

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_D_RNC
Date: 07/14/19 Time: 15:35
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-58	0.0001	43	42.9993	0	0.00066	43	0.00066
2	0.0002	0.0181	43	42.7652	0	0.23480	43	0.23609
3	0.0193	0.0557	42	41.3502	1	1.64979	43	0.26614
4	0.0558	0.0925	41	39.9611	2	3.03895	43	0.38220
5	0.0926	0.1660	39	38.4541	5	5.54591	44	0.06149
6	0.1679	0.2412	38	33.9560	5	9.04395	43	2.28984
7	0.2437	0.3440	33	30.5302	10	12.4698	43	0.68900
8	0.3445	0.5690	18	24.1301	25	18.8699	43	3.54874
9	0.5703	0.9132	5	9.95358	38	33.0464	43	3.20777
10	0.9154	1.0000	3	0.90022	41	43.0998	44	5.00005
		Total	305	305.000	127	127.000	432	15.6820

H-L Statistic	15.6820	Prob. Chi-Sq(8)	0.0472
Andrews Statistic	44.5016	Prob. Chi-Sq(10)	0.0000

Appendix 59: Logistic Regression: The Effect of Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:26
Sample: 1 433
Included observations: 432
Convergence achieved after 11 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000161	2.53E-05	-6.352574	0.0000
DURATION	-0.002958	0.003456	-0.855925	0.3920
MIN	-0.000402	0.000248	-1.622937	0.1046
DENSITY	0.068186	0.009817	6.945473	0.0000
MINREWARD	0.003179	0.001997	1.592308	0.1113
VIRALITY	0.516276	0.245390	2.103898	0.0354
INFO	-0.957504	0.324834	-2.947670	0.0032
C	-0.720563	0.348154	-2.069669	0.0385

McFadden R-squared	0.488087	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.298015
Akaike info criterion	0.657146	Sum squared resid	37.65676
Schwarz criterion	0.732487	Log likelihood	-133.9436
Hannan-Quinn criter.	0.686891	Deviance	267.8872
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	255.4188	Avg. log likelihood	-0.310055
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 60: Logistic Regression: Expectation-Prediction Table for Info

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_D_INFO
Date: 07/14/19 Time: 15:27
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	294	40	334	305	127	432
P(Dep=1)>C	11	87	98	0	0	0
Total	305	127	432	305	127	432
Correct	294	87	381	305	0	305
% Correct	96.39	68.50	88.19	100.00	0.00	70.60
% Incorrect	3.61	31.50	11.81	0.00	100.00	29.40
Total Gain*	-3.61	68.50	17.59			
Percent Gain**	NA	68.50	59.84			

Appendix 61: Logistic Regression: Goodness-of-Fit Tests for Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_D_INFO
Date: 07/14/19 Time: 15:27
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	9.E-60	0.0002	43	42.9994	0	0.00064	43	0.00064
2	0.0002	0.0143	43	42.7923	0	0.20770	43	0.20871
3	0.0146	0.0486	42	41.6185	1	1.38154	43	0.10887
4	0.0491	0.0905	41	39.9482	2	3.05176	43	0.39017
5	0.0913	0.1591	39	38.7246	5	5.27541	44	0.01634
6	0.1592	0.2266	41	34.5971	2	8.40287	43	6.06387
7	0.2277	0.3439	31	30.7442	12	12.2558	43	0.00747
8	0.3505	0.6057	15	23.8416	28	19.1584	43	7.35921
9	0.6142	0.9180	8	8.95969	35	34.0403	43	0.12985
10	0.9227	1.0000	2	0.77445	42	43.2256	44	1.97416
		Total	305	305.000	127	127.000	432	16.2593

H-L Statistic	16.2593	Prob. Chi-Sq(8)	0.0388
Andrews Statistic	53.1578	Prob. Chi-Sq(10)	0.0000

Appendix 62: Logistic Regression: The Effect of Budget Plan on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:23
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000156	2.51E-05	-6.243003	0.0000
DURATION	-0.002747	0.003199	-0.858848	0.3904
MIN	-0.000440	0.000273	-1.610700	0.1072
DENSITY	0.066347	0.009909	6.695635	0.0000
MINREWARD	0.002777	0.001864	1.490106	0.1362
VIRALITY	0.452534	0.235748	1.919562	0.0549
BUDGET_PLAN	-1.097940	0.383690	-2.861526	0.0042
C	-0.969087	0.316560	-3.061308	0.0022

McFadden R-squared	0.488379	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.296742
Akaike info criterion	0.656793	Sum squared resid	37.33576
Schwarz criterion	0.732134	Log likelihood	-133.8673
Hannan-Quinn criter.	0.686537	Deviance	267.7345
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	255.5715	Avg. log likelihood	-0.309878
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 63: Logistic Regression: Expectation-Prediction Table for Budget Plan

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_D_BUDGETPLAN
Date: 07/14/19 Time: 15:25
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	294	38	332	305	127	432
P(Dep=1)>C	11	89	100	0	0	0
Total	305	127	432	305	127	432
Correct	294	89	383	305	0	305
% Correct	96.39	70.08	88.66	100.00	0.00	70.60
% Incorrect	3.61	29.92	11.34	0.00	100.00	29.40
Total Gain*	-3.61	70.08	18.06			
Percent Gain**	NA	70.08	61.42			

Appendix 64: Logistic Regression: Goodness-of-Fit Tests for Budget Plan

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_D_BUDGETPLAN
Date: 07/14/19 Time: 15:26
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-63	6.E-05	43	42.9997	0	0.00033	43	0.00033
2	9.E-05	0.0126	43	42.8460	0	0.15404	43	0.15460
3	0.0127	0.0463	42	41.8338	1	1.16624	43	0.02436
4	0.0470	0.0863	40	40.1012	3	2.89875	43	0.00379
5	0.0893	0.1460	42	38.8322	2	5.16780	44	2.20024
6	0.1488	0.2480	33	34.7554	10	8.24461	43	0.46240
7	0.2487	0.3593	36	29.8112	7	13.1888	43	4.18885
8	0.3624	0.5872	21	23.4196	22	19.5804	43	0.54899
9	0.5888	0.9192	2	9.65345	41	33.3466	43	7.82437
10	0.9279	1.0000	3	0.74749	41	43.2525	44	6.90509
		Total	305	305.000	127	127.000	432	22.3130

H-L Statistic	22.3130	Prob. Chi-Sq(8)	0.0044
Andrews Statistic	57.5303	Prob. Chi-Sq(10)	0.0000

