Exploring the determinants of success and failure in crowdfunding: A Platform Approach

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Abstract

Crowdfunding is a global phenomenon for funding new ventures and projects, through the utilisation of crowdfunding platforms. This work focusses on the creation of a theoretical framework for determining success and failure within crowdfunding platforms. The framework is built utilising the existing crowdfunding literature and integrating it within a wider context considering signalling theory, social capital theory, network analysis, competition effects and backer motivations. The contextual framework, designed to be applicable regardless of type of crowdfunding platform examined, is applied to two separate crowdfunding platforms, Kickstarter and Kiva. This framework is then utilised for developing specific hypotheses for each platform around each of the salient themes identified from the relevant literature. These hypotheses are empirically tested on original data from over 55,000 crowdfunding campaigns, collected using web crawlers and API protocols. Moreover, by introducing the ideas of enforced and voluntary signals within a Crowdfunding context, this work also extends the set of relevant concepts originally derived from signalling theory. This thesis also introduces the concepts of formation of latent networks, and the tools for their analysis, to examine the internal social capital of a crowdfunding platform. With this work arguing, and providing evidence, that increased internal social capital has a positive impact on crowdfunding success. Finally, these findings are utilized in creating a set of recommendation to the crowdfunding participants.

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1 Introduction

Crowdfunding platforms have become a key source of funds for ventures and projects across the entire globe, after initially emerging across a number of developed economies as a response to the limited capital available after the financial crash (Bruton et al, 2015). The online crowdfunding market expanded rapidly from 2009-2015, doubling in capacity every year to an estimated 34.4 billion dollars in 2015 (Massolution, 2015), with some predictions expecting crowdfunding to increase to an estimated 300 billion dollars in 2025 (Ma and Liu, 2017). Crowdfunding platforms quickly diversified themselves, enabling key differences between the platforms to be identified (Bruton et al, 2015).

The main aim of this research is to create a broad conceptual model for identifying the key determinants of success, or failure, within these crowdfunding platforms which is relevant and applicable to the majority of crowdfunding platforms. The research is driven by an underlying research philosophy of pragmatism (Creswell and Clark, 2007; Dewey 1958), to create actionable and usable policy to assist the participants of the crowdfunding ecosystem. With the participants consisting of backers, creators and the crowdfunding platform itself (Ordanini et al, 2011). Backers provide the money for projects, creators set up the projects and the crowdfunding platform enables the interaction between backers and creators. While simultaneously providing a specific contribution through the creation of a new theoretical framework which is informed from several theoretical perspectives (signalling theory, social capital theory, competition theory and network analysis), for identifying the underlying determinants of success within crowdfunding platforms. This theoretical model was utilised to identify potential hypotheses which were further developed through observing and synthesizing various theoretical models and perspectives for both examined crowdfunding platform Kiva and Kickstarter.

The thesis is data-driven with over 53,000 crowdfunding projects on Kiva and Kickstarter, this data was collected through the usage of web crawling techniques. The datasets included projects from every single continent and over 100 countries. A quantitative approach was utilised in the analysis of the data, with the Kiva dataset analysed using a truncated regression and the Kickstarter dataset analysed using a logistic regression. These different methods were chosen based upon the underlying features of the crowdfunding platforms and collected datasets.

These results were used to test the developed hypotheses surrounding each of the theoretical perspectives. For example, consider H1a which states: Creators' overconfidence has a negative impact on the probability of the project's success. This hypothesis was developed using insights relating to signalling theory and the entrepreneurship literature in section 3.3.2.1. The results in section 4.2.1.1, provide support for this hypothesis, through increased confidence having a statistically significant and negative impact on the likelihood of a project succeeding on the crowdfunding platform Kickstarter. This finding enables the creation of a recommendation that creators should aim to limit the level of confidence they signal in reward-based crowdfunding platforms.

A key hypothesis in the examination of the Kiva platform, centered around how social capital within a crowdfunding platform can impact success within the platform. HB1 stated: Higher levels of *internal social capital* within Kiva has a positive impact on the amount of funds raised. This was developed in section 3.4.3.1, utilising literature on network theory and social capital. Social capital was captured within the platform by the creation of a latent network built from the inherent connections between participants of the crowdfunding network. This latent network enabled the usage of network analysis techniques to capture the social capital of each project. With the results in section 4.1, supporting the hypothesis HB1, as the proxy used for social capital had a positive and significant impact on the amount of money raised in Kiva.

These empirical patterns/ findings are further used in the formulation of a key set of recommendations to the participants within the crowdfunding ecosystems. Additionally, this work identifies future areas of research, based on the concepts developed and analysed within this thesis and the inherent limitations of the study. This rest of the introduction provides a systematic overview into the overarching design of the research and is separated into the following four sections.

<u>Context of the research</u>: Provides the context of crowdfunding, by exploring the history of crowdfunding, outlining the current major crowdfunding platforms and the key crowdfunding participants.

<u>Aim and objectives</u>: This section outlines the main research aim of the thesis, before considering a set of more specific objectives to achieve this aim.

Chapter design: This section considers how the chapters of the thesis were designed in order to achieve the objectives outlined in the previous section. Providing a summary of the design of each chapter and allocating objectives to each chapter.

Rationale: Outlines the underlying rationale for the research, identifying how the research can benefit specific groups and how it can contribute to the existing literature.

1.1 Context of the research

In attempting to understand the context of crowdfunding the first step taken by the author was to consider a formal definition of crowdfunding, this was achieved through an empirical collection and examination of the key interactions between participants in the crowdfunding ecosystem (section 2.1.5). There are three main participating groups within crowdfunding, i) the creators, ii) the backers and iii) the crowdfunding platform itself (Ordanini et al, 2011). Creators refers to anyone who is seeking funds for a project; it can refer to an individual, a group or an organization, dependent upon the platform and the crowdfunding project. The term backer refers to anyone who is providing money to the creators via the crowdfunding platform; this generally refers to an individual but can also represent a group or organization. Finally, the platform or crowdfunding platform, is the entity which enables and facilitates the exchange of funds, and signals, between the creators and backers. Crowdfunding can thus be described as when:

> Creators seek to obtain funds for a project, backers decide whether to provide those funds, and the platform acts as an exchange between the backers and creators, without itself making funding decisions (developed in section 2.1).

This specific definition was utilised as it enables a clear point of distinction between traditional funding and crowdfunding. That point is where the platform starts making funding decisions, i.e. choosing who receives funds, rather than the backers making this decision. And it is the inclusion of this final condition which is the major addition to the definition provided by the author of this work.

1.1.1 History of crowdfunding

Crowdfunding is not a completely new phenomenon, but rather an expansion of a system, for raising money which has existed for hundreds of years (Tavi, 2014). A prominent historical example of crowdfunding is the plinth upon which the statue of liberty stands. While the statue itself was a diplomatic gift from France, the granite plinth pedestal had to be purchased by New York. However, the Governor at the time, Grover Cleveland, rejected the use of city funds to pay for the plinth and the American Congress was unable to pass a spending bill including the Plinth. New York almost lost the statue of liberty with Baltimore, Boston, San Francisco and Philadelphia all offering to build the plinth in exchange for movement of the statue to their city. At this point, Joseph Pulitzer utilised his newspaper the New York World, asking for money from readers of the paper to support the building of the plinth, in exchange for a set of rewards to the readers, according to their donation, for example, large donations received a decorative gold coin. This raised the remaining 100,000 dollars and the plinth was built, and New York became the permanent home of the Statue of Liberty (Pitts, 2010).

This author tests whether this example can be considered crowdfunding by applying the set of required interactions for crowdfunding to occur that are outlined in the definition. Thus the creator can be viewed as Joseph Pulitzer seeking money for building the plinth, the backers as the readers of the paper providing the money for the building of the plinth and the platform, as the New York World newspaper enabling the readers and Joseph Pulitzer to exchange funds, without making any decisions about who receives the funds. Thus, the required interactions occur, and the funding of the plinth of the Statue of Liberty can be considered to be crowdfunding. More specifically, this early example, can be considered as a type of reward-based crowdfunding where backers are incentivised to back the project by the perspective of receiving rewards based upon how much money they have given.

Reward-based crowdfunding is one of the four main types of crowdfunding, as crowdfunding can be divided into subcategories based on the backer participation right of crowdfunding platforms (Giudici et al, 2012). The four main types of crowdfunding platforms identified through differing backer participation rights are reward-based, donation-based, equity-based, and lending-based. In reward-based platforms, backers are offered a reward dependent upon the amount of money they provide. In equity-based platforms, the backers are given percentage equity in the project or company as an incentive for backing. In lending-based crowdfunding, money is returned at a later date and interest may be accrued based upon the crowdfunding platforms. Finally, in donation-based, backers are given no rewards, equity or interest for supporting the project, this type can be viewed more as a charitable donation. These different crowdfunding subdivisions are examined and expanded upon within (section 2.2).

1.1.2 Current state of crowdfunding

As mentioned previously, crowdfunding has now primarily moved online reaching an estimated 34.4 billion dollars in 2015 (Massolution, 2015). Crowdfunding is still expected to continue to grow with Ma and Liu (2017) predicting that crowdfunding will reach 300 billion dollars by 2025, an increase of 30.2 percent per year. Furthermore Technavio (2019) reported a similar rate of expected growth of 30.9 per cent annually until 2022. Thus, crowdfunding has decreased from the doubling rates seen between 2009-2015 (Massolution, 2015), but is still growing at a substantial rate. This can be seen through the wide range of online crowdfunding platforms across the globe, the following are a few prominent examples:

a) Kickstarter: A reward-based crowdfunding platform, launched on the 28^{th} of April 2009, over 4.1 billion dollars have been raised for projects within the platform (Kickstarter, 2019d). Kickstarter has an all-or-nothing requirement which means that a project must reach their funding goal for creators to receive any funds. There is no specific restriction on what sort of projects can be run on Kickstarter (Kickstarter, 2019a).

b) Kiva: An interest-based platform which offers loans in the developing world, launched in 2005, 1.3 billion dollars of loans have already been raised on Kiva with a 96.8 percent repayment rate. Kiva has provided loans to 3.2 million people across 81 countries (Kiva, 2019a).

c) Indiegogo: A reward-based crowdfunding platform, founded in 2008, raised over 1 billion dollars from over 11 million backers. There is no specific restriction on what sort of projects can be run on Indiegogo as long as they are legal. Indiegogo utilises both keep-it-all and all-or-nothing funding, a project which chooses keep-it-all will receive their funds regardless of whether they reach their funding goal (Indiegogo, 2019).

d) GoFundMe: A donation-based crowdfunding platform, which focuses on providing socially aware funding for individuals or groups. For example the platform engages in medical crowdfunding, raising funds for individuals who would be unable to pay for medical treatment. It has raised over 5 billion dollars since being founded in 2010 (GoFundMe, 2019).

e) Crowdcube: An equity-based crowdfunding platform, primarily used by entrepreneurs expanding their businesses. Crowdcube projects are based within the UK and have raised over 600 million pounds since being founded in 2011. This 600 million is split between 821 successful projects, leading to each project on average raising 674 thousand pounds (Crowdcube, 2019).

f) Unbound: Is a reward-based crowdfunding platform, which only crowdfunds books. Since its founding in 2010, 317 books have been successfully funded on Unbound. One curious feature of this platform is that it does not show the funding goal of a project; instead it only showed the percentage achieved towards the funding goal. Thus the goal which the project is aiming for is obfuscated (Unbound, 2019).

g) Prosper: Is an interest-based crowdfunding platform, where creators can ask for loans to businesses or individuals. Since being founded in 2005, Prosper has provided over 14 billion dollars in loans to over 889,000 individuals. Of note, Prosper is one of the platforms where a single backer can easily provide the entire funding for a crowdfunding project (Prosper, 2019).

This not an exhaustive list of crowdfunding platforms, rather it aims to show some examples for the subdivisions of crowdfunding platforms, previously discussed, and the scale at which these platforms are operating, with these seven platforms collectively raising over 29 billion dollars in their lifetimes.

The crowdfunding platforms can be further classified into additional subsets by considering the creator participation requirements alongside the backer participation rights (See section 2.2).

One of the key aspects of online crowdfunding is the transformation of crowdfunding from being a local to becoming a global phenomenon, with crowdfunding platforms such as Kiva, Kickstarter, Indiegogo, Prosper, providing funds across the globe. This does not imply that all crowdfunding platforms are global, some platforms may only serve a specific region due to differing legal requirements between the platforms, for example, Crowdcube, an equity crowdfunding project only raises money from projects within the United Kingdom (Crowdcube, 2019).

Thus, online crowdfunding can be viewed as a revamping of crowdfunding, with the internet encouraging more crowdfunding to occur on a global scale, thus enabling crowdfunding to move from being local phenomena to a global phenomena.

1.1.3 Context of the literature utilised within this thesis

This section outlines how the crowdfunding and connected literature were utilised to form the relevant conceptual framework for this thesis, as discussed in more detail within the literature review in section 2.4.

One of the key works on crowdfunding is Mollick (2014) that examines the dynamics of crowdfunding, which provides an introduction into some of the underlying drivers of its success and failure, this work also focuses on Kickstarter from 2009 to 2012. Mollick (2014) additionally identifies limitations within the current literature, such as the lack of a broad definition for crowdfunding. This highly cited work can be seen as the theoretical starting point of the thesis. For example, the concept of utilising signalling to address crowdfunding is introduced by Mollick (2014) and extended upon by introducing the concept of multiple signalling partners in Kromidha and Robson (2016). This is then further expanded within this thesis by introducing and considering the differences between enforced and voluntary signals and the introduction of the platform itself, as a third signalling agent. While also examining how the effect of enforced signals can be interpreted as proxies for the human capital of the creators.

Another relevant example of the influence of this seminal work is that on the impact of social media, Mollick (2014), considered that the number of Facebook friends of the creator can be utilised to examine success within the crowdfunding platform, with further empirical papers both supporting (Beier and Wagner, 2015; Colombo et al, 2015) and providing evidence against this argument (Moisseyev, 2013; Kromidha and Robson, 2016), leading to this thesis adoption of utilising Facebook shares over Facebook friends (Kromidha and Robson, 2016) as the key metrics for capturing the *external social capital* of a crowdfunding project.

Another work of great importance to the development of the thesis is the work of Colombo et al (2015). They identified that crowdfunding platforms can generate their own *internal social capital*, and thus that there are two types of *social capital* to be considered in relation to their impact on the success of crowdfunding platforms: *internal* and *external social capital*. This crucial dichotomy is expanded upon within this thesis by considering how the *internal social capital* of a crowdfunding platform can be captured through the inherent connections within the crowdfunding network. These connections can be utilised to create a latent network through the crowdfunding platform, later utilised to provide proxy metrics for the *internal social capital* of a crowdfunding project. Colombo et al (2015) also introduced the key concept of utilising an *early funding* period, to analyse the initial effects of the start of the campaign on the final success of the campaign. This concept of an *early funding* period is also utilised in this thesis and expanded upon by including the *early pledge* per backer metrics. This measure was previously utilised in measuring crowdfunding success by Kromhida et al (2016) into their examination of signalling.

Outside the immediate field of crowdfunding many other contributions helped in forming the theoretical framework of this thesis, for example in regards to the impact of social capital (Adler and Kwon, 2002; Kim and Aldrich, 2005; Westlund and Bolton, 2003; Borgatti and Halgrin, 2011) were examined. The literature used outside of the field of crowdfunding is outlined in more detail within section 2.4.1.

1.2 Aim and objectives

As previously stated, the main aim of this research is to create a broad conceptual framework for identifying the key determinants of success within crowdfunding platforms, which is applicable to all types of crowdfunding platforms. In order to achieve this aim a set of more specific objectives was established, these are outlined below alongside the rationale for each specific objective:

Objective 1*: Identify/develop a broad definition of crowdfunding.*

In order to determine success within crowdfunding platforms, it is necessary to provide a broad definition of crowdfunding. This enables the author to clarify which platforms are crowdfunding platforms under the provided definition and thus determine which platforms can be examined utilising the frameworks established within this work.

Objective 2: *Identify methods of subdividing crowdfunding platforms based upon type*.

The second objective is to consider how to distinguish between crowdfunding platforms, considering the possible ways to subdivide crowdfunding platforms based upon the backers' participation rights and creator requirements. This step is necessary to highlight the many possible ways that success can be measured within a crowdfunding platform, hence enabling the creation of a theoretical framework which is relevant for the analysis of all of the different crowdfunding platforms.

Objective 3: *Create a theoretical framework for understanding success in crowdfunding platforms*.

In order to achieve the aim of identifying success across a range of crowdfunding platforms, a theoretical framework needs to be developed which can be utilised to examine the different types of crowdfunding platforms. By synthesizing the various theoretical elements, the author aims to create a more informed model. Enabling the model to be more generally applicable across crowdfunding platforms.