Appendix 65: Logistic Regression: The Effect of Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 15:28
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000154	2.40E-05	-6.416528	0.0000
DURATION	-0.002402	0.003202	-0.750095	0.4532
MIN	-0.000403	0.000257	-1.567085	0.1171
DENSITY	0.065654	0.009583	6.850963	0.0000
MINREWARD	0.003572	0.001972	1.811324	0.0701
VIRALITY	0.435084	0.232387	1.872237	0.0612
LANGUAGES	0.203182	0.184421	1.101729	0.2706
C	-1.363221	0.306927	-4.441519	0.0000

McFadden R-squared	0.473511	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.304005
Akaike info criterion	0.674803	Sum squared resid	39.18579
Schwarz criterion	0.750144	Log likelihood	-137.7574
Hannan-Quinn criter.	0.704547	Deviance	275.5148
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	247.7912	Avg. log likelihood	-0.318883
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 66: Logistic Regression: Expectation-Prediction Table for Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_D_LANGAUGES
Date: 07/14/19 Time: 15:28
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	291	40	331	305	127	432
P(Dep=1)>C	14	87	101	0	0	0
Total	305	127	432	305	127	432
Correct	291	87	378	305	0	305
% Correct	95.41	68.50	87.50	100.00	0.00	70.60
% Incorrect	4.59	31.50	12.50	0.00	100.00	29.40
Total Gain*	-4.59	68.50	16.90			
Percent Gain**	NA	68.50	57.48			

Appendix 67: Logistic Regression: Goodness-of-Fit Tests for Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_D_LANGAUGES
Date: 07/14/19 Time: 15:29
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	5.E-59	0.0001	43	42.9994	0	0.00065	43	0.00065
2	0.0001	0.0173	43	42.7669	0	0.23310	43	0.23438
3	0.0182	0.0530	42	41.4232	1	1.57677	43	0.21901
4	0.0531	0.0939	41	40.0298	2	2.97021	43	0.34043
5	0.0968	0.1626	39	38.4979	5	5.50212	44	0.05237
6	0.1677	0.2397	37	34.0307	6	8.96929	43	1.24207
7	0.2463	0.3360	34	30.5860	9	12.4140	43	1.31999
8	0.3361	0.6027	18	23.8195	25	19.1805	43	3.18751
9	0.6047	0.9099	5	9.98546	38	33.0145	43	3.24194
10	0.9106	1.0000	3	0.86120	41	43.1388	44	5.41778
		Total	305	305.000	127	127.000	432	15.2561

H-L Statistic	15.2561	Prob. Chi-Sq(8)	0.0544
Andrews Statistic	43.1628	Prob. Chi-Sq(10)	0.0000

Appendix 68: Probit Regression: The Effect of Shares Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 06/27/19 Time: 23:52
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.19E-05	1.01E-05	-6.099273	0.0000
DURATION	-0.000257	0.002083	-0.123356	0.9018
MIN	-0.000363	0.000138	-2.632125	0.0085
DENSITY	0.025302	0.003231	7.830195	0.0000
MINREWARD	0.001591	0.000885	1.796838	0.0724
S_INDEX	0.444200	0.312720	1.420440	0.1555
BUDGET_PLAN	-0.601963	0.206670	-2.912680	0.0036
INFO	-0.486601	0.176502	-2.756914	0.0058
C	-0.048008	0.197543	-0.243028	0.8080

McFadden R-squared	0.458799	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.308450
Akaike info criterion	0.697254	Sum squared resid	40.24485
Schwarz criterion	0.782013	Log likelihood	-141.6069
Hannan-Quinn criter.	0.730717	Deviance	283.2139
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	240.0921	Avg. log likelihood	-0.327794
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 69: Probit Regression: Expectation-Prediction Table for Shares Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 16:41
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	295	43	338	305	127	432
P(Dep=1)>C	10	84	94	0	0	0
Total	305	127	432	305	127	432
Correct	295	84	379	305	0	305
% Correct	96.72	66.14	87.73	100.00	0.00	70.60
% Incorrect	3.28	33.86	12.27	0.00	100.00	29.40
Total Gain*	-3.28	66.14	17.13			
Percent Gain**	NA	66.14	58.27			

Appendix 70: Probit Regression: Goodness-of-Fit Tests for Shares Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 16:42
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	3.E-07	43	43.0000	0	6.7E-07	43	6.7E-07
2	3.E-07	0.0094	43	42.9357	0	0.06427	43	0.06436
3	0.0109	0.0570	41	41.4984	2	1.50156	43	0.17144
4	0.0592	0.1159	41	39.4161	2	3.58392	43	0.76367
5	0.1176	0.1792	38	37.5191	6	6.48088	44	0.04184
6	0.1797	0.2653	38	33.2763	5	9.72371	43	2.96530
7	0.2668	0.3665	38	29.5499	5	13.4501	43	7.72516
8	0.3703	0.5213	16	23.9577	27	19.0423	43	5.96874
9	0.5235	0.8178	5	14.1519	38	28.8481	43	8.82184
10	0.8238	1.0000	2	2.17481	42	41.8252	44	0.01478
		Total	305	307.480	127	124.520	432	26.5371

H-L Statistic	26.5371	Prob. Chi-Sq(8)	0.0008
Andrews Statistic	52.6298	Prob. Chi-Sq(10)	0.0000

Appendix 71: Probit Regression: The Effect of Shares Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 06/27/19 Time: 23:55
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-5.94E-05	9.57E-06	-6.213957	0.0000
DURATION	-2.32E-06	0.001939	-0.001198	0.9990
MIN	-0.000336	0.000135	-2.487703	0.0129
DENSITY	0.024766	0.003162	7.832917	0.0000
MINREWARD	0.002140	0.000921	2.324079	0.0201
S_INDEX	0.298826	0.305173	0.979202	0.3275
PROFILE	0.074887	0.166837	0.448864	0.6535
PURPOSE	0.099514	0.194746	0.510991	0.6094
R_C	0.053602	0.173077	0.309703	0.7568
LANGUAGES	0.116485	0.103041	1.130478	0.2583
C	-0.719476	0.237840	-3.025045	0.0025

McFadden R-squared	0.429787	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.321304
Akaike info criterion	0.741658	Sum squared resid	43.46258
Schwarz criterion	0.845252	Log likelihood	-149.1980
Hannan-Quinn criter.	0.782556	Deviance	298.3960
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	224.9100	Avg. log likelihood	-0.345366
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 72: Probit Regression: Expectation-Prediction Table for Shares Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 16:44
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	295	50	345	305	127	432
P(Dep=1)>C	10	77	87	0	0	0
Total	305	127	432	305	127	432
Correct	295	77	372	305	0	305
% Correct	96.72	60.63	86.11	100.00	0.00	70.60
% Incorrect	3.28	39.37	13.89	0.00	100.00	29.40
Total Gain*	-3.28	60.63	15.51			
Percent Gain**	NA	60.63	52.76			