Objective 4: *Apply said theoretical framework to existing platforms, to develop a specific conceptual framework and set of hypotheses for each platform.*

As each crowdfunding platform has its own unique features and characteristics, the general theoretical framework needs to be applied to each platform creating a specific conceptual framework for that platform. This can then be utilised to derive the key hypotheses for the platform.

Objective 5: *Collect data to test the developed hypotheses across each examined crowdfunding platform*.

In order to test the hypotheses for each platform, a dataset must be developed for each platform, utilising the hypotheses to identify the key pieces of information that are required from the platform and developing the relevant methods required to capture this information.

Objective 6: *Identify a methodology to analyse the data collected for each platform to test the hypotheses.*

Alongside identifying a data collection methodology, it is necessary to determine the best possible methodology for testing the developed hypotheses. Each platform may require its own different modelling strategy, due to the inherent differences in measuring success between platforms.

Objective 7: *Test the set of hypotheses derived from the conceptual framework.*

After testing the theoretical hypotheses, it must be considered whether the model predictions are applicable and thus whether the conceptual framework has achieved its desired function.

Objective 8: *Develop a generalized set of findings based upon the combined results of the crowdfunding models.*

From the empirical results, a key set of findings can be developed, demonstrating the specific contributions provided by this thesis to the existing crowdfunding literature and an underlying assessment of the ability of the conceptual framework.

Objective 9: *Develop a key set of recommendations for the three key parties in crowdfunding*.

A key set of recommendations can be developed based upon the findings, for each of the three major parties involved in crowdfunding, i.e. backers, creators and the crowdfunding platform itself.

Objective 10: *Outline a key set of recommendations for future research into the topic*

Due to the inherent limitations of any study, it is necessary to provide a consideration for future research which will further boost the understanding of the examined area.

1.3 Chapter design

The chapters of the thesis were designed to achieve these objectives. Their overarching design principles and the objectives they were designed to address are outlined in the following sub-sections.

1.3.1 Literature review

The three objectives addressed in the literature review are as follows:

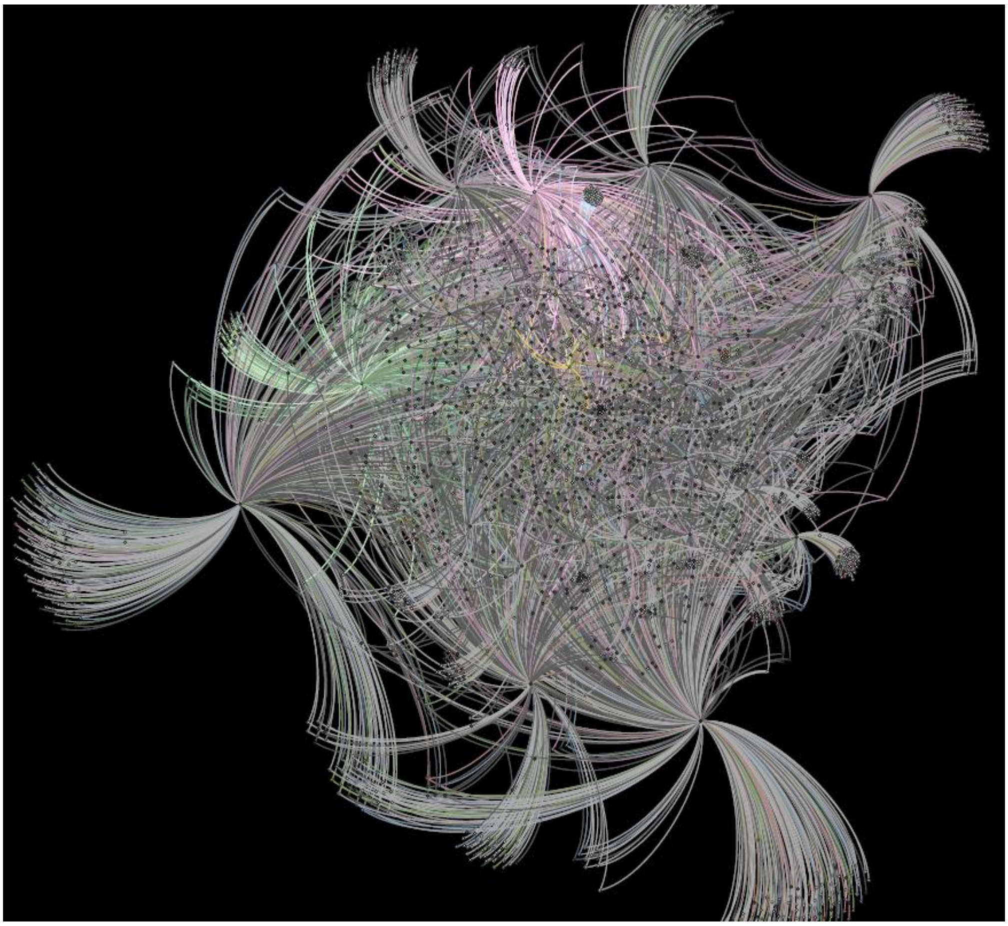
Objective 1*: Identify/develop a broad definition of crowdfunding*

Objective 2: *Identify methods of subdividing crowdfunding platforms based upon type*.

Objective 3: *Create a theoretical framework for understanding success in crowdfunding platforms*.

To develop the literature review, an initial examination of the existing state of the crowdfunding literature was considered. As a first step, a citation network around the crowdfunding literature was constructed (a citation network creates a network based on the citations of the articles (Garfield et al, 1964). In such a network, two articles are connected if one article references the other article, this is a directed connection with the article which is cited, and it does not imply the reverse direction of the connection. To create this citation network, first, the term "Crowdfunding" was searched in google scholar with the top ten articles by citation count captured in November 2016. Second, all the citations for these top ten articles were also captured. With the citations for the original ten collected, the process was then repeated for all the articles identified as references of the first ten. This was achieved through using *import.io*, a web crawling software which was utilized to extract the citations from google scholar. Alongside extraction, the papers, the titles of the papers were also extracted and used to identify key themes within the titles. The citations and terms used to create the visualization of the network in Figure 1-1 below.

Figure 1-1 Crowdfunding citation matrices



Created by the Author, 16946 links (edges), 2589 crowdfunding projects (nodes).

The colour of the link on the diagram was chosen to show different groups within the crowdfunding literature, with pink links showing 133 links between equity crowdfunding, green ones showing the 93 links between business centered crowdfunding papers, the 10 gold links show medical crowdfunding papers. The 95 black links donate papers which contain the term social in their title, while the 18 dark green links donate papers focusing on the more specific term social capital. The 977 green links donate papers which simply used the term crowdfunding. The 1243 white links simply denote linked papers which don't have crowdfunding or other subcategories in their titles. This analysis was utilised to consider what were the current key papers, based on citations and centrality and thus used as a starting point for the literature review. Additional articles were identified as the research went on, through a continuous monitoring processes, one such monitoring process utilised google alerts which was set up such that whenever a new article concerning crowdfunding was released on google scholar the author was informed by email (Google alerts, 2019). Obviously, in addition to this automated search criterion, articles were also identified more fluidly throughout the traditional manual research process, by researching specific topics and reading papers from other connected themes.

With the key literature identified, the section was then structured around four key sections. The first section defined crowdfunding, the second outlined how crowdfunding can be subdivided, the third considered what is meant by success in crowdfunding and finally the fourth considered how these could be brought together to develop the theoretical framework. Each of these sections was necessary to address objectives 1-3 and they provided a structure in which to critically analyze the existing literature.

1.3.2 Methodology

The three objectives addressed in the methodology are as follows:

Objective 4: *Apply said theoretical framework to existing platforms, to develop a specific conceptual framework and set of hypotheses for each platform.*

Objective 5: *Collect data to test the developed hypotheses across each examined crowdfunding platform*.

Objective 6: *Identify a methodology to analyse the data collected for each platform to test the hypotheses.*

In order to achieve these objectives, the methodology chapter was separated into four key sections:

In the first section (3.1), the underlying research philosophy and connected research design were outlined. *Pragmatism* was selected as the underlying research philosophy as it aligned both with the author's personal viewpoint on the ontological construction of the universe and enabled practical application to the examination of crowdfunding (Creswell and Clark, 2007; Dewey 1958). Applying the basis of utilising the best measure available under the pragmatic world view, lead to the selection of a quantitative process over a qualitative process. Additionally, applying a pragmatic approach, it was outlined that each platform should be examined separately, due to the innate difference between the crowdfunding platforms.

The second section (3.2), outlines how the quantitative data can be collected for each of the crowdfunding platforms through the utilisation of web crawling software in collecting primary data and through multiple secondary data sources. Critically assessing the ethical impacts of the utilisation of each data collection method.

The third section (3.3) outlines the specific methodology surrounding the Kickstarter crowdfunding platform (Kickstarter, 2019a). The chapter first applies the theoretical framework to Kickstarter, developing a conceptual framework for the platform and deriving a set of hypotheses to be tested within this framework. The specific data procedure for Kickstarter is then outlined based on the data required to address the developed hypotheses. This was followed by a selection of the different methods for data analyses in relation to the specific format of the collected data.

Finally, section (3.3.13) outlines the specific methodology utilized for the Kiva crowdfunding platform. This consisted in applying the general theoretical framework for the creation of a new Kiva-specific conceptual framework and set of hypotheses. Before outlining the data new collection and data analysis procedure for the platform. By completing these four sections, it was possible to address objectives 4-6 discussed above.

1.3.3 Results

The objective addressed in the results is:

Objective 7: *Test the set of hypotheses derived from the conceptual framework*

Section 4.1 contains the results from the logistics regression carried out to examine the Kickstarter dataset. Section 4.3 contains the truncated regression results examining the Kiva model. Each platform was examined with multiple model specifications, to enable the comparision of said models in order to ensure that the most appropriate model would have been utilised in the testing of the relevant hypotheses. These hypotheses are tested against the collected results in section 4.2 for Kickstarter and section 4.4 for Kiva, whereby the hypotheses are ordered based on the parts of the conceptual framework they are dervied from. In detail, these hypotheses were separated into four groups based on whether they were derived using signalling theory, competition theory, social capital or backer incentives. Thus aiming to achieve the outlined objective through the analysis of the proposed hypotheses based on the empirical evidence and results for each model.

1.3.4 Findings

Objective addressed in the findings section are as follows:

Objective 8: *Develop a generalized set of findings based upon the combined results of the crowdfunding models*

Objective 9: *Develop a key set of recommendations for the three key parties in crowdfunding.*

Objective 10: *Outline a key set of recommendations for future research into the topic*

This section combines the results from the examination of the hypotheses developed for both Kiva and Kickstarter and creates a set of generalized findings structured around the different elements of the theoretical framework. These findings are then critically analysed with consideration to the literature and the inherent limitations of the study, in the formulation of a set of recommendations for the different components of crowdfunding ecosystems: backers, creators and the crowdfunding platform itself. Furthermore, a set of possibilities for future research is outlined based on the findings and the limitations.

1.3.5 Conclusion

The final section of the thesis entails the conclusions of this work. This section serves to consider whether the main aim and objectives of the research have been achieved and to what degree. It also highlights the key points of this works' contribution to the literature, before drawing the work to a close with a set of final remarks.

1.4 Rationale

The previous two sections consider the context and underlying design choices of the thesis; however, they don't address the underlying rationale for carrying out the thesis. The author distinguishes the rationale into two distinct sections, one focusing on the personal rationale and the second on the external rationale. Personal rationale considers the underlying reasons why the author is intrigued by the topic area and connected literature, which drove his desire to research this area. Conversely the section on external rationale considers why the research should be carried out regardless of the personal motivations of the author, by considering who may benefit from the research and how this research can contribute to the existing literature.

1.4.1 Personal rationale

The author's interest in crowdfunding was first raised by considering how it can be utilised to overcome asymmetric information between suppliers and consumers (Agrawal et al., 2011). Specifically, how crowdfunding could overcome the age-old problem of how suppliers can identify how much to spend on developing a product if the demand for that product cannot yet be seen. Crowdfunding enables future demand not only to be identified but utilised in directly funding the creation of the product and thus enables the development of new products without the need to forecast unknown demand (Mollick, 2014). This drew the author's interest to the topic area, but what sustained and grew this interest was the versatility demonstrated in crowdfunding both within the literature and through examinations of crowdfunding platforms.

The broad nature of crowdfunding enables it to be examined from a multi-disciplinary approach. Leading to papers ranging from how crowdfunding can be utilised to overcome medical bankruptcy (Burtch and Chan, 2014), to whether crowdfunding was just an attempt in fleecing the masses out of their money (Griffin, 2012) or to how it could be considered a way of democratizing innovation (Mollick and Robb, 2016). This breadth of literature intrigued the author and greatly contributed in choosing to research the topic area. Additionally, the author is a pragmatist and took into consideration two key factors, firstly how crowdfunding can enable both failure and success to be observed, compared to other cases whereby failure can be obfuscated and only success viewable. Secondly, as crowdfunding platforms are primarily online, the data can be collected with relative ease, compared to offline companies which may often wish to obfuscate data for the benefit of the business or individual. Thus, the author's personal motivations for choosing to examine this topic was drawn from the breadth and expanse of the literature and the practicality of obtaining data.

1.4.2 External rationale

Regardless of the whims of the author, this research is of relevance due to how it can benefit the participants of crowdfunding and contribute to the existing crowdfunding literature. The three different participants within the crowdfunding ecosystems, creators, backers and the platform itself, can each benefit from an examination into success in crowdfunding which observes how crowdfunding functions. This is demonstrated through the set of tailored recommendations provided to each of the participants (section 5.5). This set of recommendations is possible due to the findings identifying specific actions which can be taken by each set of participants to increase the likelihood of them achieving their goals. A possible additional rationale in carrying out crowdfunding research is in addressing and considering how crowdfunding could be regulated. Regulation affects how crowdfunding platforms are designed and what types of crowdfunding are legally possible. These effects are of relevance for each of the crowdfunding participants, from protecting backers, to ensuring the long-term stability of platforms and to improve the ability for creators to obtain funds. Additionally, one could also consider how wide-ranging fraud could permeate crowdfunding platforms and whether the existing ways in which platform structures, are currently separating creators and backers, enable or limit the possible emergence of fraud.

Furthermore, this specific research can contribute to the crowdfunding literature in multiple ways; Firstly, by providing a broad definition of crowdfunding which can be utilised regardless of the type of crowdfunding examined, such a definition may then enable the development of a more informed conceptual frameworks. Secondly, by considering how human capital can be utilised to address the impact of enforced signalling and by highlighting how latent network conceptualisation can be utilised in the identification and measurement of social capital. Detailed evaluations of these and other contributions are explained in detail within the findings (section 5), while the ongoing impact of the paper is highlighted in the conclusions (section 6).

Thus, the underlying rationale for carrying out the research can be attributed to the personal desire of the author, the ability for the research to serve as a practical tool for assisting the participants of crowdfunding and finally to how it can contribute to the existing literature, increasing our understanding of the phenomenon under study.

2 Literature review

The literature review is divided into four key sections along specific themes, as follows:

1.1) **Defining crowdfunding**: this section critically considers the existing crowdfunding definitions. It examines the individual characteristics which comprise each of the existing definitions, before creating a general definition of crowdfunding via critically analysing the interaction between the three-key parties in crowdfunding, the creators, the backers and the platform itself. This general definition provides a key point of distinction between crowdfunding and other traditional funding methods.

1.2) **Subdividing crowdfunding**: This section considers the existing subdivision methods for crowdfunding, of reward-based, donation-based, equity-based and lending-based. These sub-division are constructed based upon the backer participation rights of the crowdfunding platforms. The theoretical framework of the thesis is developed through critically analysing the existing literature, with each section being dedicated to existing and new subdivision within crowdfunding. Additional subdivisions were added based upon creator and backer participation rights. The last part of this section shows this subdivision methodology in action across a set of crowdfunding platforms.

1.3) **Success in Crowdfunding**: This section develops the broad definition of success which is crucial in developing the theoretical framework, in section 1.4. And considers the impact of failure in crowdfunding.

1.4) **Theoretical framework development**: This section considers the development of the main theoretical framework for the thesis, based on five key theoretical areas. These areas are signals, incentives, social capital, competition and backer motivations. Each area critically utilises the developing crowdfunding literature to consider how crowdfunding success may occur. The findings from this section are combined to create a theoretical framework, which becomes the core of the creation of the conceptual frameworks for each crowdfunding platform.

2.1 Defining crowdfunding

Finding a distinct definition of crowdfunding has been an unmet goal, as Mollick (2014, pg2), stated: “a broad definition of crowdfunding is therefore elusive, especially as crowdfunding covers so many current (and likely future) uses across many disciplines.” This thesis aims to offer such a broad definition through challenging the existing definitions and creating a more-focused, precise and informed definition. This is achieved firstly, by critically considering the existing definitions of crowdfunding and the underlying restrictions each definition imposes, and then suggesting an alternative method for defining crowdfunding, based upon the interactions between creators, backers and the platform.

2.1.1 Characteristic 1: Number of crowdfunding participants

One of the key characteristics utilised within existing crowdfunding definitions is the concept that funds are raised via a large group of people, as shown by the following non-exhaustive list of examples:

“The idea of crowdfunding is to obtain funding from a large group of people where each individual provides a small amount, instead of raising money from a very small group of experienced investors.” (Voorbraak et al, 2011, pg V)

“Crowdfunding can be defined as the collection of funds, usually through a web platform, from a large pool of backers to fund an initiative.” (Wilson and Testoni, 2014, pg 1).

“The basic idea is always the same: instead of raising the money from a very small group of sophisticated investors, entrepreneurs try to obtain it from a large audience, where each individual will provide a very small amount” (Belleflamme et al, 2010, pg 1).

Across these definitions, there is a continuous characteristic of a large number of participants being key to the crowdfunding process. The author considers that a large number of crowdfunding participants can refer to two different scenarios, firstly it can refer to a large number of backers directly supporting the project. Or it can be considered to refer to a project that must have the potential to be supported by a large number of backers regardless of whether a project is or isn’t supported by the backers. As the first condition is more restrictive than the second condition, this was critically considered first.

2.1.1.1 A large number of backers supporting a campaign

Suggesting that a large number of backers are always needed to support a crowdfunding campaign is flawed as a campaign could be supported by a single backer. For example, consider a crowdfunding project which aims to raise 100 dollars. This project can be founded by 1 person who provides 100 dollars or 100 people that each fund 1 dollar. Both of these projects sit on a crowdfunding platform on the web, however, under this characteristic, only the second scenario would be crowdfunding, without any other aspect of the platform or project having to change. If this condition is upheld, then only completed projects could be assessed to be crowdfunding projects. Within crowdfunding projects, backers can join or leave at any point in time. Therefore one could only be certain that the project has a large number of backers at the end of a campaign. This restriction of only being able to define completed projects is problematic due to the existence of continuously funded crowdfunding projects which don't have a clear completion point (see section 2.2.6.2). A second point rendering this characteristic undesirable is that one needs to be able to define what is meant by large. Large could be defined as 100 people or a 1000 people, or 10000? For example, if one were to argue that a large campaign has over 1000 backers, then this would mean that the average crowdfunding campaign on Kickstarter doesn't have a large number of backers, as the average campaign has 102 backers extrapolated from (Kickstarter, 2019a). Furthermore, using a number of backers in defining the platform creates an odd scenario where at a specific point in a crowdfunding campaign, a single backer supporting the project transforms the project from a non-crowdfunding project into a crowdfunding project.

2.1.1.2 The large potential pool of backers

In the aforementioned scenario, it thus becomes necessary to define who are the pool of backers. However, defining the pool of backers becomes difficult when considering online crowdfunding platforms, as does this refer to the users of the platform or anyone using the internet? Without defining who forms the pool of backers, it becomes impossible to determine whether this is large or small. However, even when the pool of backers is clearly defined there is no reason that crowdfunding has to have a large pool of backers. Consider a new crowdfunding platform that has just started and only has five visitors a day; it has one open project which is seeking a hundred dollars. These five backers support the project with twenty dollars each, and it is successfully funded. In this theoretical example, there have only been five potential backers, yet they have fully supported the project. Leading to two plausible outcomes, either this platform is not a crowdfunding platform or using size as part of the definition of crowdfunding is flawed. The author argues the latter and thus considers that the number of backers should not be a component of a crowdfunding definition, regardless of whether this is referring to the potential number of backers or an actual number of backers.

2.1.2 Characteristic 2: An online aspect of crowdfunding.

One characteristic utilised in defining crowdfunding is the usage of the internet demonstrated by the non-exhaustive list below:

"Crowdfunding is an emerging internet fundraising mechanism for soliciting capital from the online crowd to support innovative projects" (Li and Duan, 2014, pg 2).

"Crowdfunding is a relatively new phenomenon that merges modern social web technologies with project-based fundraising" (Wash, 2013, pg 631).

"Crowdfunding is a new funding practice through which people, often living in different geographical areas, contribute to funding a project they share an interest in. Money is raised via online platforms, thus, utilising the Web 2.0 technologies" (Borello et al, 2015, pg 1).

There is no doubt that the internet is key to the current form of crowdfunding as demonstrated by the expansive network of online crowdfunding platforms, for a specific list of platforms, please see (Röthler and Wenzlaff, 2011, pg 52). Although this is not an exhaustive list of platforms as they can be added or removed from the web at any moment, making it difficult to state the exact size of the online crowdfunding network. Nevertheless, it demonstrates the large variety of sites involved in crowdfunding.

However, the use of being online as an implicit part of a broad crowdfunding definition is flawed due to how crowdfunding has occurred historically. A prominent example of historical crowdfunding is the pedestal upon which the statue of liberty stands. The money for the pedestal was raised by New York newspaper asking its readers for a sum of money, and in return they received a wide range of reward-based on the amount given, one such reward was a small statuette of the Statue, thus providing a historical example of reward-based crowdfunding (Pitts, 2010).

A second example is of Alexander Pope who in 1713 wanted to translate 15,693 lines of ancient Greek poetry, to do this he asked for two gold guineas, and in return, those who backed his project were listed in an early edition of the book (Kazmark, 2013). The translation of the poems formed an English version of Homer's Illiad which endures to this day. Even the great musicians of history utilised crowdfunding, Mozart's first attempt to utilise crowdfunding to fund the creation of his concertos failed. It was only on his second attempt that he was successful (Kazmark, 2013). A more general example is charities that have used donation boxes to enable people to support their cause anonymously. These donation boxes can be placed in streets or public places to attract the attention and funds of the public crowd (Perrine et al, 2000). It can also be noted that offline crowdfunding is not only historically, but also can be occurring within Modern business, Muller et al (2013) demonstrated, both theoretically and via a trial system within a large multinational company, that crowdfunding could be utilised within a business, enabling employees to spend their money on specific organisational needs. Demonstrating offline crowdfunding by a multinational company, however, the business did utilise their *internal* intranet as a replacement for the internet, in this case, nevertheless still highlighting the theoretical possibility of modern offline crowdfunding.

Crowdfunding utilising the internet is thus not desirable as part of a broad crowdfunding definition; however, the internet has enabled substantial larger amounts of crowdfunding to occur**.** Cumming et al (2014, pg 25), argued that “thanks to the emergence of Internet platforms, crowdfunding has become accessible to a large number of entrepreneurs as an alternative form of funding.” This growth has led to the crowdfunding market being worth over 16.2 billion dollars in 2014, and an expected 32 billion in 2015 (Massolution, 2015). Thus, although crowdfunding often utilises the internet, it doesn’t have to use the internet, and as such, it shouldn’t be used as a key characteristic in its definition. This distinction can be noted within the crowdfunding literature, where new additions to the literature add the suffix online when referring to crowdfunding which takes place on the internet (Li and Duan,2014; Meer, 2014; Althoff and Leskovec, 2015).

2.1.3 Characteristic 3: Building from the concept of crowdsourcing

One of the suggested ways to frame the definition of crowdfunding is to utilise the already existing form of crowdsourcing, as shown in the following non-exhaustive list of definitions;

“the concept of crowdfunding finds its root in the broader concept of crowdsourcing, which uses the “crowd” to obtain ideas, feedback and solutions in order to develop corporate activities. In the case of crowdfunding, the objective is to collect money for investment (Belleflamme et al, 2010, pg 1).

“The term crowdfunding itself is derived from the better-known term crowdsourcing, which describes the process of outsourcing tasks to a large, often anonymous number of individuals, a "crowd of people” (here: the Internet community) and drawing on their assets, resources, knowledge or expertise. In the case of crowdfunding, the objective is to obtain money.” (Ibrahim, 2012, pg 392)

However, utilising crowdsourcing to obtain a broad definition of crowdfunding when examined in detail shows that it can lead a specific set of restrictions. This is demonstrated via Estellés-Arolas and González-Ladrón-De-Guevara (2012), definition of crowdsourcing:

“Crowdsourcing is a type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task. The undertaking of the task, of variable complexity and modularity, and in which the crowd should participate bringing their work, money, knowledge and/or experience, always entails mutual benefit. The user will receive the satisfaction of a given type of need, be it economic, social recognition, self-esteem, or the development of individual skills, while the crowdsourcer will obtain and utilize to their advantage what the user has brought to the venture, whose form will depend on the type of activity undertaken.” (Estellés-Arolas and González-Ladrón-De-Guevara, 2012, page 197)

This definition was characterised as having eight key characteristics, which were then considered across multiple platforms which self-identified as crowdsourcing sites, with the majority supporting at least half of these characteristics. Demonstrating that even a very developed crowd-sourcing definition is not consistently applied across crowdsourcing sites. Leaving it uncertain which characteristics should be utilised in the process of defining crowdfunding.

Furthermore, one of the major characteristics is being online, which has already been shown to be unnecessary in crowdfunding. Demonstrating that key differences between crowdfunding and crowdsourcing must be identified. Creating a fundamental problem with utilising crowd-sourcing to define crowdfunding, that requires an implicit understanding of what crowdfunding is. Which can only really be obtained by creating a definition of crowdfunding. Therefore crowd-sourcing can be utilised as a source of characteristics for crowdfunding, but fundamentally cannot be used to create a definition by itself.

A second point is raised in (Belleflamme et al, 2010) definition which suggested that money collected by crowdfunding must be used for investment. However, this then means that any crowdfunding purpose which is not raising money for investment is no longer crowdfunding. Including a requirement to how the money raised in crowdfunding is used dramatically restricts the possible crowdfunding platforms. Instead, the usage of the money could be seen as a method of subdividing crowdfunding, subdivisions methodology is considered in (section 2.2).

2.1.4 Characteristic 4: utilising the concept of the crowd.

Another term which has been utilised across multiple definitions is “the crowd”. As demonstrated in the non-exhaustive list of definition below;

“Crowdfunding is an emerging internet fundraising mechanism for soliciting capital from the online crowd to support innovative projects.” (Li and Duan, 2014, pg 2)

“Entrepreneurs and businesses can utilise the crowd to obtain ideas, collect money, and solicit input on the product, overall fostering an environment of collective decision-making and allowing businesses to connect with potential customers.”

“Crowdfunding is a nascent ecosystem for early-stage innovation and finance enabling businesses to utilise the Crowd to obtain resources. Such as ideas, money and feedback on the product” (Scholz, 2015, pg vii)

If the term “crowd” is to be utilised as part of the definition, then it must be clearly defined. However, the definition of the crowd will change based upon the surroundings it is based as demonstrated by Ibrahim (2012) which consider the crowd to be the internet community, while crowds have also referred to the social group surrounding young adults (Cross and Fletcher, 2009). In utilising the term as part of a general definition creates uncertainty in the meaning of the definition, as it can refer to multiple different definitions.

The inclusion of the crowd term can thus be considered to only transform the problem from how to broadly define crowdfunding, to how to broadly define the crowd. The author would argue that this reshaping of the problem makes it even more difficult to find a broad definition, due to how the term crowd can be used with multiple different meaning as discussed above. Therefore, the inclusion of a crowd term is not considered to assist in the creation of a broad definition of crowdfunding.

2.1.5 The three players involved in Crowdfunding

Fundamentally, focusing on the characteristics of the crowdfunding networks does not enable a succinct way of defining crowdfunding, which achieves the goal of creating a distinction between crowdfunding and traditional funding methods. Hence, instead of considering the characteristics of the crowdfunding platform themselves, the author proposes to follow a different approach. Kromidha and Robson (2016) paper on signalling within crowdfunding noted that there are two different signalling parties active within the crowdfunding platform, the creators of the crowdfunding projects and the backers (those providing funds) of the crowdfunding project. Moreover, that these parties both utilise the platform to signal potential future backers into supporting the project they have supported or created. This interaction is considered in detail in the development of the theoretical framework of this thesis, but the important point for the development of a key definition of crowdfunding is that the concept that crowdfunding contains three distinct parties, the backers, the creators and the platform itself, this three different parties originally outlined in Ordanini et al (2011). The author proposes that crowdfunding can be defined via considering interactions between these groups. Before considering the interaction, it is necessary to clearly define each group, the author defines the groups as the following:

1) The 'creators' are the core of crowdfunding. They are a person or group who is seeking money for any venture, task, idea or concept, who decides to utilise a platform to raise said money.

2) The 'backers' are the fund providers; they provide money via the platform to support the creators. The backers can support the projects for any reason.

3) The 'platform' exists to connect the creators and the backers; each platform can set its own rules for both the creators and the backers, it enables money to be transferred without the necessity of a direct connection between backers and creators. However, a platform does not make funding decisions (who receives funds) as these are made by the backers.

The author considers that a definition for crowdfunding can be created solely through considering the relationship between these three parties. Specifically, that all that is necessary for crowdfunding to occur is backers to be able to provide funds to creators through using a crowdfunding platform. Thus this can be formally defined as the following:

Crowdfunding is the interaction between three parties: creators, backers and a platform. Creators seek to obtain funds for a project, backers provide those funds, and the platform acts as an exchange between the backers and the creators, without itself making funding decisions.

Under this definition, creators can be anyone seeking to fund any project for any purpose. As can backers - for example they could be long-established investors or people who have never invested before. The platforms can be anything from an offertory box outside a church to the entirety of the World Wide Web, as the only condition is that it enables backers to support creators without specifically deciding who receives funds. This last condition is incredibly important, as it is this condition which enables a clear point of separation between crowdfunding and traditional financing. The condition stems from the concept that crowdfunding can be disassociated with traditional financing through disintermediation, i.e. the removal of intermediaries between producers and consumers (Beaulieu et al, 2015). This condition is necessary for backers to choose which projects succeed and which don't, enabling the claim that crowdfunding is democratising the access to finance (Nasrabadi, 2016). The distinct point at which crowdfunding becomes traditional funding is demonstrated in the following examples created by the author:

Example a) A church offertory box, sitting on a public street. The creator of the box is the church, the potential backers are anyone who passes it, and the platform is the box. The box can make no funding decisions; it is, in the end, a box, the backer can put money into the box which will be transferred to the church. Therefore, under the definition given this is a clear case of crowdfunding.

Example b) Venture capitalism, in this case, the venture capitalist raises money from its investors and then invest this money in multiple start-ups, the venture capitalist could be defined as the platform, the start-ups as the creators and the backers as the investors. The decision on whom to invest in is made by the venture capitalist company, the backers are not choosing whom they are backing, and thus this is not crowdfunding. To turn this traditional funding form into crowdfunding, the decision on who is funded would have to change from the venture capitalist company to the backers.

Example c) Online funding platforms: Within online funding platforms, the creators can be seen as anyone attempting to raise money on the platform, the backers can be seen as the online internet users who support the project. The platform is the website itself. For the platform to be a crowdfunding platform, it must enable backers to fund projects without interfering in how the funds are used. As soon as there is interference in how the funds are allocated, the platform it is no longer a crowdfunding platform, but instead a traditional funding platform. Example of such interference would be directly choosing which projects receive funds or pooling together funds and then assigning the money to projects based on the platform's whims.

These examples show that this definition can be utilised across both offline and online crowdfunding. This condition of funding choice being in backers' control is vital for the usage of signalling theory in explaining crowdfunding success, this theory has been utilised across all classical subdivision of crowdfunding (Ahlers et al, 2015; Boudreau et al, 2015; ;Kromidha and Robson, 2016; Moss et al, 2015; Vismara, 2018). Signalling quality between backers and creators can only matter if the backers are making the funding decision. Thus this condition must hold for signalling to be key in understanding success in crowdfunding.

This definition proves two clear points of distinction between crowdfunding and traditional financing. The first is when the platform starts making funding decision, i.e. choosing who receives backing. The second is when the number of parties involved is reduced to two, by removing the platform and having a direct exchange between backers and creators. Therefore, achieving the goal set out in providing a broad definition of crowdfunding with clear points at which it can be distinguished from traditional funding. The next section considers the traditional methodology of subdividing crowdfunding and then builds upon them suggesting further subdivision methodology based on creator participation rights.