Appendix 73: Probit Regression: Goodness-of-Fit Tests for Shares Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 16:45
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	2.E-06	43	43.0000	0	5.6E-06	43	5.6E-06
2	2.E-06	0.0151	43	42.8465	0	0.15348	43	0.15403
3	0.0161	0.0688	40	41.0767	3	1.92335	43	0.63091
4	0.0700	0.1393	43	38.7732	0	4.22680	43	4.68758
5	0.1407	0.2067	39	36.4608	5	7.53921	44	1.03204
6	0.2069	0.2748	36	32.3959	7	10.6041	43	1.62595
7	0.2749	0.3409	31	29.8694	12	13.1306	43	0.14016
8	0.3422	0.4865	20	25.5960	23	17.4040	43	3.02271
9	0.5055	0.7926	7	15.2442	36	27.7558	43	6.90728
10	0.8074	1.0000	3	2.61220	41	41.3878	44	0.06120
		Total	305	307.875	127	124.125	432	18.2619

H-L Statistic	18.2619	Prob. Chi-Sq(8)	0.0193
Andrews Statistic	76.4786	Prob. Chi-Sq(10)	0.0000

Appendix 74: Probit Regression: The Effect of Updates Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:11
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.07E-05	9.91E-06	-6.124458	0.0000
DURATION	-0.000258	0.002052	-0.125793	0.8999
MIN	-0.000355	0.000136	-2.615231	0.0089
DENSITY	0.025529	0.003253	7.846739	0.0000
MINREWARD	0.001508	0.000869	1.735366	0.0827
U_INDEX	-0.043119	0.078358	-0.550283	0.5821
BUDGET_PLAN	-0.576024	0.204904	-2.811196	0.0049
INFO	-0.478652	0.176206	-2.716440	0.0066
C	-0.027210	0.197265	-0.137939	0.8903

McFadden R-squared	0.455848	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.309385
Akaike info criterion	0.700829	Sum squared resid	40.48929
Schwarz criterion	0.785588	Log likelihood	-142.3791
Hannan-Quinn criter.	0.734292	Deviance	284.7582
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	238.5478	Avg. log likelihood	-0.329581
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 75: Probit Regression: Expectation-Prediction Table for Updates Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 17:13
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	295	43	338	305	127	432
P(Dep=1)>C	10	84	94	0	0	0
Total	305	127	432	305	127	432
Correct	295	84	379	305	0	305
% Correct	96.72	66.14	87.73	100.00	0.00	70.60
% Incorrect	3.28	33.86	12.27	0.00	100.00	29.40
Total Gain*	-3.28	66.14	17.13			
Percent Gain**	NA	66.14	58.27			

Appendix 76: Probit Regression: Goodness-of-Fit Tests for Updates Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 17:13
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	4.E-07	43	43.0000	0	1.2E-06	43	1.2E-06
2	5.E-07	0.0103	43	42.9286	0	0.07144	43	0.07156
3	0.0134	0.0548	41	41.4897	2	1.51026	43	0.16459
4	0.0568	0.1237	41	39.3634	2	3.63659	43	0.80456
5	0.1247	0.1882	39	37.3463	5	6.65375	44	0.48426
6	0.1885	0.2699	36	33.2186	7	9.78140	43	1.02380
7	0.2702	0.3652	37	29.5344	6	13.4656	43	6.02622
8	0.3656	0.5138	18	24.1426	25	18.8574	43	3.56369
9	0.5236	0.8130	5	14.1754	38	28.8246	43	8.85977
10	0.8186	1.0000	2	2.30335	42	41.6967	44	0.04216
		Total	305	307.502	127	124.498	432	21.0406

H-L Statistic	21.0406	Prob. Chi-Sq(8)	0.0070
Andrews Statistic	47.6936	Prob. Chi-Sq(10)	0.0000

Appendix 77: Probit Regression: The Effect of Updates Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:16
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-5.87E-05	9.17E-06	-6.399031	0.0000
DURATION	1.76E-05	0.001937	0.009104	0.9927
MIN	-0.000334	0.000134	-2.498159	0.0125
DENSITY	0.024854	0.003181	7.813889	0.0000
MINREWARD	0.002082	0.000921	2.260955	0.0238
U_INDEX	-0.021603	0.075429	-0.286399	0.7746
PROFILE	0.070602	0.166677	0.423582	0.6719
PURPOSE	0.052486	0.187056	0.280590	0.7790
R_C	0.067541	0.171859	0.392999	0.6943
LANGUAGES	0.115431	0.102985	1.120855	0.2623
C	-0.665343	0.229323	-2.901332	0.0037

McFadden R-squared	0.428206	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.321090
Akaike info criterion	0.743572	Sum squared resid	43.40471
Schwarz criterion	0.847166	Log likelihood	-149.6115
Hannan-Quinn criter.	0.784470	Deviance	299.2230
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	224.0830	Avg. log likelihood	-0.346323
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 78: Probit Regression: Expectation-Prediction Table for Updates Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 17:17
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	51	347	305	127	432
P(Dep=1)>C	9	76	85	0	0	0
Total	305	127	432	305	127	432
Correct	296	76	372	305	0	305
% Correct	97.05	59.84	86.11	100.00	0.00	70.60
% Incorrect	2.95	40.16	13.89	0.00	100.00	29.40
Total Gain*	-2.95	59.84	15.51			
Percent Gain**	NA	59.84	52.76			

Appendix 79: Probit Regression: Goodness-of-Fit Tests for Updates Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 17:17
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	3.E-06	43	43.0000	0	7.7E-06	43	7.7E-06
2	3.E-06	0.0166	43	42.8309	0	0.16914	43	0.16980
3	0.0171	0.0671	40	41.0748	3	1.92524	43	0.62811
4	0.0717	0.1333	41	38.7768	2	4.22322	43	1.29783
5	0.1345	0.2097	41	36.3462	3	7.65384	44	3.42561
6	0.2098	0.2830	38	32.1633	5	10.8367	43	4.20284
7	0.2831	0.3414	30	29.7547	13	13.2453	43	0.00657
8	0.3433	0.4874	20	25.7822	23	17.2178	43	3.23857
9	0.4877	0.7986	6	15.4158	37	27.5842	43	8.96505
10	0.8057	1.0000	3	2.64060	41	41.3594	44	0.05204
		Total	305	307.785	127	124.215	432	21.9864

H-L Statistic	21.9864	Prob. Chi-Sq(8)	0.0049
Andrews Statistic	50.6788	Prob. Chi-Sq(10)	0.0000