2.2 Subdividing Crowdfunding: -

Crowdfunding can be subdivided into multiple different categories, the main approach to the classification of crowdfunding, was suggested by Giudici et al (2012). This author argued that each crowdfunding platform is administered under different, individual, rules affecting the set of permissible actions for both backers and creators of *innovation projects* and that they can be divided based on the backers' participation rights leading to the creation of four major categories:

i. *Equity-based* crowdfunding, where a backer is entitled to a share of the company or of the product they are backing and are thus entitled to a residual income from the product or title.
ii. *Lending (debt) based* crowdfunding, where backers are given an interest payment for their backing.

iii. *Donation-based* crowdfunding, where no physical return is given to the backer, this is mainly used for charitable causes.

iv. *Reward-based* crowdfunding, in which the backer is given a reward, based on the size of his donation which can be, for example, a product, art work, game. The reward can be anything specified by the project creator. (adapted from, Giudici et al, 2012, p. 8)

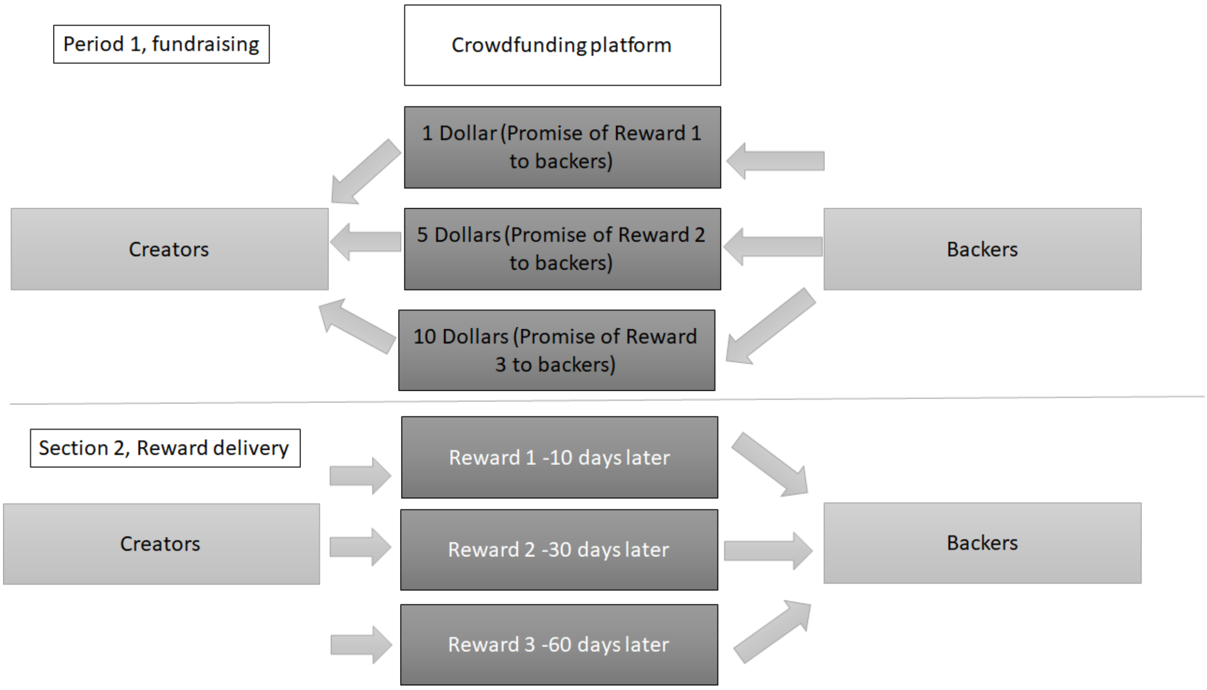
This method of sub-division can be used to identify the different section of the crowdfunding literature. The following sections of this chapter consider each of these types of crowdfunding separately, identifying prominent platforms of each type of crowdfunding as well as key themes and concepts highlighted in the existing literature.

2.2.1 Reward-based crowdfunding

2.2.1.1 Definition and visualisation

Reward-based crowdfunding is considered the most prominent as of 2017 and can be identified via creators not having to provide any financial incentive to the backers in return for their funds, instead backers receive a specific reward-based on the amount of funds given to the project (Bi et al, 2017). Alternatively, regarding backer participation rights, the backer has the right to a specific reward-based upon the amount of funds given to the project. Any legal products or service can be funded on a reward-based crowdfunding platform. However, they may be restricted by the crowdfunding platform, for example, reward-based crowdfunding on Unbound.com can only be utilised in funding books (Unbound, 2019). The rewards can be any legal product or service and are often grouped together into reward levels, which contain a set of rewards. A project can set multiple rewards or reward levels, and backers are free to choose between any of these. It has been considered within the literature that rewards are one of the key motivators in reward-based platforms (Bretschneider and Leimeister, 2017). Rewards do not have to be provided during the project. Instead, they can be given to the backer at a future date, this can be compared to pre-ordering phenomena observed in video games and the technology market: where users purchase a project with the knowledge that they will not receive the product for at least a certain period of time which can be extended due to delays in production (Hernandez and Handan, 2014). This expected delay means that reward-based crowdfunding can be divided into two different sections: the funding period and delivery period, the funding period considers when the project is raising its funds, and the delivery period considers when rewards are delivered, these may occur at the same time or at different times. From this information Figure 2-1 below is created.

Figure 2-1 Visualising reward-based crowdfunding



This visualisation shows the scenario when the creator of a reward-based crowdfunding project offers three different rewards for his project. The second period demonstrates the delivery of the rewards to the backers; each reward is delivered at a different time. It is worth noting that the reward delivery is not tied to the crowdfunding platform, as at this point the direct connection between backer and creators has been established, the reward is sent directly to the backer.

2.2.1.2 Moral Hazard in reward-based crowdfunding

This visualisation in Figure 2-1 highlights the moral hazard problem that can occur within reward-based crowdfunding, as the rewards only have to be delivered after the money is received (Agrawal, 2014). This raises the following key questions around reward-based crowdfunding: do the projects successfully deliver the rewards and are platforms open to fraudulent projects where the creator has no intention or ability to deliver the rewards? Mollick (2014) recorded that in a set of 471 Kickstarter projects, only 3.6% failed to deliver the rewards, although 75 % of the projects were delayed in their delivery. Mollick (2015) then expanded his original study, in this new study he surveyed 47,188 backers from Kickstarter, within which he found that failure to deliver accounted for 9% of all projects, with a possible range lying between 5-14%. Highlighting that even in the most pessimistic scenario, only 14% of crowdfunding projects failed to deliver. In understanding whether this figure of 14 % is good or bad, one can consider the failure rate of start-ups based upon different failure conditions. 30-40 percent of United States of America start-ups fail to return any money to investors. 75 percent fail at returning all of the original investment and 95 percent fail at reaching profit expectations (Gage, 2012). The failure of start-ups is not a perfect comparison as they are under different constraints and delivering the rewards does not mean that the individual or crowdfunding company will not fail, especially considering that this was only looking at start-ups within the United States of America. However, the author still argues, it gives a basis for arguing that a 14 % failure rate is low and thus that moral hazard of not delivering rewards is not an inherent problem in reward-based crowdfunding.

2.2.1.3 Kickstarter: the most prominent reward-based crowdfunding platform

One point to consider is that the crowdfunding platform which Mollick addressed was Kickstarter, which is considered to be the most prominent example of a reward-based crowdfunding platform (Belleflamme et al, 2013). Kickstarter was founded on the 28th of April, 2009. Over 140,000 projects have been supported providing over 3.7 billion dollars to crowdfunding projects with the support of 15 million backers (Kickstarter, 2019a). Smaller less established reward-based crowdfunding platform may have different characteristics and may not benefit from the number of backers and thus inherent crowd wisdom on Kickstarter (Sadiku et al, 2017). Kickstarter has been utilised across multiple papers in identifying factors of success in reward-based crowdfunding.

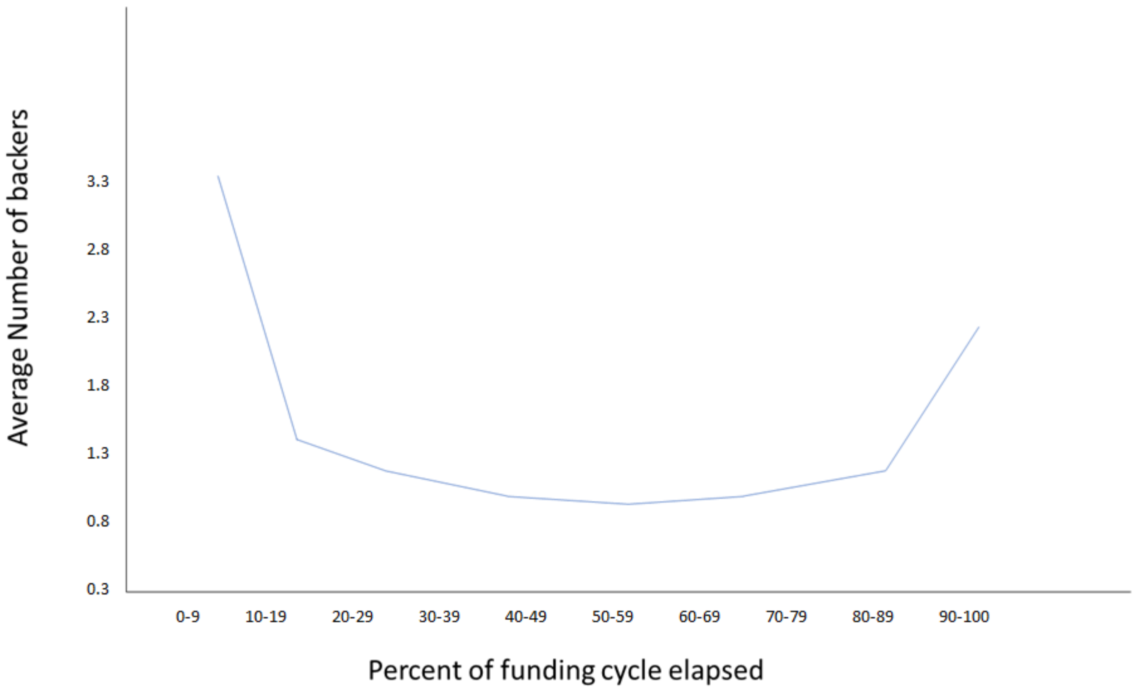
Kromidha and Robson (2016) utilised signalling theory to examine the 5000 projects who attracted the most funds on Kickstarter. Arguing that the greater the number of signals which were exchanged between the creators and backers the more successful the projects were in raising funds. The specific signals they considered were the numbers of comments and updates of the crowdfunding project. Comments are the online questions posed by the backers of the projects; these comments are displayed on the crowdfunding page, representing signals sent by the backers to other backers and the creators of the campaign. While updates are information provided by the creator of the campaign after the start of the campaign that are used to represent signals sent by creators to the current backers and potential backers. The dependent variable tested in this paper was the pledge to backer ratio, with a higher pledge to backer ratio considered to be more successful. Numbers of comments was statistically significant and had a positive correlation, however number of updates, although positively correlated, was not significantly significant. Conversly, a high number of updates at the end of successful projects was observed in (Kuppuswamy and Bayus, 2018). It must be taken into consideration that Kromidha and Robson (2016) only examined the most successful campaigns and thus it can be questioned whether the same result would be considered in less successful and unsuccessful campaigns. Especially considering how signals sent by backers could be used to also identify flaws in the lower quality campaigns, persuading other backers not to support these campaigns. Thus, an extension of this research which considers a more varied set of project outcomes would enable a clearer role of these creator and backers' signals to be identified. Furthermore, within Kickstarter, signalling theory can also be used to identify proxies for human capital, such as experience, which was a key theme of a paper written during the construction of this thesis (Davies and Giovannetti, 2018).

Alongside signalling theory, Kromidha and Robson (2016) also identified how social capital is key to success in crowdfunding, arguing its importance through the lens of the expansive social identity theory. They found that the number of friends on Facebook had a positive and significant effect on the success of campaigns, supporting results in (Mollick, 2014; Zheng et al, 2014), and the authors' work (Davies and Giovannetti, 2018). Colombo et al (2015) further expanded this concept by making a specific distinction. They distinguished that there were two types of interacting social capital, external and *internal social capital*. The *external social capital* was the type provided by an external network such as Facebook or LinkedIn. They, however, proposed that the crowdfunding platform itself could start to create *internal social capital*. Arguing that *internal social capital* could be captured by considering the numbers of previously backed campaigns by the creator of the new project. This measure of *internal* capital was found to have a positive and significant impact on the number of early backers and the amount of early funds received for campaigns. The author considers that if a crowdfunding platform is generating *internal social capital*, then it could be considered a pseudo social network. If it is possible to connect projects based on latent links given within the platform then the latent network can be mapped, enabling network analysis techniques to be considered in assessing success in crowdfunding.

Wessel et al (2016), considered how social information can be manipulated within Kickstarter to create false signals. This false information was noted to have a positive short-term effect, but negatively affecting projects in the long run. They demonstrate that fake social information usage occurs more on projects with higher quality indicators rather than projects with low-quality indicators.

Colombo et al (2015) also considered that early backers and early funders were key indicators of a successful crowdfunding campaign. They set the early funding period at 1/6th of the duration the campaign, such that a 30-day campaign, would have an early funding period of 5 days. Finding that both of these were significant and positively correlated to the amount of funds raised in a campaign. However, the choice of 1/6th of duration seems rather arbitrary, is the early backing period best defined as a 1/6th of the duration, why not a 1/8th or a 1/10th. Solomon et al (2015) and Kuppuswamy et Bayus (2018) noted that Kickstarter reports a boat/bathtub shaped funding pattern with both the beginning and the end of the cycle having the highest point of return, with the middle of the boat having a lower amount of backing, as displayed in Figure 2-2.

Figure 2-2 Boat shaped funding period, extrapolated from (Kuppuswamy et Bayus, 2018)



Thus, the early funding period could be considered to be at the point where the curve starts to flatten out; it may be possible to endogenously capture this point across each project's campaign. This boat-shaped funding period also highlights that the beginning of the campaign is crucial to the success of the campaigns. Kuppuswamy et Bayus (2018) also supported Mollick (2014) finding that once projects reach 50 % funding, they are highly likely to succeed.

The early funding period effect is increased, due to the occurrence of herding within crowdfunding (Kuppuswamy and Bayus, 2018). Herding is the phenomenon whereby there is a behavioural similarity brought about through the interaction of individuals. Hirshleifer and Teoh (2003) argue that herding was originally restricted to a physically delimited space, but this restriction was removed by economists, in favour of any actionable space. Herding can be seen as a form of momentum trading, where after a project receives some initial interest, it will receive increased interest from other groups and parties for the rest of its duration (Park and Sabourian, 2011). Whereby the individual action is no longer determined by interpreting the private information signal they receive, but rather the observation of the other (Bikhchandani et al, 1992). Herding can have many implications for the affected individuals, due to the following factors:

Idiosyncrasy: Signals sent by the first few individuals, which impact behaviour, can drastically affect behaviour of the individuals who follow.

Fragility: When cascades occur, they are fundamentally fragile and can be sensitive to small shocks.

Simultaneity: Endogenous events can lead to sudden changes, leading to vast increases or decreases in the observed actions.

Paradoxicality: That the act of herding itself can limit the effects that public information might otherwise have on the likelihood of rational support.

Path-dependency: The probability process driving the outcome paths of the event depends on the temporal order at which the information arrives.

(See Hirshleifer and Teoh 2003, pg 32)

These five factors can clearly be linked to crowdfunding, *Idiosyncrasy* can lead to early funders having larger than rational effects on the likelihood of a project to succeed, which should be considered when capturing success (Oh and Baek, 2016). *Fragility* could suggest that crowdfunding platforms and projects could be very susceptible to shifts of information. This may have an impact on the long-term sustainability of platforms, if serial creators are unable to consistently utilise crowdfunding, due to fundamental instability caused by fragility. *Simultaneity* could lead to crowdfunding platforms being greatly affected by shifts of information from outside the platform. *Paradoxicality* could imply that high quality crowdfunding projects may be unable to successfully signal their quality due to the herding effects. *Path-dependency* suggests that specific project information and advertising efforts will be more impactful if provided at the very beginning of the campaign, otherwise specific investors may be missed (Agrawal et al, 2011). Thus, the herding phenomena deeply affect crowdfunding through these phenomena.

Mollick (2014) work highlights that geographic location may affect success within Kickstarter in two specific ways, firstly via observing that projects are concentrated in specific geographic locations, with individual categories of projects more concentrated than general crowdfunding concentrations. Thus, projects of the same category are more likely to be geographically concentrated. While also noting that campaigns located within an area of higher population were more likely to succeed. Contrary to this point, Kromidha and Robson (2016) tested the impact of success on the top 5000 projects across 13 different regions in the world, only discovering that only two of them were statistically significant in affecting the pledge/backer ratio of the top 5000 crowdfunding projects on Kickstarter. These geographical considerations all focus on the creator locations; however, it may be that the relative geographical differences between backers and creators are key to capturing the effects on crowdfunding. Agrawal et al (2011) did consider the effects of distance between creators and backers on the equity crowdfunding platform Sellaband, finding that distance related funding frictions were removed. However, Sellaband failed and became bankrupt in February 2010, thus causing the result not to be generalisable, especially considering the expansion of crowdfunding, where it doubled every year between 2009-2012 (Massolution,2015).