Appendix 80: Probit Regression: The Effect of Videos Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:28
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.35E-05	1.05E-05	-6.034531	0.0000
DURATION	-0.000509	0.002027	-0.251253	0.8016
MIN	-0.000350	0.000137	-2.555250	0.0106
DENSITY	0.025546	0.003241	7.881433	0.0000
MINREWARD	0.001564	0.000883	1.771314	0.0765
V_INDEX	0.056605	0.048502	1.167055	0.2432
BUDGET_PLAN	-0.579487	0.205541	-2.819325	0.0048
INFO	-0.505256	0.177952	-2.839287	0.0045
C	-0.063556	0.198222	-0.320632	0.7485

McFadden R-squared	0.457714	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.309408
Akaike info criterion	0.698568	Sum squared resid	40.49528
Schwarz criterion	0.783327	Log likelihood	-141.8907
Hannan-Quinn criter.	0.732031	Deviance	283.7814
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	239.5246	Avg. log likelihood	-0.328451
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 81: Probit Regression: Expectation-Prediction Table for Videos Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 17:29
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	45	341	305	127	432
P(Dep=1)>C	9	82	91	0	0	0
Total	305	127	432	305	127	432
Correct	296	82	378	305	0	305
% Correct	97.05	64.57	87.50	100.00	0.00	70.60
% Incorrect	2.95	35.43	12.50	0.00	100.00	29.40
Total Gain*	-2.95	64.57	16.90			
Percent Gain**	NA	64.57	57.48			

Appendix 82: Probit Regression: Goodness-of-Fit Tests for Videos Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 17:30
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	4.E-07	43	43.0000	0	1.3E-06	43	1.3E-06
2	5.E-07	0.0088	43	42.9366	0	0.06338	43	0.06347
3	0.0128	0.0519	41	41.5194	2	1.48063	43	0.18868
4	0.0523	0.1210	41	39.4219	2	3.57809	43	0.75918
5	0.1216	0.1793	39	37.3841	5	6.61588	44	0.46451
6	0.1815	0.2594	38	33.3013	5	9.69874	43	2.93938
7	0.2598	0.3630	38	29.5844	5	13.4156	43	7.67299
8	0.3706	0.5283	14	24.2235	29	18.7765	43	9.88133
9	0.5354	0.8231	6	14.0644	37	28.9356	43	6.87155
10	0.8259	1.0000	2	2.27629	42	41.7237	44	0.03537
		Total	305	307.712	127	124.288	432	28.8765

H-L Statistic	28.8765	Prob. Chi-Sq(8)	0.0003
Andrews Statistic	54.5960	Prob. Chi-Sq(10)	0.0000

Appendix 83: Probit Regression: The Effect of Videos Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:30
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.00E-05	9.83E-06	-6.098814	0.0000
DURATION	-0.000111	0.001915	-0.058144	0.9536
MIN	-0.000331	0.000134	-2.464894	0.0137
DENSITY	0.024861	0.003168	7.847115	0.0000
MINREWARD	0.002130	0.000923	2.308648	0.0210
V_INDEX	0.032067	0.048961	0.654941	0.5125
PROFILE	0.065839	0.166357	0.395771	0.6923
PURPOSE	0.053271	0.187022	0.284838	0.7758
R_C	0.074856	0.172638	0.433600	0.6646
LANGUAGES	0.117228	0.102869	1.139584	0.2545
C	-0.699313	0.235905	-2.964382	0.0030

McFadden R-squared	0.428841	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.321266
Akaike info criterion	0.742803	Sum squared resid	43.45230
Schwarz criterion	0.846397	Log likelihood	-149.4454
Hannan-Quinn criter.	0.783701	Deviance	298.8908
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	224.4152	Avg. log likelihood	-0.345938
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 84: Probit Regression: Expectation-Prediction Table for Videos Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 17:31
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	296	50	346	305	127	432
P(Dep=1)>C	9	77	86	0	0	0
Total	305	127	432	305	127	432
Correct	296	77	373	305	0	305
% Correct	97.05	60.63	86.34	100.00	0.00	70.60
% Incorrect	2.95	39.37	13.66	0.00	100.00	29.40
Total Gain*	-2.95	60.63	15.74			
Percent Gain**	NA	60.63	53.54			

Appendix 85: Probit Regression: Goodness-of-Fit Tests for Videos Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 17:32
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	2.E-06	43	43.0000	0	6.9E-06	43	6.9E-06
2	6.E-06	0.0153	43	42.8427	0	0.15734	43	0.15791
3	0.0161	0.0691	40	41.0438	3	1.95616	43	0.58356
4	0.0696	0.1344	42	38.8264	1	4.17360	43	2.67260
5	0.1345	0.2104	40	36.4488	4	7.55123	44	2.01609
6	0.2144	0.2784	36	32.2127	7	10.7873	43	1.77495
7	0.2787	0.3453	34	29.7597	9	13.2403	43	1.96217
8	0.3468	0.4782	18	25.7207	25	17.2793	43	5.76730
9	0.4945	0.7876	6	15.3644	37	27.6356	43	8.88058
10	0.7971	1.0000	3	2.66035	41	41.3397	44	0.04615
		Total	305	307.879	127	124.121	432	23.8613

H-L Statistic	23.8613	Prob. Chi-Sq(8)	0.0024
Andrews Statistic	53.0545	Prob. Chi-Sq(10)	0.0000

Appendix 86: Probit Regression: The Effect of Images Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:37
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-6.04E-05	9.98E-06	-6.049941	0.0000
DURATION	-0.000314	0.002113	-0.148601	0.8819
MIN	-0.000389	0.000144	-2.703822	0.0069
DENSITY	0.023924	0.003226	7.415074	0.0000
MINREWARD	0.001551	0.000890	1.742256	0.0815
I_INDEX	0.127347	0.057634	2.209600	0.0271
BUDGET_PLAN	-0.541330	0.205429	-2.635117	0.0084
INFO	-0.476134	0.176404	-2.699112	0.0070
C	-0.197112	0.209088	-0.942722	0.3458

McFadden R-squared	0.465082	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.305907
Akaike info criterion	0.689644	Sum squared resid	39.58386
Schwarz criterion	0.774402	Log likelihood	-139.9630
Hannan-Quinn criter.	0.723106	Deviance	279.9260
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	243.3800	Avg. log likelihood	-0.323988
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 87: Probit Regression: Expectation-Prediction Table for Images Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 17:37
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	39	336	305	127	432
P(Dep=1)>C	8	88	96	0	0	0
Total	305	127	432	305	127	432
Correct	297	88	385	305	0	305
% Correct	97.38	69.29	89.12	100.00	0.00	70.60
% Incorrect	2.62	30.71	10.88	0.00	100.00	29.40
Total Gain*	-2.62	69.29	18.52			
Percent Gain**	NA	69.29	62.99			

Appendix 88: Probit Regression: Goodness-of-Fit Tests for Images Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_BP_INFO
Date: 07/14/19 Time: 17:38
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	7.E-08	43	43.0000	0	2.3E-07	43	2.3E-07
2	2.E-07	0.0078	43	42.9424	0	0.05760	43	0.05767
3	0.0099	0.0535	41	41.6011	2	1.39895	43	0.26692
4	0.0539	0.1184	42	39.4037	1	3.59626	43	2.04540
5	0.1187	0.1820	38	37.5424	6	6.45759	44	0.03800
6	0.1831	0.2631	38	33.3509	5	9.64906	43	2.88806
7	0.2669	0.3533	36	29.9241	7	13.0759	43	4.05688
8	0.3572	0.5323	16	23.9377	27	19.0623	43	5.93747
9	0.5343	0.8524	6	14.0845	37	28.9155	43	6.90083
10	0.8578	1.0000	2	1.97308	42	42.0269	44	0.00038
		Total	305	307.760	127	124.240	432	22.1916

H-L Statistic	22.1916	Prob. Chi-Sq(8)	0.0046
Andrews Statistic	49.2239	Prob. Chi-Sq(10)	0.0000

Appendix 89: Probit Regression: The Effect of Images Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:39
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-5.83E-05	9.30E-06	-6.265921	0.0000
DURATION	-4.02E-05	0.001972	-0.020387	0.9837
MIN	-0.000366	0.000143	-2.566924	0.0103
DENSITY	0.023412	0.003159	7.410461	0.0000
MINREWARD	0.002087	0.000947	2.202528	0.0276
I_INDEX	0.131699	0.056021	2.350876	0.0187
PROFILE	0.054533	0.167645	0.325289	0.7450
PURPOSE	0.087575	0.190652	0.459345	0.6460
R_C	0.073320	0.173662	0.422197	0.6729
LANGUAGES	0.109210	0.102366	1.066855	0.2860
C	-0.845657	0.245355	-3.446668	0.0006

McFadden R-squared	0.439124	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.317622
Akaike info criterion	0.730347	Sum squared resid	42.47197
Schwarz criterion	0.833941	Log likelihood	-146.7550
Hannan-Quinn criter.	0.771246	Deviance	293.5099
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	229.7961	Avg. log likelihood	-0.339711
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 90: Probit Regression: Expectation-Prediction Table for Images Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 17:39
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	50	347	305	127	432
P(Dep=1)>C	8	77	85	0	0	0
Total	305	127	432	305	127	432
Correct	297	77	374	305	0	305
% Correct	97.38	60.63	86.57	100.00	0.00	70.60
% Incorrect	2.62	39.37	13.43	0.00	100.00	29.40
Total Gain*	-2.62	60.63	15.97			
Percent Gain**	NA	60.63	54.33			

Appendix 91: Probit Regression: Goodness-of-Fit Tests for Images Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: P_CRS_P_P_R_L
Date: 07/14/19 Time: 17:40
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	7.E-07	43	43.0000	0	1.9E-06	43	1.9E-06
2	8.E-07	0.0173	43	42.8731	0	0.12687	43	0.12724
3	0.0175	0.0671	42	41.3636	1	1.63641	43	0.25729
4	0.0690	0.1289	41	38.7308	2	4.26918	43	1.33908
5	0.1314	0.2054	38	36.5636	6	7.43642	44	0.33389
6	0.2055	0.2696	39	32.6524	4	10.3476	43	5.12780
7	0.2698	0.3473	33	29.7904	10	13.2096	43	1.12568
8	0.3478	0.4854	17	25.7294	26	17.2706	43	7.37404
9	0.4892	0.8052	7	14.9878	36	28.0122	43	6.53487
10	0.8128	1.0000	2	2.34879	42	41.6512	44	0.05472
		Total	305	308.040	127	123.960	432	22.2746

H-L Statistic	22.2746	Prob. Chi-Sq(8)	0.0044
Andrews Statistic	46.2098	Prob. Chi-Sq(10)	0.0000

Appendix 92: Logistic Regression: The Effect of Shares Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 06/27/19 Time: 23:58
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000157	2.43E-05	-6.451812	0.0000
DURATION	-0.002651	0.003470	-0.764047	0.4448
MIN	-0.000447	0.000259	-1.721581	0.0851
DENSITY	0.069139	0.010012	6.905579	0.0000
MINREWARD	0.002464	0.001773	1.389855	0.1646
S_INDEX	0.747336	0.558727	1.337568	0.1810
BUDGET_PLAN	-1.161065	0.394290	-2.944695	0.0032
INFO	-0.926307	0.325433	-2.846385	0.0044
C	-0.133205	0.343088	-0.388255	0.6978

McFadden R-squared	0.499362	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.291935
Akaike info criterion	0.648117	Sum squared resid	36.05054
Schwarz criterion	0.732876	Log likelihood	-130.9934
Hannan-Quinn criter.	0.681580	Deviance	261.9867
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	261.3193	Avg. log likelihood	-0.303225
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 93: Logistic Regression: Expectation-Prediction Table for Shares Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 16:36
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	32	329	305	127	432
P(Dep=1)>C	8	95	103	0	0	0
Total	305	127	432	305	127	432
Correct	297	95	392	305	0	305
% Correct	97.38	74.80	90.74	100.00	0.00	70.60
% Incorrect	2.62	25.20	9.26	0.00	100.00	29.40
Total Gain*	-2.62	74.80	20.14			
Percent Gain**	NA	74.80	68.50			

Appendix 94: Logistic Regression: Goodness-of-Fit Tests for Shares Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 16:37
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-64	0.0001	43	42.9996	0	0.00036	43	0.00036
2	0.0001	0.0090	43	42.8665	0	0.13352	43	0.13393
3	0.0094	0.0454	40	41.8396	3	1.16038	43	2.99734
4	0.0455	0.0834	43	40.2712	0	2.72882	43	2.91373
5	0.0846	0.1433	39	38.9731	5	5.02690	44	0.00016
6	0.1435	0.2251	37	35.1535	6	7.84651	43	0.53153
7	0.2266	0.3533	37	30.6144	6	12.3856	43	4.62408
8	0.3663	0.6058	17	22.5141	26	20.4859	43	2.83471
9	0.6163	0.9294	4	8.99020	39	34.0098	43	3.50212
10	0.9389	1.0000	2	0.77775	42	43.2223	44	1.95536
		Total	305	305.000	127	127.000	432	19.4933

H-L Statistic	19.4933	Prob. Chi-Sq(8)	0.0124
Andrews Statistic	88.9084	Prob. Chi-Sq(10)	0.0000