Other explanatory variables can be explored across geographic divides, Zheng et al (2014) demonstrated this by considering the differences in the impact of social capital on success in crowdfunding between the US and China. Utilising Kickstarter for the US and Demohour for China. Concluding that social capital had a positive and significant impact in both cases, however, it had a stronger impact in China than in America.

2.2.1.4 Other Platforms

However, as all these papers utilise Kickstarter as the major source of data and Kickstarter is the most or one of the most prominent examples of the reward-based crowdfunding sites (Belleflamme et al, 2013), it could be that these results are only true for Kickstarter. Crosetto and Regner (2018), examine the biggest German reward-based crowdfunding platform Startnext, in this platform 75% of the projects that eventually succeed only manage to succeed in the final 25 percent of the duration. Leading to the conclusion that the final periods of funding are essential, in contrast to the results for Kickstarter which focuses on the early funding period (Colombo, 2015). Cumming et al (2016) examined Indiegogo, a crowdfunding platform which enables both keep-it-all and all-or-nothing creator crowdfunding rights. Keep-it-all funding refers to when the creator of a project receives all of the money backed at the end of the project, even if the funding goal was not reached. Conversely in all-or-nothing funding creators only receive the money if the funding goal is reached. The inclusion of both types of funding mechanisms enabled a comparison between these two factors which would not have been possible on Kickstarter, coming to the conclusion that all-or-nothing funding would on average raise more money than keep-it-all funding.

Bi et al (2017) examined the Chinese crowdfunding platform Demohour, utilising the elaboration likelihood model. This model, developed by Petty and Cacioppo (1986), argues that there are two different routes of communications which can be utilised to explain how people are persuaded to support a position. There is a central route of persuasion in which a person utilises the actual information provided to them to change their opinion and a peripheral route which considers a concept of induced value. The latter is not connected to the actual information provided, but rather associated with some underlying aspects of the communication, such as the quality or credibility of the broadcaster. Bi et al (2017) identified that this model could be utilised to consider crowdfunding, suggesting that the signals of project quality can be considered central root factors, capturing this quality by the inclusion of videos and the number of words utilised in the campaign page. Peripheral effects were captured by the electronic word of mouth, utilising the number of like of the project and the number of reviews as a measure of electronic word of mouth. They carry out a combination of correlation analysis and linear regression models with their preliminary results suggesting that each factor had almost equal effects on success within Demohour.

However, when the specific category of the project was also considered, science technology and agriculture projects were more greatly affected by the central route factors than the peripheral routes. On the other hand, entertainment and art were more greatly affected by the peripheral routes than the central routes. Therefore, demonstrating key differences to success based upon the category of the project. However it may be argued that this work does not accurately capture project quality, as it only considers word count and video count, while other variables should also be included. One possible additional variable, specifically for text, could be the impact of spelling errors, as demonstrated by Dorfleitner et al (2016) who took into account spelling errors as an additional measure while considering peer-to-peer lending. Upon saying this it is worth noting that including spelling errors is not a simple process with Chinese characters, as there are no word delimiters, and the length of each word is very short, although this problem can be addressed as done within Wu et al (2013), it may not be practical to carry out on large-scale research. In light of this, different languages may restrict the signals which can be captured from the crowdfunding platform based upon the structure of the language. Some may naturally use far fewer words or be more punishing for mistakes, this makes using analysis of text between platforms increasingly complex as the language differences would have to be taken into account.

Language has also been utilised in considering differences in gender outcomes in crowdfunding. Gorbatai and Nelson (2015), examined the differences between female and male funding outcomes within Indiegogo. To the contrary, for offline funding they discovered that female lead funding was more likely to succeed then male lead funding. Arguing that the language differences between male and female creators are a key factor in affecting the success of a project. Utilising past literature which suggested that men and women have different writing styles (McMillan et al, 1977). They separate languages into four separate categories, a language which is inclusive, a language which contains positive emotion, business language and vivid language. Finding that positive emotion and inclusive language have a positive effect on crowdfunding projects, while business language has a negative effect, whilst not finding a significant effect for vivid language. Further investigating the differences in language between men and women they identify that women utilise more emotive inclusive and vivid language but less business-related terms. Concluding that gender has a 15-20 percent effect on money raised in favour of women, demonstrating that women raise more money in crowdfunding, partially based on their language usage. This can be linked to the concept of how crowdfunding can democratise access to capital providing capital to those who have been traditionally denied access to capital (Mollick and Robb, 2016).

2.2.1.5 Backer motivation in reward-based crowdfunding

The rewards have been identified as a key motivator of backers in reward-based crowdfunding (Belleflamme et al, 2013; Bretschneider and Leimeister, 2017) and their effects are shown to be positive across the literature. Mollick and Nanda (2015), identified a positive effect on success of increased reward levels and Qiu (2013) identified that projects which utilise a public good as a reward are 5 to 10 percent more likely to reach their funding goal. Where a public good in this context is considered one which when supported will be given freely to the rest of the public. The specific example utilised was a DVD which would also be uploaded to YouTube. Enabling both the backers and the general public to view the content, while only the backers paid for the content. Zhang and Chan (2019) argued that the reward level may not accurately calculate the different number of rewards, as they considered that reward levels can include multiple rewards. Therefore a project with one reward level can plausibly have more rewards than a project with two reward levels, therefore arguing that the number of rewards should be considered over the number of reward levels. They find that the average number of rewards has a u-shaped effect on the number of backers. However separating reward levels into rewards may be problematic as it then introduces the problem of specifically defining different rewards. Consider the example of a set of videos, is this one reward or several, or take the case of a day trip, is this one reward or multiple rewards based upon the activities in the day.

Furthermore, it may be impossible to view the number of rewards, for example suppose there is a gift box offered as a reward, this box could contain any number of smaller rewards. Furthermore, backers may calculate rewards entirely differently based on subjective preferences. Therefore, the author argues that reward levels which are clearly defined should be used over the uncertain variable of number of rewards, even though they may in some cases underestimate the number of rewards.

2.2.1.6 Competition effects in reward-based crowdfunding.

The evolution of competition in crowdfunding can be considered via how creators have moved from being funded on their websites (Belleflamme et al, 2013) which would have very limited competition, to competing within online crowdfunding platforms, with over 16.2 billion dollars of funds being raised in 2014 (Massolution, 2015). The crowdfunding platforms can be considered to be two-sided markets, with two separate groups of economic participants, the backers and the creators with both benefitting from increased cross platform network effects (Rochet and Tirole, 2003). Specifically, the creators benefit if more backers are drawn to the platform as it increases the chance that their project will be funded, while backers benefit from increased numbers of creators as it increases the probability that a project which reflects the backer preferences will be fulfilled. Additionally, the crowdfunding platform benefits as they receive a small percentage of each successful project and assuming that the additional projects increase the overall number of success, then the owners of the platform also benefit (Viotto, 2015). Two sided markets need to overcome the chicken and egg problem, i.e. which of the creators or backers are drawn in first. However, in crowdfunding, this is not greatly problematic as one can focus on creators, as each creator has their social capital and can draw in backers from this, therefore platforms can focus on drawing in creators and then backers (Viotto, 2015). One possible future impact on the two-sided market approach, is to consider the transfer of ownership of the platform from a third party to the users of said platform, bringing ownership of the platform to the users would remove the extra cost to the third party organising the platform and may overcome monopoly rent issues (Scholz, 2014).

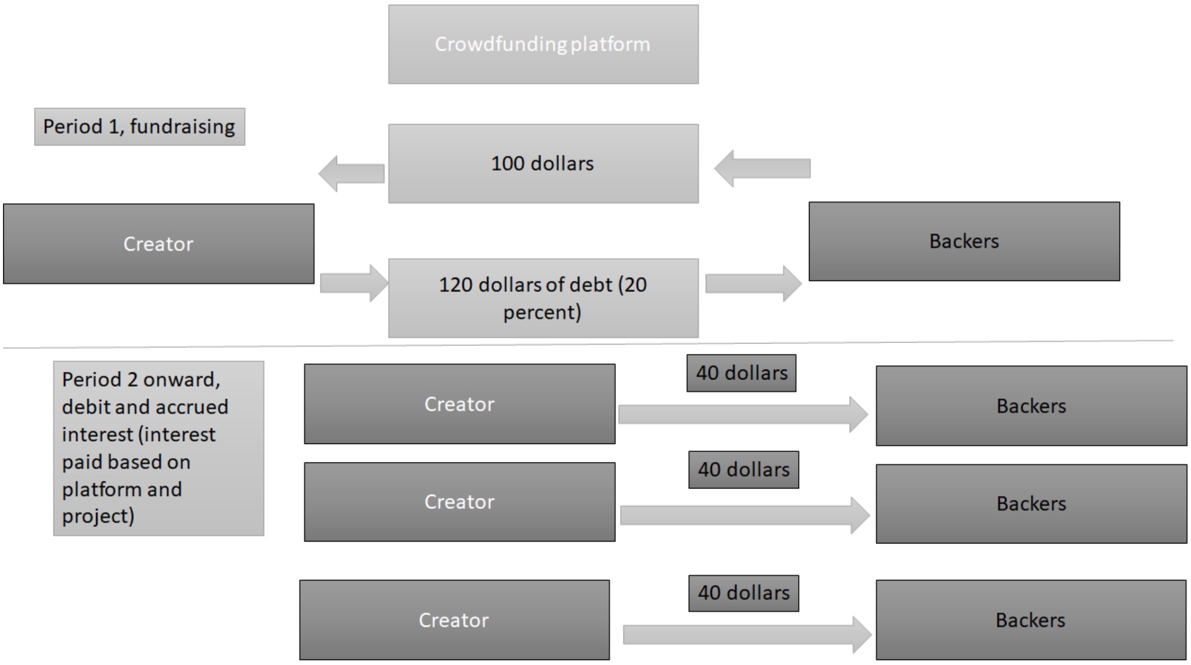
Crowdfunding platforms are also affected by competition from within the paltform itself. Liu et al (2015) demonstrated how projects which greatly overperform, which they defined as blockbusters, can affect the success of the surrounding projects within the same category of Kickstarter. This utilises the internal structure of Kickstarter where projects are separated into categories, the categories a project belongs to is chosen by the creator of the project. Conversely, projects outside the category were considered to be negatively affected by the existence of a blockbuster in another category. These hypotheses were then tested on a dataset of 735 observations from November 2010 to November 2014, with each observation representing a category within Kickstarter. With their results supporting the aforementioned hypotheses.

2.2.2 Lending-based crowdfunding

2.2.2.1 Definition and visualisation

In lending-based crowdfunding backers lend the money out to creators with the expectations that the money will be returned in the future. The rate at which the money is returned and whether interest is accrued will depend upon the platform and project (Meyskens and Bird, 2015). The backer’s money is thus at risk as if the loan is defaulted on, the platform may not cover the debt (Everett, 2015). Two periods can thus be considered, the original delivery of the funds and the return of the funds as displayed in the following visualisation:

Figure 2-3 Lending-based crowdfunding visualisation



In the visualisation displayed in Figure 2-3, the creator asks for 100 dollars, in return, the backers are given 120 dollars of debt, which is then paid back in the second period. In this example, it is paid back in three occurrences, and 20 dollars of interest was accrued. The major risk to the backers is default which can be caused by moral hazard issues within debt-based crowdfunding.

2.2.2.2 Moral Hazard and Hold up problems within debt-based crowdfunding

Everett (2015) examined how the crowdfunding platform Prosper attempts to overcome moral hazard via the grouping of creators (in this case creators are those seeking loans). At the time Everett collected their data Prosper utilised an internet adapted Dutch auction approach, where loan return rate went up until the debt was bought by backers, conversely to the traditional function of the Dutch auction where the price dropped until a product was sold (Rockoff et al, 1995). Creators within the platform at the time had the option to join self-monitoring groups; these groups could be joined before the Dutch auctions were carried out and were identified to reduce uncertainty when personal links were used in the creation of these groups. These groups created by personal connections led to lower cost loans and lower default rates, benefiting both creators and backers. Suggesting that the moral hazard of the creators may be overcome via peer to peer monitoring between creators.

Conversely, Everett (2015) also examined how the hold-up problem that results from current lenders only seeing the quality of firm they lend to is still prevalent within debt-based crowdfunding. The informational holdup problem originates from how banks can obtain proprietary positive information regarding borrowers (Fama, 1985). Sharpe (1990) formally developed the hold-up concept from utilising this propriety information. Sharpe (1990) developed a model considering the relationship between firms and banks, with the assumption that only the current bank can see the actual quality of the firm. The bank will hold on to this information rather than passing it to other banks as this would aid competitors in obtaining their clients. Therefore, the true quality of the firm cannot be observed outside of the bank, enabling the bank to charge higher rates of interest compared to if the actual quality of the firm was known across the market. Everett (2015) found evidence that hold-up problem is still pervasive within Prosper, based upon the informational level of the backers, this problem was worsened with users with low credit ratings. Thus, traditional hold-up-problems are still a relevant issue within debt-based crowdfunding.

2.2.2.3 Kiva: Lending-based crowdfunding platform

One of the most established of these platforms is Kiva which was founded in 2005. Kiva delivers microloans to alleviate poverty around the world; it has enabled 2.9 million borrowers to access in excess of 1.16 billion dollars' worth of loans. Moral hazard has not been a problem within Kiva, with a repayment rate of 96.9 %, one possible key to this high repayment rate is the usage of partners who facilitate the delivery of the loans and are based in the local country (Kiva, 2019a). This form of microlending has been proposed as a solution to fund and develop small business across the developing world (Ibrahim, 2012).

Contrary to this expectation Allison et al (2015) research into Kiva itself noted that projects are more likely to be successful if the narrative of the venture focuses on the intrinsic value generated by the project rather than the extrinsic values, furthermore arguing that business ventures were less likely to succeed than ventures which were seen as opportunities to help people. Even though Moss et al (2015) work demonstrated that business ventures returned investment faster than virtuous projects. Highlighting that backer participation for Kiva is not solely driven by seeking a stable return to investment but can be suggested to be more altruistic. Kiva runs an all-or-nothing policy, with money only going to the creators if they successfully reach the funding goal. The creators of the projects on Kiva in most circumstances are not the end users receiving the loan but instead are the partner organisation, who run the projects as representatives of the creators. The author would argue this is still crowdfunding as the backers can choose which project they are supporting and thus signalling can still occur. However, it is signalling between the partner organisation and the backers, not the end user. The platform still acts as an exchange without making funding decisions.

Rate Setter and Prosper offer a very different direction for debt-based crowdfunding. They focus on the interest rate offered to the creators (those seeking funds), which can be used for any purpose, they deem themselves to be peer to peer loan platforms. Rate Setter has facilitated 3 billion dollars in lending, with over 600,000 investors and borrowers (Rate Setter, 2019). While Prosper has leant over 12 billion dollars (Prosper, 2019).

However, under the definition of crowdfunding discussed in the previous section, Rate Setter would not be considered a crowdfunding platform. This is due to how in Rate Setter backers do not get to choose which specific project they fund, when funding they get to choose from between 5 different yearly markets, with different rates of return, but not where their funds are utilised within these markets. Thus, the backers are not deciding who receives funds, the platform decides who receives funding, thus under the definition developed within this thesis this is no longer crowdfunding. Compare this to Prosper, which is functionally very similar to Rate Setter, backers can look at each project and choose which projects they wish to support. Prosper thus still satisfies the definition and can be considered a crowdfunding platform. Highlighting how peer to peer lending platforms can be either crowdfunding or traditional funding.

2.2.2.4 Signalling in lending crowdfunding

Moss et al (2015) examined how signalling can be considered in the lending-based crowdfunding platform Kiva. They argued that creator signals could be identified via the specific narratives utilised within the project page of the Kiva platform. Specifically identifying two key narrative areas of entrepreneurial orientation and virtuous orientation. Entrepreneurial orientation captures a firm’s strategic level, managerial and strategic decisions which are entrepreneurial in nature, in general referring to decisions focused on innovation, proactiveness and risk-taking (Lumpkin and Dess, 1996). While virtuous orientation refers to a set of characteristics which can be seen as virtuous in nature, defining the individual ethical character traits and virtuous behaviour (Payne et al, 2011).

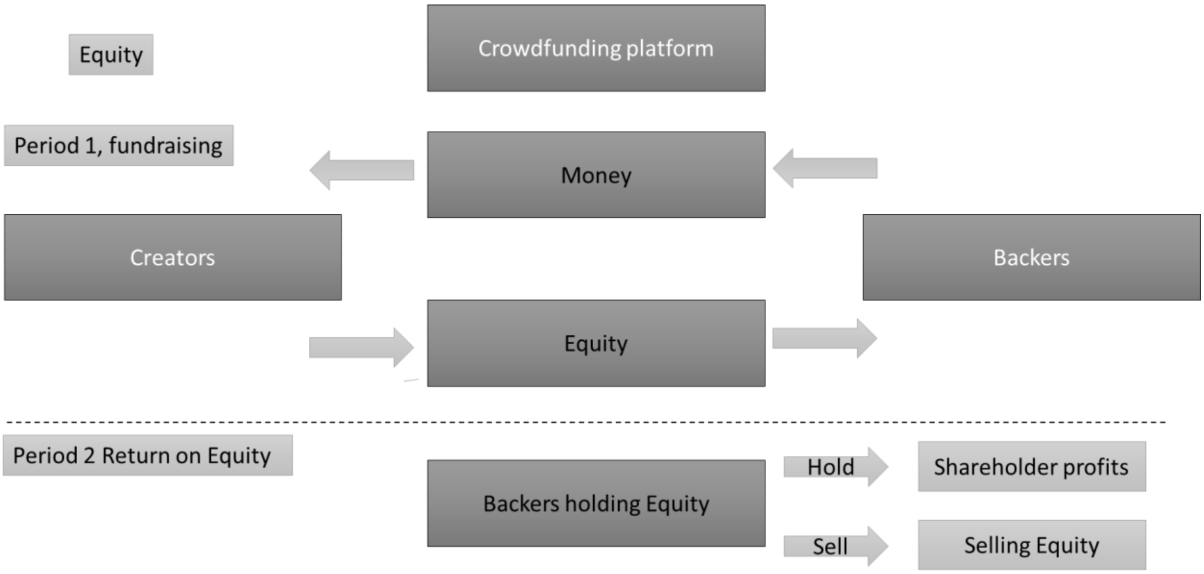
Furthermore, they proposed that virtuous orientation can be seen as a signal of the creator’s reliability and ethicality, thus increasing the speed at which microloans reach there funding goal. Entrepreneurial orientation signalled via five key terms, is considered to have a positive effect via making investment more desirable and reducing asymmetric information between creators and backers. A textual analysis was used to identify these aspects through an examination of 400,000 projects from Kiva. Their results were contrasting, with some elements of virtuous orientation being supported and other elements having a negative impact. Entrepreneurial orientation had similarly mixed results, with some terms having significant effects and others no affect at all. One of the limitations of this paper is that the role of the partner organisation was not taken into consideration, within Kiva partner organisations can be seen as the creators, as the partners are the ones who set up the campaigns. The reason for this is a result of the assumption that digital and physical literacy rates of the poorest are likely to mean that they would be unable to run a campaign. Thus it is more likely to be run for them by a partner organisation. Nevertheless, this work demonstrates the concept of utilising signals to capture factors of success in lending crowdfunding. Another key result from the literature regarding signals is that they can be indirectly generated, Gonzalez and Loureiro (2014), identified that the photos of users can act as signals, with those who are younger, or individuals who are more attractive being offered more money. This work does have the problem of defining attractiveness, which can be somewhat subjective.

2.2.3 Equity-based crowdfunding

2.2.3.1 Definition and visualisation

In equity crowdfunding creators offer a form of equity to the backer in return for their funding, this could be a portion of equity in the company or a profit-sharing agreement. In general, for a project to raise more money greater amount of equity must be offered, although this can depend upon the project (Wilson and Testoni, 2014). Backers can then sell or trade the equity in the future and may receive a proportion of the profits while holding the equity. This is visualised in the Figure 2-4 below:

Figure 2-4 Visualisation of Equity crowdfunding



In the first-period creator's exchange funds for equity in the business, in the second-period backers have two choices, either they hold the equity and retain some form of shareholder profits or they sell the equity hoping that it is worth more than what they paid. Thus, the key question for this type of crowdfunding stems from the value of the equity held by the backers and the regulatory frameworks necessary for its development. These can be separated into adverse selection problems and moral hazard problems, in order to examine adverse selection, one needs to discern how many equity crowdfunding companies have become insolvent after running a campaign. Hornuf and Schmitt (2016), examined data from Germany and England on insolvency of equity crowdfunding start-ups, finding higher survival rates in England, 42 weeks after the campaigns ended 80% of English companies still survived compared to the 70% of German companies. Hornuf and Schmitt (2016) suggested these results demonstrated that equity crowdfunding is not only a market for lemons, utilising the famous concept from (Akerlof, 1978). Furthermore, Hornuf and Schmitt (2016) suggested that the moral hazard issue of creators not fulfilling their promises can be overcome by utilising multiple crowdfunding rounds and considering the approach utilised by companies where a portion of the money is held back for a certain period until the backers' vote on the performance of the creators and the funds are released. This links to the emerging concept of conditional crowdfunding (please see section 2.2.5).

2.2.3.2 Unique Regulatory challenges in Equity Crowdfunding

Equity crowdfunding creates some unique regulatory challenges; this was highlighted in the United States of America by the Jumpstart Our Business Startups Act (JOBS Act) which had to be enacted for equity crowdfunding to occur (Dorff, 2013). Regulatory differences across countries mean that equity crowdfunding platforms cannot be truly global as in the case of other types of crowdfunding, in general countries can only participate if they share a similar regulatory framework. For example, the UK can support other projects in Europe, for the time being at least. However a backer in the UK would not be able to support projects in China or America (Vismara, 2018).

2.2.3.3 Examples of Equity crowdfunding platforms

Even with these legal restrictions, there is a growing segment of equity crowdfunding platforms. The UK has the most developed equity crowdfunding markets with platforms competing such as Crowdcube and Seedrs. Crowdcube has raised over 466 million pounds in investment since being founded in 2011 and Seedrs has raised over 380 million pounds since being launched on 6 July 2012. The average amount of money raised per successful campaign is 0.66 million pounds for Crowdcube and 0.59 million pounds for Seedrs (Seedrs, 2019; Crowdcube, 2019). Compare this to the most established reward-based crowdfunding platform Kickstarter, which on average raises only 20,000 dollars per successful project (Kickstarter, 2019a). America has a less developed equity crowdfunding platforms, as title III of the JOBS Act only came into force in May 2016, which was required to enable American equity crowdfunding platforms to emerge. Since then multiple platforms have emerged, Wefunder has raised 61.5 million dollars for 195 start-ups (Wefunder, 2019), StartEngine is also noteworthy, not just as an equity platform, but also an emerging crypto-funding platform which utilises cryptocurrency as part of its fund-raising activities, StartEngine has raised money for over 133 campaigns (StartEngine, 2019).

2.2.3.4 Moral hazard in Equity Crowdfunding

Even with regulatory allowances, there is still a suggestion within the literature that equity crowdfunding is far too lightly regulated and will lead to a "*fleecing of the American Masses"* by encouraging people to invest who do not have enough knowledge in the area to invest securely (Griffin, 2012). This is further considered in Ibrahim (2015) paper which considered that there are two types of Equity crowdfunding based on Title II and Title III of the JOBS Act. Title II of the JOBS Act enabled existing credited investors to seek additional money online and is more of an extension online of existing venture capital and angel investor networks. However, Title III requires no such existing credited investors and it is equity crowdfunding platforms which are linked to this type of crowdfunding which is more likely to fund unsuccessful projects. Although he further suggested that this can be overcome by the wisdom of the crowds and intermediation.

According to Felin (2012), the wisdom of the crowd is a concept the origins of which can be drawn back as far as Galton (1907), who considered that aggregated information, drawn from individual sources, which may be biased, can still provide key insights into the nature of reality and the aggregated preferences of individuals. This approach was further expanded by Hayek (1945) who argued that the aggregated subjective evaluations of individuals is reflected in the prices emerging from the market mechanisms. No one individual has access to all the information, rather prices act to enable co-ordination between users based upon their own private information. Organisations can aggregate information, to try and simulate the underlying wisdom of the crowds (Felin and Zenger, 2011). Thus, the crowd has access to information and skills which may enable it to make decisions more beneficial than if the action was carried out via a single individual (Polzin et al, 2018). Hence, within crowdfunding, the wisdom of the crowd can be seen when backers collectively follow aggregate signals sent by projects to judge the quality of the projects (Ahlers et al, 2015). Furthermore, due to the online nature of the crowdfunding platforms, the wisdom of the crowd can also be seen to be directed by the social actions specifically allowed within the platforms. The comments shared via the platform can be seen as a way of directing the wisdom of the crowd, due to the limited ability of the backers to interact on the platforms (Clauss et al, 2018). Thus, it could be seen that the comments of other backers can be used to highlight weaknesses and strengths within a specific project, enabling others to benefit from the knowledge of those other backers and to more clearly identify high quality projects.

Intermediation is demonstrated through how equity crowdfunding platform attempt to demonstrate high-quality projects. For example, Crowdcube and Seedrs intermediates by offering validation of the creators' pitch and a valuation of the creators company (Crowdcube, 2019; Seedrs, 2019). However, there is no clear process in how these valuations are gathered, and there is the possibility that a platform could be incentivised to overvalue a project to secure the money it receives for funding. Especially as Vulkan et al (2016) demonstrated that a higher valuation increases success within the Seedrs and the crowdfunding platforms are incentivised to encourage success as they receive a portion of the raised funds.

Furthermore, Vulkan et al (2016) also considered the effect that tax relief had on success in equity crowdfunding. As within the UK, SEIS (Social Enterprise Investment Schemes) and EIS (Enterprise Investment Schemes) tax relief can be claimed, thus offering a potential incentive in investing in Equity Crowdfunding. However, within their model the effects of SEIS and EIS were uncertain, they were positively correlated, however they were both insignificant. Thus, leaving the effect of the tax relief to be uncertain.

2.2.3.5 Signal and uncertainty in equity crowdfunding

Ahlers et al (2015) considered that success in crowdfunding could be captured by a combination of a signal of venture quality and the level of uncertainty in the equity campaign. They derive their argument of the necessity of signals by comparing asymmetric information in equity crowdfunding to asymmetric information in entrepreneurial finance, noting that information asymmetries are far higher in crowdfunding due to the distance between the backers and the creators (Agrawal et al., 2011). In order to overcome this asymmetric information, backers utilise the observable information as a signal for the unobservable information, projects which cannot show a set of information are assumed by the backers to be unable to show the information and are thus more likely to be considered low quality.

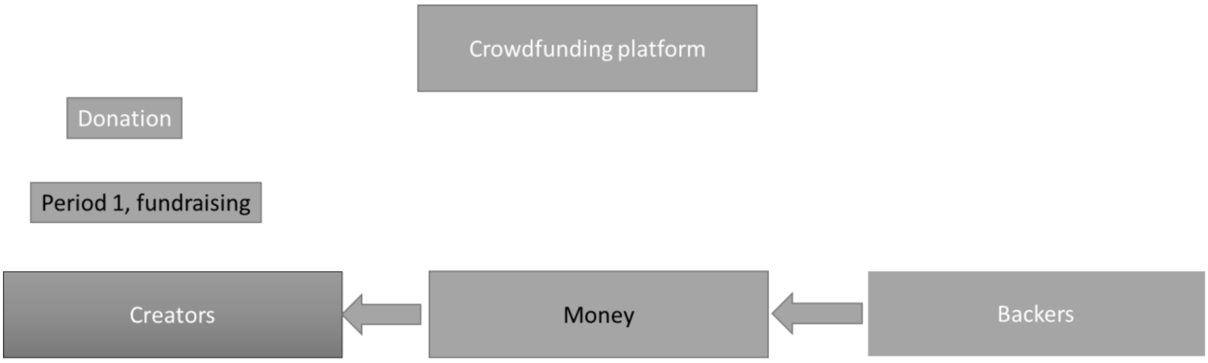
Ahlers et al (2015) examined three different set of signals, human capital, social capital and intellectual capital. However, only human capital was found to have a significant effect on the number of investors supporting the project. Human capital was captured via two proxies, firstly the number of members on the board and secondly the percentage of board members with an MBA. Thus, one of the possible limitations with this work is that these proxies may not accurately capture human capital and that human capital may be captured via alternative measurements. Furthermore, this paper examined the impact of uncertainty in equity crowdfunding. Defining the level of uncertainty as the amount of equity offered relative to the amount of information provided about the campaign. The less information provided, the higher the level of uncertainty within the decision making of potential backers. The results supported this argument by showing that projects which did not include a financial forecast were negatively correlated to the amount of funds raised in the project and were statistically significant. This paper suggests that success in equity crowdfunding can be captured via examination of financial commitments and human capital, however, a large number of variables were insignificant, highlighting the need for further consideration of the specific variables used to capture these phenomena.

2.2.4 Donation-based crowdfunding

2.2.4.1 Definition and visualisation

Donation-based crowdfunding in some ways is the simplest form of crowdfunding because backers receive no compensation for their backing, funds are given freely with no additional requirements on the creators (Belleflamme et al, 2013). This is visualised in Figure 2-5 below:

Figure 2-5 Visualisation of donation-based crowdfunding



Due to how backers receive no direct financial benefit in this form of crowdfunding, it has often been utilised for social enterprises, charities and projects with social objectives (Bone and Baeck, 2016). One such example was how donation-based crowdfunding was utilised to crowdfund research into Amyotrophic Lateral Sclerosis (ALS) via the use of the *ice-bucket challenge*, where individuals poured a bucket of ice over themselves in order to raise awareness and funds for ALS research. This was not carried out on a specific crowdfunding platform, but instead, it was carried out through social media platforms (Hildebrandt and Bushardt, 2015). Alongside this usage of social media, donation-based platforms have been established, for example, GlobalGiving has raised over 383 million dollars supporting over 894,000 individuals across 170 countries. Projects on the platform support non-profit organisations across the globe focusing on providing funds, training and support to these organisations (Globalgiving, 2019).

2.2.4.2 Medical crowdfunding

Medical crowdfunding is a key subtopic of donation-based crowdfunding and refers to the usage of crowdfunding in order to pay medical bills or to support medical research as shown by the ALS campaign. Renwick and Mossialos (2017), identified that medical crowdfunding could be further divided into four different types of projects. Health expenses, which utilises crowdfunding to fund individual medical bills which they would be unable to pay. Health initiatives which aim to improve the health of a group or community via a non-profit organisation. Health research where crowdfunding focuses on funding research into the treatment of diseases, specifically those which are normally underinvested in by for-profit research. These three can all utilise donation-based crowdfunding. However the fourth area of commercial health innovation which focuses on for-profit research would be more likely to be funded via equity or debt-based crowdfunding.

Burtch and Chan (2014), considered that the effect of health expense crowdfunding could be demonstrated via its ability to alleviate the high number of bankruptcies caused by medical debt. They considered that medical debt is seen as responsible for an estimated 62 % of individual bankruptcies within the United States of America. They considered the effect that giving forward a medical donation-based crowdfunding platform had on the number of bankruptcies within Americans states. Finding that the amount of money given on the platform was significant and negatively correlated to the number of bankruptcies across the different states. Supporting the argument that medical crowdfunding can be used to reduce bankruptcy rates. Dragojlovic and Lynd (2014), considered whether research into Ontology can be funded via the utilisation of crowdfunding. They discovered that Crowdfunding was a viable way of supporting the early development of research, as it acted as a proof of concept which then enabled researchers to attract more substantial traditional sources of funding. Another key point of there work was how crowdfunding enabled research into rare diseases. Thus there work supports the argument that medical crowdfunding can be used to carry out medical research by acting as a early source of funds for research.

For creators engaged in medical crowdfunding, they have to be able to demonstrate the credibility of their medical need. Kim et al (2016), examined the effect of credibility on medical crowdfunding by examining Reddit comments related to specific medical crowdfunding campaigns, across multiple medical platforms. Alongside interviewing members of the public in how their perceived credibility of a set of campaigns. From these sources, they identified 11 different factors which could impact the credibility of the campaigns. Most impactful within Reddit comments was the detail of external financial support, while interviewers were most persuaded of credibility by communication between creators and backers. Furthermore, Kim et al (2016) argued that credibility by individuals occurs via collective endorsement, where the personal comments sent by friends of the creators are key to the success of the project. However, Kim et al (2016) did consider that their study is limited both by the number of participants and how Reddit comments may be biased due to the structure of Reddit as a combination of small communities interacting together.

Snyder et al (2017), identified some unique ethical issues which have to be addressed in medical crowdfunding. Firstly, they consider how medical privacy has to be abandoned in order for the creator to seek funds, the exact cost of this depends on the value of privacy, which can be considered via a philosophical approach (Necley, 2017). The question becomes is it ethical for creators to be forced to lose their privacy in exchange for participation on the medical crowdfunding platform?

The second ethical aspect Snyder et al (2017) considers possible moral hazard problems involving the incentives of medical crowdfunding platforms. As in general, they are for-profit companies who seek to maximise profits. However these actions of attempting to maximise profits may lead them to decisions against the individual creators. For example, they have absolute control of who is allowed to fund on the platform, and they could be incentivised to remove individuals whom they perceive will not draw sufficient funds. There has been attempts to overcome these moral hazard problems within medical crowdfunding, Jin (2019) notes how within China, medical crowdfunding platforms must work with charities, this could overcome this moral hazard problem due to the charities having different incentives than the platforms.