Appendix 95: Logistic Regression: The Effect of Shares Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 06/28/19 Time: 00:02
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000151	2.30E-05	-6.584310	0.0000
DURATION	-0.001914	0.003159	-0.605694	0.5447
MIN	-0.000393	0.000251	-1.566405	0.1173
DENSITY	0.066654	0.009577	6.959840	0.0000
MINREWARD	0.003448	0.001946	1.771670	0.0764
S_INDEX	0.444616	0.561681	0.791582	0.4286
PROFILE	-0.069825	0.305866	-0.228286	0.8194
PURPOSE	0.217138	0.348224	0.623558	0.5329
R_C	0.072629	0.314994	0.230572	0.8176
LANGUAGES	0.222049	0.183433	1.210522	0.2261
C	-1.272824	0.419606	-3.033377	0.0024

McFadden R-squared	0.468653	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.306801
Akaike info criterion	0.694577	Sum squared resid	39.62738
Schwarz criterion	0.798171	Log likelihood	-139.0285
Hannan-Quinn criter.	0.735475	Deviance	278.0571
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	245.2489	Avg. log likelihood	-0.321825
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 96: Logistic Regression: Expectation-Prediction Table for Shares Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 16:39
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	293	42	335	305	127	432
P(Dep=1)>C	12	85	97	0	0	0
Total	305	127	432	305	127	432
Correct	293	85	378	305	0	305
% Correct	96.07	66.93	87.50	100.00	0.00	70.60
% Incorrect	3.93	33.07	12.50	0.00	100.00	29.40
Total Gain*	-3.93	66.93	16.90			
Percent Gain**	NA	66.93	57.48			

Appendix 97: Logistic Regression: Goodness-of-Fit Tests for Shares Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 16:40
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	1.E-57	0.0002	43	42.9993	0	0.00070	43	0.00070
2	0.0002	0.0183	43	42.7497	0	0.25027	43	0.25173
3	0.0183	0.0565	40	41.3977	3	1.60232	43	1.26638
4	0.0571	0.0957	43	39.8233	0	3.17667	43	3.43007
5	0.0970	0.1649	39	38.3247	5	5.67535	44	0.09227
6	0.1661	0.2419	38	33.9714	5	9.02857	43	2.27529
7	0.2422	0.3338	32	30.6665	11	12.3335	43	0.20216
8	0.3368	0.6072	17	24.0688	26	18.9312	43	4.71553
9	0.6086	0.9038	7	10.0237	36	32.9763	43	1.18937
10	0.9047	1.0000	3	0.97482	41	43.0252	44	4.30264
		Total	305	305.000	127	127.000	432	17.7261

H-L Statistic	17.7261	Prob. Chi-Sq(8)	0.0234
Andrews Statistic	84.1404	Prob. Chi-Sq(10)	0.0000

Appendix 98: Logistic Regression: The Effect of Updates Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:23
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000159	2.38E-05	-6.684802	0.0000
DURATION	-0.002466	0.003454	-0.713928	0.4753
MIN	-0.000420	0.000252	-1.667649	0.0954
DENSITY	0.071529	0.010432	6.856524	0.0000
MINREWARD	0.002229	0.001578	1.412135	0.1579
U_INDEX	-0.168382	0.155662	-1.081714	0.2794
BUDGET_PLAN	-1.106003	0.388851	-2.844287	0.0045
INFO	-0.934550	0.326345	-2.863689	0.0042
C	-0.077159	0.339936	-0.226981	0.8204

McFadden R-squared	0.498350	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.292152
Akaike info criterion	0.649344	Sum squared resid	36.10431
Schwarz criterion	0.734103	Log likelihood	-131.2583
Hannan-Quinn criter.	0.682806	Deviance	262.5166
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	260.7894	Avg. log likelihood	-0.303839
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 99: Logistic Regression: Expectation-Prediction Table for Updates Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 17:24
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	33	330	305	127	432
P(Dep=1)>C	8	94	102	0	0	0
Total	305	127	432	305	127	432
Correct	297	94	391	305	0	305
% Correct	97.38	74.02	90.51	100.00	0.00	70.60
% Incorrect	2.62	25.98	9.49	0.00	100.00	29.40
Total Gain*	-2.62	74.02	19.91			
Percent Gain**	NA	74.02	67.72			

Appendix 100: Logistic Regression: Goodness-of-Fit Tests for Updates Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 17:25
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	6.E-62	0.0001	43	42.9996	0	0.00042	43	0.00042
2	0.0002	0.0100	43	42.8587	0	0.14132	43	0.14178
3	0.0102	0.0431	40	41.9148	3	1.08522	43	3.46596
4	0.0492	0.0846	43	40.2125	0	2.78748	43	2.98070
5	0.0854	0.1394	39	38.9183	5	5.08174	44	0.00149
6	0.1395	0.2285	37	35.0611	6	7.93890	43	0.58076
7	0.2298	0.3537	35	30.4631	8	12.5369	43	2.31748
8	0.3559	0.6057	19	22.7403	24	20.2597	43	1.30576
9	0.6057	0.9359	4	9.07912	39	33.9209	43	3.60193
10	0.9395	1.0000	2	0.75247	42	43.2475	44	2.10428
		Total	305	305.000	127	127.000	432	16.5006

H-L Statistic	16.5006	Prob. Chi-Sq(8)	0.0358
Andrews Statistic	84.6759	Prob. Chi-Sq(10)	0.0000

Appendix 101: Logistic Regression: The Effect of Updates Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:26
Sample: 1 433
Included observations: 432
Convergence achieved after 10 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000153	2.29E-05	-6.678586	0.0000
DURATION	-0.001697	0.003194	-0.531270	0.5952
MIN	-0.000386	0.000249	-1.550573	0.1210
DENSITY	0.068187	0.009899	6.888251	0.0000
MINREWARD	0.003249	0.001906	1.704410	0.0883
U_INDEX	-0.120003	0.153872	-0.779891	0.4355
PROFILE	-0.059536	0.306738	-0.194094	0.8461
PURPOSE	0.158552	0.336298	0.471463	0.6373
R_C	0.097275	0.314029	0.309766	0.7567
LANGUAGES	0.226559	0.182182	1.243585	0.2137
C	-1.200778	0.405325	-2.962503	0.0031

McFadden R-squared	0.468636	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.306001
Akaike info criterion	0.694598	Sum squared resid	39.42105
Schwarz criterion	0.798192	Log likelihood	-139.0331
Hannan-Quinn criter.	0.735496	Deviance	278.0662
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	245.2398	Avg. log likelihood	-0.321836
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 102: Logistic Regression: Expectation-Prediction Table for Updates Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 17:27
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	293	40	333	305	127	432
P(Dep=1)>C	12	87	99	0	0	0
Total	305	127	432	305	127	432
Correct	293	87	380	305	0	305
% Correct	96.07	68.50	87.96	100.00	0.00	70.60
% Incorrect	3.93	31.50	12.04	0.00	100.00	29.40
Total Gain*	-3.93	68.50	17.36			
Percent Gain**	NA	68.50	59.06			