A final ethical consideration identified by Snyder et al (2017) is how medical crowdfunding affects medical funding, specifically how it may alter funds going to those with the greatest medical need, to those who have the most emotional story. With only those who can sell themselves being able to receive funds on medical crowdfunding. Further arguing that this may result in the long run to obscure the systematic inequality which is occurring in the medical systems. Duynhoven et al (2019) empirically support this point by demonstrating that those who are relatively socio-economically privileged, in Canada, are disproportionally using medical crowdfunding.

2.2.4.3 Signals in donation-based crowdfunding

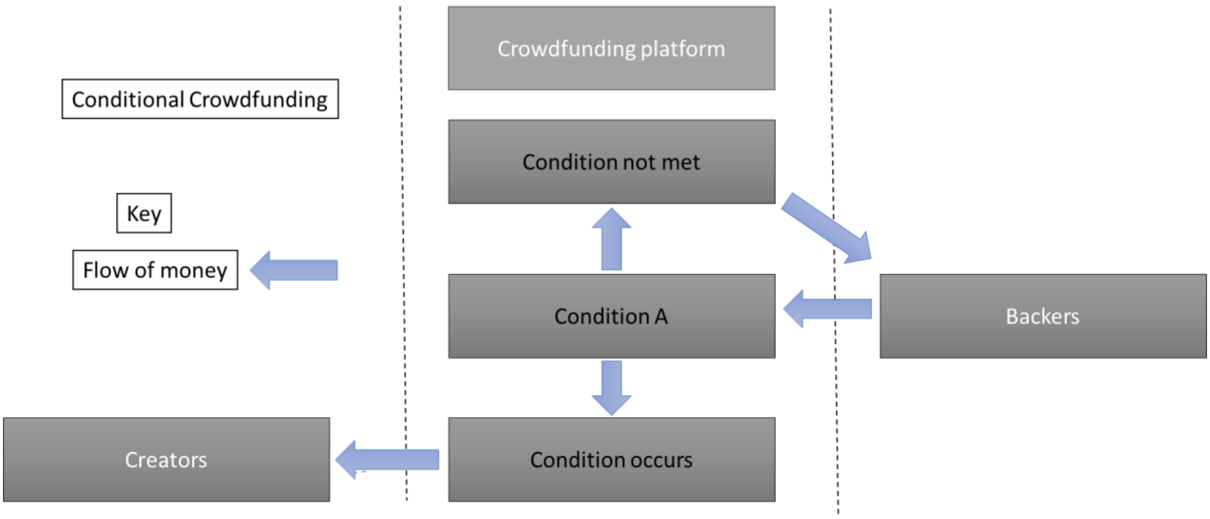
Donation-based crowdfunding utilise signals to demonstrate high-quality campaigns and overcome asymmetric information, however, there also appears a form of collective endorsement formed by the external communities surrounding the campaigns (Kim et al, 2016). This form of external endorsement could be seen as a representation of the impact of the social capital of the project creators and project backers. Linking to areas of reward-based crowdfunding study, which considered if social capital affected the success of projects outlined in (Kromidha and Robson, 2016) and (Colombo et al, 2015).

2.2.5 Conditional crowdfunding

2.2.5.1 Definition and visualisation

Conditional crowdfunding is an emerging form of crowdfunding separate from the original four subdivisions. In this form of crowdfunding the backer does not immediately provide any form of funding, funding is only provided when a specific condition is achieved. This type of crowdfunding was first considered as part of the literature by Beltran et al (2015) and has been more recently expanded on by Elsden et al (2019) who considered how automated third-party conditional donations systems could be designed and implemented. Conditional crowdfunding can be stated to have been occurring since at least 2013, as demonstrated via the existence of Patreon since 2013 (Patreon, 2018a). As with previous subdivisions of crowdfunding, conditional crowdfunding is visualised in Figure 2-6 below.

Figure 2-6 Visualisation of conditional crowdfunding



This type of crowdfunding enables backers to demand a specific condition to occur before their backing is received. This condition can occur multiple times, and if the backer remains committed to the condition across these multiple occurrences, the creator will receive multiple rounds of funding. For example, consider the scenario when a backer chooses to provide five dollars on the condition that a musician releases a song. If one song is released than the backer will provide five dollars if ten songs are released, then the backer will provide fifty dollars. The backer can withdraw from the conditional arrangement at any time and thus if they no longer wish to support the musician they cancel the condition. This exact form of conditional support is demonstrated on the Patreon page of Miracle of sound, where 2032 patrons together offered 4,151 dollars per song (Patreon, 2018b). Another demonstrated form of conditional crowdfunding is temporal conditioning, in this version backers agree to give creators an amount of money each month. Therefore, if the backers remained committed each month, the creators are provided with a continuous stream of income. Again this is demonstrated on Patreon with the writers of comic Kill Six billion demons having 1805 patrons who give them 6280 dollars per month (Patreon, 2018c). Patreon thus enables a new stream of continuous funding for ongoing projects which are continually developed. This funding enables content creators on Patreon to more actively focus on developing their content and increase the output of their chosen medium (Wilson, 2017).

Conditional crowdfunding offers an intriguing way of overcoming the traditional asymmetric problem within crowdfunding (Agrawal, 2014). Rather than engaging in a single signalling exchange to demonstrate the quality of the campaigns, the backers can identify the quality of the campaigns based upon the actual output delivered by the creators. Of note other types of crowdfunding also utilise specific conditions in the delivery of funds, for example, the all-or-nothing condition requires funding to be returned if a funding goal is not met. The key difference between this and conditional crowdfunding, is these specific conditions occur after funding has been given, they are conditions which upon being met funding has to be returned, where conditional crowdfunding is the opposite, funds are given when the condition is met. Conditional platforms can also utilise the other four basic types of crowdfunding, as they can offer reward, donation, equity or debt based in exchange for the condition being fulfilled. This is demonstrated on Patreon as backers can receive different rewards based upon how much they agree to conditionally give (Patreon, 2018b; Patreon, 2018c). Conditional crowdfunding can be seen as an additional layer of subdivision of crowdfunding rather than a direct substitute to the other four major types of crowdfunding. For example, a platform could be a conditional reward-based crowdfunding or a conditional equity-based crowdfunding platform. This method of adding a new adjective based division to highlight differences between crowdfunding platforms is extended in the next section by considering additional subdivisions based on the creator participation rights of crowdfunding platforms.

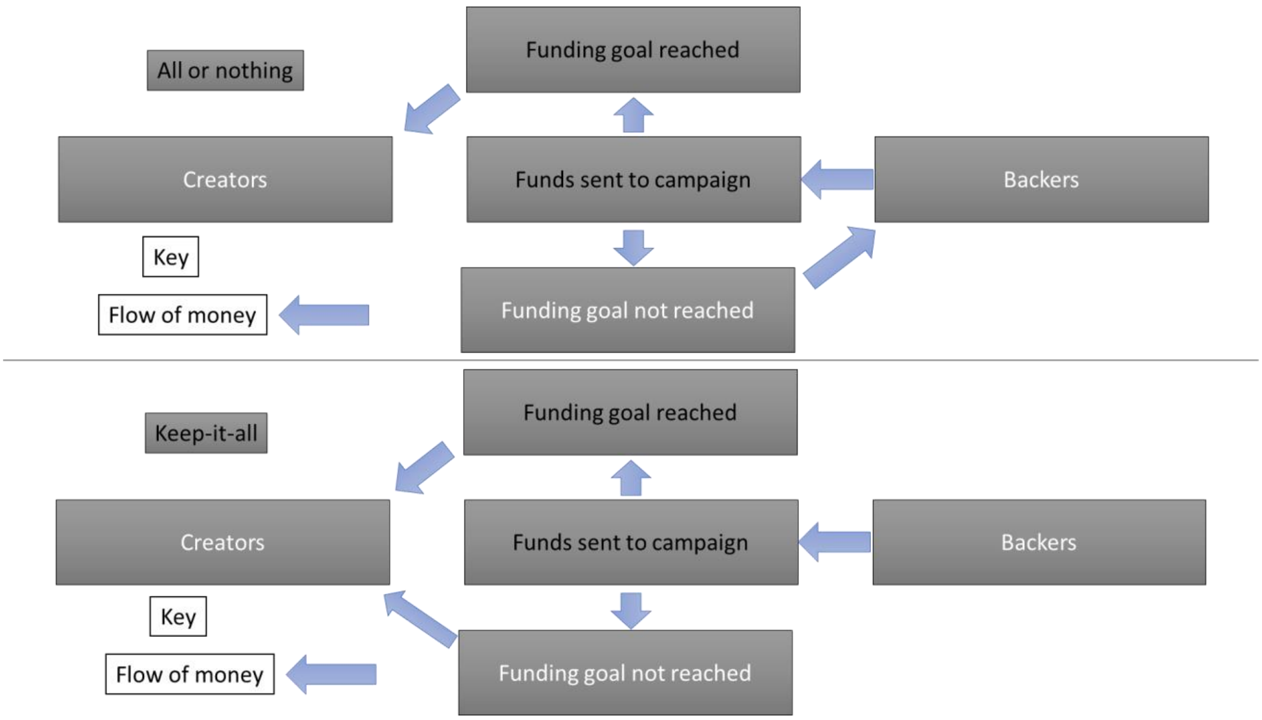
2.2.6 Creator participation rights and requirements.

Each crowdfunding platform gives creators specific rights and requirements for the projects that they create within the platform. These creator participation rights and requirements can be used as an additional method of subdividing crowdfunding on top of backer participation rights.

2.2.6.1 All-or-nothing versus keep it all.

One key creator participation right is what happens in the situation when the funding goal of a campaign is not reached. There are two distinctly different creator participation rights used across crowdfunding platforms, firstly there is all or nothing, in this case, the creator only has the right to receive the money if the funding goal is reached, if the funding goal is not reached then all of the money is returned to the backers. Secondly, there is keep-it-all, in this case, the creator has the right to retain the money raised in the campaign even if the funding goal is not reached. These two distinctions have been visualised in the Figure 2-7 below:

Figure 2-7 Visualisation of Keep-it-all versus All-or-nothing platforms



These different creator participation rights greatly alter the design of the crowdfunding platform to such an extent that different types of campaigns will be successful under different conditions. Cumming et al (2016) used a sample of 22850 campaigns from Indiegogo to examine these differences, Indiegogo enables creators to choose between keep-it-all and all-or-nothing, thus enabling these rights to be considered within the same crowdfunding platform. They concluded that all-or-nothing funding campaigns tended to have higher funding goals and to be more successful in reaching these funding goals. However, keep-it-all funding was more successful in raising funds for lower funding goals and those with scalable outcomes.

If a crowdfunding platform is utilising keep-it-all funding it restricts how success can be defined in the platform, the funding goal becomes a rather arbitrary number as the funding goal can be reached or not reached and the creator still receives the funds. Thus, setting success as reaching the funding goal makes little sense when keep-it-all funding is considered. Instead, success would have to be calculated in other means, perhaps using the backer/pledge suggested by Kromidha and Robson (2016) or utilising the total amount of funds raised. The case demonstrates how success has to be defined based on the crowdfunding platform and generalising a definition of success across platforms may not always be feasible.

2.2.6.2 Continuous versus limited

Platforms can require creators to finish their campaigns within a specific duration, for example in Kickstarter, projects can only run for a maximum of 60 days (Kickstarter, 2019c). This requires the creators to limit the duration of the campaign. However this restriction is not universal across crowdfunding platforms, some crowdfunding platforms are continuous, this means the projects can run as long as they want. An example of this is the conditional crowdfunding on Patreon; there is no distinct end to campaigns, they can carry on for as long as they wish (Patreon, 2018a). Continuous campaigns are not ubiquitous only to conditional crowdfunding, they also occur in donation-based crowdfunding such as Just Giving, within this platform users can continuously support campaigns over an indefinite amount of time. Just Giving also highlights how continuous crowdfunding campaigns can have funding goals (JustGiving, 2019). There is limited work into how continuous projects affect success however Kuppuswamy and Bayus (2018) did propose that most crowdfunding projects without an explicit deadline would lose momentum after a short period due to backers seeing that other backers could always fund the project, thus needing not to take responsibility themselves, thus leading to a low amount of support from backers. However, this is looking through the lens of reward-based crowdfunding; it may be that other types of crowdfunding are far more suited to continuous funding arrangements.

Continuous funding platforms create an interesting conundrum on how to measure success. If they have funding goals, as is the case for Just Giving, then these could be used as a measure of success. However, they may not have funding goals, if a project is raising money every month, is success measured as a monthly measure, or as a total amount of funds raised across all fundraising periods. Of course, these features can be easily taken into account, but it demonstrates how this type of condition can alter what is meant by success in a crowdfunding platform.

2.2.6.3 Specialist versus generalist

The creator participation requirement determines what types of projects can be raised on the crowdfunding platform. The author suggests there are two clear distinct groups of crowdfunding platforms regarding what the creators can fund; there are generalist platforms which enable creators to crowdfund any feasible activity as long as it is legal and specialist platforms which restrict creators to only support a single type or subset of projects. Although this distinction may be somewhat subjective, there are clear examples of both types of crowdfunding platforms. For example, Kickstarter could be considered a generalist crowdfunding platform, as people can fund any legal project, this had led to some truly bizarre Kickstarter projects, such as the case of Zack Danger Brown, who raised 55,492 dollars to create potato salad, for no discernible reason other than making potato salad (Kickstarter, 2014). Unbound is an example of a specialist crowdfunding platform, on Unbound creators can only publish books, no other types of crowdfunding are allowed. One intriguing fact about Unbound is that it does not display the funding goal of the project completely, it only displays the percentage of the funding goal which has been reached. Obfuscating the amount of money which the creator is aiming to raise (Unbound, 2019). A second example of a specialist crowdfunding platform is Experiment; this is a crowdfunding platform solely for raising money for academic research (Experiment, 2019). Past work already showed that different categories within crowdfunding platforms have different success rates (Mollick, 2014; Kromidha and Robson, 2016), thus does the act of removing a category and creating a crowdfunding platform solely for that category increase its likelihood of succeeding? At this point this question is left unanswered, it may be that having all projects in one platform benefits from economies of scale or are more successful due to the *internal social capital* generated within the network as mentioned by Colombo et al (2015). Further work needs to be done in this area to consider if creating a specialist crowdfunding platform enables greater levels of funding or not. Fundamentally, differences should be highlighted between specialist and generalist crowdfunding platforms.

2.2.6.4 Crypto-currency

One of the major creator crowdfunding participation requirements is what currency the creator is allowed to raise in, for example on Kickstarter the creators can use one of 18 different currencies (Kickstarter, 2019c). However, crowdfunding platforms have started to embrace the usage of cryptocurrencies enabling sub-division based between traditional currencies and cryptocurrencies. Kickico is an example of such a platform, which uses a combination of Ethereum and its crypto-tokens Kick coins, to fund and support new initial coin offerings (Kickico, 2018). Indiegogo has also announced its intention to launch cryptocurrency-based crowdfunding, by working alongside Microventures, however, there are currently no active cryptocurrency campaigns on Microventures (Microventures, 2019).

Alternatively, new American equity crowdfunding platform StartEngine has just begun to launch its own ICO (StartEngine, 2019). Initial coin offerings (ICO’s) are a process where creators seek to fund and establish a new cryptocurrency by offering an exchange of this new cryptocurrency for existing cryptocurrency. This is usually tied to some business idea or purpose for the new cryptocurrency, with the aim to increase the value of the new cryptocurrency, thus benefiting the backers who are now holding this new cryptocurrency (Fenu et al, 2018). This can be seen as a form of equity crowdfunding, where the equity obtained is the new cryptocurrency. Cryptocurrency is known to be particularly volatile, as demonstrated by fluctuation in the price of Bitcoin and how after reaching from a high of almost 20,000 in 2017, Bitcoin lost 80 percent of its value in 2018 (Coindesk, 2019). ICO’s are also known to be particularly fraudulent, as demonstrated by an ongoing market investigation by the United States and Exchange Comission (SEC)which advises against the use of ICO’s and outlines the major risk factors proposed by investing in ICO’s (SEC, 2019). This uncertainty and possibility of fraud demonstrates how crowdfunding platform should be separated based on the differences between cryptocurrency and traditional currencies.

2.2.7 Combining subdivision to clearly define crowdfunding platforms.

Combining the five backer participation rights and the four creator participation rights/ requirements, enables a clear subdivision for each crowdfunding platform. Figure 2-8 below demonstrates how these methods can be used to subdivide crowdfunding platforms.