Appendix 103: Logistic Regression: Goodness-of-Fit Tests for Updates Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 17:27
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	4.E-57	0.0002	43	42.9993	0	0.00074	43	0.00074
2	0.0002	0.0170	42	42.7487	1	0.25133	43	2.24332
3	0.0177	0.0585	41	41.4750	2	1.52499	43	0.15340
4	0.0592	0.0925	42	39.8384	1	3.16157	43	1.59515
5	0.0943	0.1746	41	38.3447	3	5.65529	44	1.43059
6	0.1759	0.2526	37	33.7555	6	9.24450	43	1.45056
7	0.2536	0.3300	32	30.6335	11	12.3665	43	0.21197
8	0.3386	0.5951	18	24.1031	25	18.8969	43	3.51644
9	0.6090	0.9126	7	10.1865	36	32.8135	43	1.30621
10	0.9132	1.0000	2	0.91538	42	43.0846	44	1.31244
		Total	305	305.000	127	127.000	432	13.2208

H-L Statistic	13.2208	Prob. Chi-Sq(8)	0.1045
Andrews Statistic	22.4555	Prob. Chi-Sq(10)	0.0129

Appendix 104: Logistic Regression: The Effect of Videos Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:32
Sample: 1 433
Included observations: 432
Convergence achieved after 11 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000160	2.48E-05	-6.465402	0.0000
DURATION	-0.003056	0.003413	-0.895466	0.3705
MIN	-0.000419	0.000256	-1.637935	0.1014
DENSITY	0.070241	0.010133	6.932275	0.0000
MINREWARD	0.002391	0.001741	1.373888	0.1695
V_INDEX	0.110769	0.084432	1.311930	0.1895
BUDGET_PLAN	-1.140649	0.393483	-2.898854	0.0037
INFO	-0.960049	0.328445	-2.923016	0.0035
C	-0.182001	0.346518	-0.525227	0.5994

McFadden R-squared	0.499318	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.292642
Akaike info criterion	0.648171	Sum squared resid	36.22541
Schwarz criterion	0.732930	Log likelihood	-131.0049
Hannan-Quinn criter.	0.681633	Deviance	262.0099
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	261.2962	Avg. log likelihood	-0.303252
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 105: Logistic Regression: Expectation-Prediction Table for Videos Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 17:33
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	297	34	331	305	127	432
P(Dep=1)>C	8	93	101	0	0	0
Total	305	127	432	305	127	432
Correct	297	93	390	305	0	305
% Correct	97.38	73.23	90.28	100.00	0.00	70.60
% Incorrect	2.62	26.77	9.72	0.00	100.00	29.40
Total Gain*	-2.62	73.23	19.68			
Percent Gain**	NA	73.23	66.93			

Appendix 106: Logistic Regression: Goodness-of-Fit Tests for Videos Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 17:34
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	6.E-62	0.0001	43	42.9996	0	0.00040	43	0.00040
2	0.0001	0.0096	43	42.8594	0	0.14062	43	0.14108
3	0.0102	0.0454	41	41.8732	2	1.12681	43	0.69487
4	0.0492	0.0828	41	40.2681	2	2.73190	43	0.20938
5	0.0839	0.1402	40	38.9077	4	5.09232	44	0.26497
6	0.1405	0.2315	38	35.2070	5	7.79299	43	1.22257
7	0.2400	0.3501	36	30.4596	7	12.5404	43	3.45555
8	0.3594	0.6104	16	22.8166	27	20.1834	43	4.33871
9	0.6253	0.9353	5	8.83561	38	34.1644	43	2.09569
10	0.9388	1.0000	2	0.77323	42	43.2268	44	1.98115
		Total	305	305.000	127	127.000	432	14.4044

H-L Statistic	14.4044	Prob. Chi-Sq(8)	0.0718
Andrews Statistic	45.7108	Prob. Chi-Sq(10)	0.0000

Appendix 107: Logistic Regression: The Effect of Videos Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:34
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000153	2.32E-05	-6.569860	0.0000
DURATION	-0.002080	0.003141	-0.662176	0.5079
MIN	-0.000387	0.000250	-1.546994	0.1219
DENSITY	0.067105	0.009621	6.974573	0.0000
MINREWARD	0.003445	0.001940	1.775760	0.0758
V_INDEX	0.065771	0.084777	0.775813	0.4379
PROFILE	-0.081764	0.306156	-0.267067	0.7894
PURPOSE	0.160705	0.336411	0.477705	0.6329
R_C	0.103381	0.315469	0.327707	0.7431
LANGUAGES	0.227657	0.184783	1.232027	0.2179
C	-1.277247	0.419581	-3.044101	0.0023

McFadden R-squared	0.468598	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.306742
Akaike info criterion	0.694644	Sum squared resid	39.61208
Schwarz criterion	0.798238	Log likelihood	-139.0430
Hannan-Quinn criter.	0.735542	Deviance	278.0860
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	245.2200	Avg. log likelihood	-0.321859
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 108: Logistic Regression: Expectation-Prediction Table for Videos Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 17:35
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	293	42	335	305	127	432
P(Dep=1)>C	12	85	97	0	0	0
Total	305	127	432	305	127	432
Correct	293	85	378	305	0	305
% Correct	96.07	66.93	87.50	100.00	0.00	70.60
% Incorrect	3.93	33.07	12.50	0.00	100.00	29.40
Total Gain*	-3.93	66.93	16.90			
Percent Gain**	NA	66.93	57.48			

Appendix 109: Logistic Regression: Goodness-of-Fit Tests for Videos Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 17:35
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	3.E-57	0.0002	43	42.9993	0	0.00072	43	0.00072
2	0.0002	0.0181	43	42.7477	0	0.25234	43	0.25383
3	0.0197	0.0587	41	41.4152	2	1.58479	43	0.11294
4	0.0587	0.0907	41	39.9080	2	3.09199	43	0.41554
5	0.0934	0.1764	40	38.2845	4	5.71554	44	0.59180
6	0.1777	0.2466	37	33.8210	6	9.17897	43	1.39978
7	0.2470	0.3258	33	30.6916	10	12.3084	43	0.60654
8	0.3372	0.5833	18	24.0763	25	18.9237	43	3.48454
9	0.5845	0.9056	7	10.0764	36	32.9236	43	1.22674
10	0.9061	1.0000	2	0.98003	42	43.0200	44	1.08571
		Total	305	305.000	127	127.000	432	9.17815

H-L Statistic	9.1782	Prob. Chi-Sq(8)	0.3275
Andrews Statistic	39.6990	Prob. Chi-Sq(10)	0.0000

Appendix 110: Logistic Regression: The Effect of Images Index, Budget Plan, and Info on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:42
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000161	2.46E-05	-6.558264	0.0000
DURATION	-0.002976	0.003603	-0.825865	0.4089
MIN	-0.000465	0.000265	-1.757078	0.0789
DENSITY	0.069116	0.010241	6.749045	0.0000
MINREWARD	0.002275	0.001616	1.407710	0.1592
I_INDEX	0.290461	0.111592	2.602889	0.0092
BUDGET_PLAN	-1.036788	0.391697	-2.646916	0.0081
INFO	-0.949127	0.329267	-2.882545	0.0039
C	-0.463299	0.365843	-1.266388	0.2054

McFadden R-squared	0.510474	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.286831
Akaike info criterion	0.634657	Sum squared resid	34.80103
Schwarz criterion	0.719416	Log likelihood	-128.0859
Hannan-Quinn criter.	0.668119	Deviance	256.1717
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	267.1343	Avg. log likelihood	-0.296495
Prob(LR statistic)	0.000000		

Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 111: Logistic Regression: Expectation-Prediction Table for Images Index, Budget Plan, and Info

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 17:43
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	295	30	325	305	127	432
P(Dep=1)>C	10	97	107	0	0	0
Total	305	127	432	305	127	432
Correct	295	97	392	305	0	305
% Correct	96.72	76.38	90.74	100.00	0.00	70.60
% Incorrect	3.28	23.62	9.26	0.00	100.00	29.40
Total Gain*	-3.28	76.38	20.14			
Percent Gain**	NA	76.38	68.50			

Appendix 112: Logistic Regression: Goodness-of-Fit Tests for Images Index, Budget Plan, and Info

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_BP_INFO
Date: 07/14/19 Time: 17:43
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	1.E-66	9.E-05	43	42.9997	0	0.00031	43	0.00031
2	0.0001	0.0101	43	42.8721	0	0.12789	43	0.12827
3	0.0102	0.0406	41	41.9147	2	1.08530	43	0.79088
4	0.0415	0.0866	42	40.4096	1	2.59041	43	1.03904
5	0.0867	0.1329	39	39.2022	5	4.79782	44	0.00956
6	0.1340	0.2246	38	35.2099	5	7.79006	43	1.22036
7	0.2257	0.3608	36	30.7919	7	12.2081	43	3.10271
8	0.3638	0.6164	17	22.4518	26	20.5482	43	2.77027
9	0.6221	0.9429	5	8.60794	38	34.3921	43	1.89073
10	0.9539	1.0000	1	0.54015	43	43.4599	44	0.39636
		Total	305	305.000	127	127.000	432	11.3485

H-L Statistic	11.3485	Prob. Chi-Sq(8)	0.1827
Andrews Statistic	43.1208	Prob. Chi-Sq(10)	0.0000

Appendix 113: Logistic Regression: The Effect of Images Index, Profile, Purpose, Risk and Challenges, and Languages on Probability of Success

Dependent Variable: PROB
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 07/14/19 Time: 17:44
Sample: 1 433
Included observations: 432
Convergence achieved after 9 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
TARGET	-0.000155	2.33E-05	-6.664673	0.0000
DURATION	-0.002186	0.003263	-0.670177	0.5027
MIN	-0.000410	0.000259	-1.582026	0.1136
DENSITY	0.066397	0.009738	6.818202	0.0000
MINREWARD	0.003241	0.001919	1.688738	0.0913
I_INDEX	0.289481	0.106766	2.711359	0.0067
PROFILE	-0.105790	0.310853	-0.340321	0.7336
PURPOSE	0.256301	0.347895	0.736719	0.4613
R_C	0.118515	0.318953	0.371576	0.7102
LANGUAGES	0.212290	0.189067	1.122827	0.2615
C	-1.635522	0.449074	-3.641990	0.0003

McFadden R-squared	0.482633	Mean dependent var	0.293981
S.D. dependent var	0.456112	S.E. of regression	0.301612
Akaike info criterion	0.677642	Sum squared resid	38.29840
Schwarz criterion	0.781236	Log likelihood	-135.3706
Hannan-Quinn criter.	0.718540	Deviance	270.7413
Restr. deviance	523.3060	Restr. log likelihood	-261.6530
LR statistic	252.5647	Avg. log likelihood	-0.313358
Prob(LR statistic)	0.000000		
Obs with Dep=0	305	Total obs	432
Obs with Dep=1	127		

Appendix 114: Logistic Regression: Expectation-Prediction Table for Images Index, Profile, Purpose, Risk and Challenges, and Languages

Expectation-Prediction Evaluation for Binary Specification
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 17:44
Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	291	39	330	305	127	432
P(Dep=1)>C	14	88	102	0	0	0
Total	305	127	432	305	127	432
Correct	291	88	379	305	0	305
% Correct	95.41	69.29	87.73	100.00	0.00	70.60
% Incorrect	4.59	30.71	12.27	0.00	100.00	29.40
Total Gain*	-4.59	69.29	17.13			
Percent Gain**	NA	69.29	58.27			

Appendix 115: Logistic Regression: Goodness-of-Fit Tests for Images Index, Profile, Purpose, Risk and Challenges, and Languages

Goodness-of-Fit Evaluation for Binary Specification
Andrews and Hosmer-Lemeshow Tests
Equation: L_CRS_P_P_R_L
Date: 07/14/19 Time: 17:45
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	8.E-60	0.0001	43	42.9994	0	0.00058	43	0.00058
2	0.0002	0.0167	43	42.7793	0	0.22068	43	0.22182
3	0.0169	0.0509	42	41.5327	1	1.46725	43	0.15406
4	0.0512	0.0907	41	40.0252	2	2.97480	43	0.34317
5	0.0913	0.1588	39	38.4830	5	5.51699	44	0.05539
6	0.1601	0.2334	39	34.4056	4	8.59440	43	3.06960
7	0.2399	0.3403	31	30.7185	12	12.2815	43	0.00903
8	0.3418	0.5796	18	23.9726	25	19.0274	43	3.36278
9	0.5884	0.9268	8	9.36801	35	33.6320	43	0.25541
10	0.9298	1.0000	1	0.71564	43	43.2844	44	0.11486
		Total	305	305.000	127	127.000	432	7.58669

H-L Statistic	7.5867	Prob. Chi-Sq(8)	0.4748
Andrews Statistic	38.4219	Prob. Chi-Sq(10)	0.0000