Figure 2-8 Expanded subdivisions methodology applied to crowdfunding platforms

	Backer participation rights	Funding goal condition	Duration	Specific or generalized products	Currency type
Kickstarter	Reward	All or nothing	Limited	Generalist	Traditional
Indiegogo	Reward	Keep-it-all/ all-or nothing	Limited	Generalist	Traditional
Kickico	Reward	All or nothing	Limited	Generalist	Crypto-funding
Kiva	Lending (debt)	All or nothing	Limited	Generalist	Traditional
Patreon	Conditional	Keep-it-all	Continous	Generalist	Traditional
Crowdcube	Equity	All or nothing	Limited	Generalist	Traditional
Experiment	Reward	All or nothing	Limited	Specialist	Traditional
Unbound	Reward	All or nothing	Limited	Specialist	Traditional
Prosper	Lending (debt)	All or nothing	Limited	Generalist	Traditional
Seedrs	Equity	All or nothing	Limited	Generalist	Traditional
Just Giving	Donation	Keep-it-all	Continuous	Generalist	Traditional

The table is not an exhaustive list of all crowdfunding platforms but rather aims to demonstrate differences between crowdfunding platforms. For example, a study could consider the differences between Unbound and Kickstarter, as they share all the same subdivisions, except that Kickstarter is generic and Unbound is specific.

2.3 Success in crowdfunding

The aim of this section is to create a broad definition of success in crowdfunding, to be utilised in the development of the theoretical framework. The theoretical framework was designed with the aim to be utilised across multiple crowdfunding platforms. Therefore, a broad definition of crowdfunding success is necessary which can be used across the platforms.

Ahlers et al (2015), outlined four main success measure which can be utilised in crowdfunding, that of whether a project reaches its funding goal, the number of backers a project obtains and how much funding was raised and the rate at which the venture reached their funding goal. Arguing that faster raising of funds was especially important within high tech industries which require timely execution to gain early-mover advantages. Kromidha and Robson (2016), examined only successful projects and utilised the pledge per backer measurement as an alternate measurement of success. Each of these measures is considered in more detail below:

2.3.1 Reaching their funding goal/ percentage of funding goal reached:

This measure is very useful in all-or-nothing platforms. In these platforms projects which don't reach their funding goal don't receive any funds. Thus, creating a clear point of separation between success or failure. Conversely, it is less useful in keep-it-all platforms, where the funding goal doesn't restrict the creator receiving funds. On these platforms the funding goal becomes more arbitrary and using this measure of success can be flawed, due to how projects can raise more money but have a lower percentage of the funding goal reached. Another point to take into account is just because two projects both reach their funding goal doesn't mean they are equally successful. Firstly, one projects funding goal could be much lower than another projects funding goal. Secondly, projects may greatly exceed their funding goal and achieve a large amount of overfunding (Li et al, 2018). Therefore, this measure may be restrictive in capturing the full range of success within a platform.

2.3.2 Number of backers supporting a project:

This measure of success utilised by itself can be problematic. As having more backers does not necessarily mean that more funds will be raised, or that the funding goal will be reached. The author would argue this variable doesn't capture success itself, but rather can be used to explain how success was reached, as a high number of backers may not lead to a successful project. Kromidha and Robson (2016) measure of pledge per backer can also be considered in the same way, a method of describing the path to success rather than capture success itself.

2.3.3 The amount of funds which were raised:

This measure of success is the simplest measure of success; however, projects are aiming to raise different amount of funds as each project has a different scope, therefore saying a project is more successful then another simply because it raised more funds may be incorrect.

2.3.4 Utilising temporal measurements

As mentioned above Ahlers et al. (2015) argue for the usage of temporal measurements of success, i.e. the rate at which projects achieve these goals. This measurement will be useful in continuous crowdfunding platforms, where a specific funding goal may not exist. However, in platforms where there are limited possible differences in duration of projects and money is only received at the end of the project, this measurement will be less useful.

2.3.5 Broad definition for framework

Considering these measures, the author argues that these different measures can be captured via the following definition; raising greater amounts of funds relative to a specific funding goal by the end of a specific timeframe. This will be utilised in the theoretical framework. The exact measure used for each platform will be considered in the conceptual framework, in the methodology section.

2.3.6 Failure in crowdfunding

The previous sections considered success in crowdfunding, conversely this section briefly considers the effects of failure in crowdfunding specifically failing to reach a funding goal within and all-or-nothing platform. Greenberg and Gerber (2014), work considered the impact of failure within the crowdfunding platform Kickstarter, discovering additional negative effects beyond not receiving the funding. Creators with failed funding projects reported that it negatively impacted their social capital, through utilising their social capital in requesting support for their campaigns on social media. Leading to only 2% of the sampled creator relaunching their campaigns. However, the 2% who did relaunch had a 43% chance of reaching their funding goal. Greenberg and Gerber (2014), suggested that the creators utilised their failure to realign their projects, utilising information obtained from the backers of their first campaign. Demonstrating that even in failure key information can be obtained, this highlights the potential of utilising crowdfunding as a marketing tool (Brown et al, 2017). In specific platforms, it can be impossible for an individual campaign to fail, for example in Patreon (2018a) as campaigns are continuous and don't have funding goals, failure becomes more difficult to define.

2.4 Theoretical Framework development

In the previous sections it is stated that the measures of success which can be utilised across all crowdfunding platforms, is successfully raising greater amounts of funds relative to specific funding goals by the end of a specific timeframe. The author argues that two key areas can be considered in order to capture this measurement of success. The first is the ability of the crowdfunding participants supporting the project (creators, backers and the platform) to draw potential backers to the specific crowdfunding project. While the second is the ability of the participants to convince those drawn to the specific project to support that project. The factors are considered individually before being combined into a single theoretical framework.

For a project to be successful, the participants supporting the project must be able to draw potential backers to the project. If no one is drawn to a project no matter how high quality the project, it cannot succeed. The author proposes that each agent can draw backers from external sources and internal sources. With external sources referring to anything outside of the crowdfunding platform, and internal referring to actions within the platform. For the backers and creators, the author argues that the ability to draw in backers can be captured via the social capital of these two participants. Specifically utilising the concept of separate internal and external capital types which was utilised relative to crowdfunding in (Colombo et al, 2015). The platform effects on drawing potential backers to the project is also considered via internal and external forces. With internal competition capturing the impact on drawing project to the category based upon competition between projects within the crowdfunding platform. And external competition captures the effects of cross-platform competition between crowdfunding platforms.

Once the potential backers have been drawn to the project, they still need to be convinced to support the project. This can be compared to how once a shopper has been drawn to a digital marketplace, they still need to be convinced to purchase a good and the number of goods purchased (Kuan et al, 2005). Furthermore, unlike the purchase of a good, backers are free to support projects at multiple different levels. Therefore the participants are aiming to convince the backers to spend as much money as possible. This can be compared to how within free digital gaming, the majority of funds can be obtained from a limited number of higher paying users known as “whales” (Shi et al, 2015).

The author argues that the factors which impact the drawing of customers will also impact the ability to convince backers to support the project. Due to how social capital can be utilised to adopt new technologies (Isham, 2000; Katungi, 2006). This demonstrates that social capital can encourage specific behaviour and thus in the case of crowdfunding utilised to convince backers to support the project Competition internally and externally, both affecting the ability of the campaign to convince backers to support it. Due to backers being able to compare the examined project with other existing projects, within and outside of the crowdfunding platform. This enables a framework focused only on convincing backers to also include all of the factors suggested for attracting backers.

Additionaly on top of these factors, the author argues that the ability to convince backers to support will also be impacted by the signals sent by the creators and the backers. The signals sent directly link to the concepts of signalling discussed across the literature in the previous sections. Finally the potentinal motivation for the backers is considered to impact the ability of creators to convince backers to support their project. Simply due to how these are the direct benefits the backers receive for participating in the platform. Combining these concepts together leads to the following visualisation of the conceptual framework shown in Figure 2-9 below, which captures factors drawing backers to the project and factors convincing them to back the project.

Figure 2-9 Theoretical Framework

	Social Capital	Competition effects	Signalling	Backer motivations
Internal	Social capital of backers within the platform. Social capital of creators within the platform.	Competition between projects on the platform.	Signals sent by backers on the platform. Signals sent by the creators on the platform. Signals sent by the platform.	Incentives provided by the creators. Internal incentives to backers on the platform not provided by creators.
External	Social capital of backers external to the platform. Social capital of creators outside the platform.	Competition between crowdfunding platforms. Competition affects from projects on other crowdfunding platforms.	Signals sent by the creators outside the platform. Signals sent by backers outside the platform.	External incentives to backers, provided by creators. External incentives to backers not provided by creators.

This framework is thus built from 3 major theory areas, social capital, signalling and competition and also includes the motivations of the backers. The next sections expand upon these four areas, to provide clear theoretical foundations to be utilised in the development of the paper's hypotheses.

2.4.1 Key theories used in the theoretical frameworks

2.4.1.1 Signalling theory and overcoming asymmetric information

Due to the very structure of crowdfunding, there is extensive asymmetric information between the backers and creators of crowdfunding projects. The impact of this asymmetric information on crowdfunding was captured within Belleflamme et al, (2010) and (2013), who noted that the amount of asymmetric information which was occurring depended upon the creator's knowledge of the quality of their crowdfunding project, the greater the creators knowledge of the quality of their crowdfunding project, the greater the amount of asymmetric information between creators and backers, this observation being further supported in (Miglo, 2018). From an economic perspective Ahlers et al (2015) crowdfunding literature review identifies asymmetric information as a major factor impacting the success of crowdfunding. Oddly due to the wisdom of the crowd (Ibrahim, 2015), it may be possible in specific circumstances for the backers to have a greater knowledge of the quality of the campaign then the creator. Whether this is through greater theoretical understanding of the technological limitations or through an understanding of the other products available on the market, which implicitly affect the quality of the new product. Creating a rather unusual situation where both sides, creators or backers may have informational advantages.

To address how asymmetric information can be considered in crowdfunding, an examination of how traditional credit markets have overcome asymmetric information was considered. Information asymmetry has been a core feature of traditional credit markets interaction between lenders and backers as exhaustively argued in Gorton and Winston (2003) review. Credit markets have increasingly failed to provide much needed financial resources, most acutely to early stage finance innovation projects characterised by high uncertainty. Stiglitz and Weiss (1981) provide the seminal theoretical contribution in deriving the conditions for this type of market failure. Identifying that credit rationing is an equilibrium resulting from rational choice of lenders in the presence of asymmetric information. Adverse selection is one of the mechanisms via which asymmetric information disrupts credit markets, (Akerlof, 1978; Rothschild and Stiglitz, 1978). Adverse selection occurs if lenders are unable to distinguish the quality and thus the associated risk with a specific borrower. Lenders are unable to discern between low quality and high-quality campaigns, thus in an attempt to ensure the return on investment lenders ask for a higher rate of return. However, the problem with this stance is the fundamental relationship between risk and reward in investment, generally the higher the level of risk the higher the level of reward. Thus, by asking for a higher rate of return the lenders drive away lower risk projects, as they are likely to have a lower rate of return, thus these become unable to seek credit through the system. Conversely high-risk projects *adversely select* themselves for credit application having the potential to make a higher rate of return than the rate offered by the lenders. Exacerbating this problem is how rational acting lenders will eventually increase the lending rate as a reaction to the now riskier pool of investment, restricting the possible investment to even riskier investments. Creating a self-replicating process where only the projects with the highest levels of risk are able to be funded, creating a shortage of funding for low risk projects.

2.4.1.1.1 Signalling theory

To overcome the negative impact of asymmetric information, the better-informed party can create an action to signal the quality of its product to the less informed party, this process of signalling was first identified in the seminal work in Ross (1977) and Spence

(1978) essays on job market signalling, which highlighted the asymmetric information within the job market and that without some forms of signals, employers are unable to identify high quality workers from low quality workers. Thus, high-quality workers need to send some form of signal to distinguish themselves from low quality workers. Signals are specifically attributes which can be changed by the worker, such as the level of education they have received, or the type of clothes that they wear. Spence considered characteristics of the worker that affected employability but were outside of the control of the worker to be indices rather than signals. For a signal to be effective in reducing the existing informational asymmetry, the signal has to have a higher cost for a low-quality sender than for a high-quality sender. This enables the emergence of *separating equilibria* whereby signals reveal the underlying quality of the person, object or business. Thus, reducing or eliminating the informational asymmetry (Riley, 1979; Cho and Kreps, 1987). Thus, for crowdfunding to effectively utilise signals the creators of poor-quality campaigns must have a higher cost of signalling than those of high-quality campaigns. Additionally, Spence argued that the signals must also be observable and manipulatable by the sender of the signals. If a signal is not observable by the other party within the signalling game, then the other party cannot alter their actions based on this signal and thus it cannot be utilised to overcome asymmetric information. The signal must be manipulatable by the original party, due to how as mentioned above, if the characteristic is outside the control of the signalling party, Spence would classify this as an indices rather than a signal. If the signalling party cannot manipulatable the signal, then by definition it is out of control of the signalling party.

2.4.1.1.2 Signalling within crowdfunding

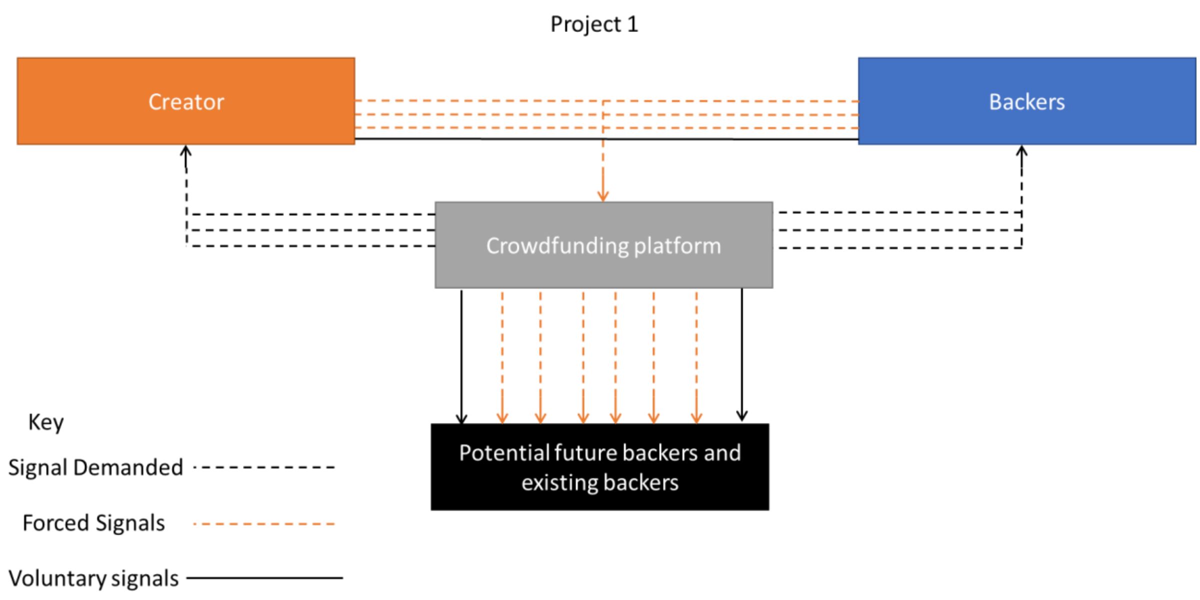
Kromidha and Robson (2016) identified that signalling can occur from multiple parties in reward-based-crowdfunding, with creators and backers able to send signals. Specifically, in the context of Kickstarter they suggested that backers' signals can be identified via the comments on the projects. While creators' signals could be identified via the number of updates on the project. Comments can be considered only to be of backers and not general users of the crowdfunding platform as to comment on a project you must back the project. The study examined the top 5000 successful projects within Kickstarter and utilised the pledge per backer ratio as the key measure of success. There results found empirical evidence showing that number of comments increases the pledge per backer ratio within Kickstarter, conversely there the number of updates had no significant impact on the pledge per backer ratio. However, the project was limited by the fact it only examined highly successful projects, specifically the top 5000 projects on Kickstarter, adding in comparison to less successful project may increase the effects of comments and updates. This point is further supported by Block et al (2018) who found that increased number of updates within equity crowdfunding platforms in Germany did have a positive impact on the number of investment raised by the crowd. Furthermore, the author proposes that comments may not necessarily have a positive effect within failures, as although to comment you have to back the project, this doesn’t mean you have to back the project to completion as you are able to withdraw your backing at any point. Thus, comments can also be utilised by the community to highlight problems they have with the project, giving the ability for these signals to have a negative effect on success.

Signals can also be examined via the other main subdivisions of crowdfunding. Ahlers et al (2015), examined signalling within the context of equity crowdfunding, demonstrating that venture quality characterised via human capital was key to success in equity crowdfunding. To capture the human capital of the project, they used the number of board members and the percentage of MBA within the board members as proxies. However, in their main model the number of board members had a significant effect on crowdfunding success while the percentage with an MBA did not have a significant effect. This looked solely at the signals sent by creators in equity crowdfunding and did not consider signal sent by the backers. Piva and Rossi-Lamastra (2017), work further supports the use of human capital as a signal in equity crowdfunding, demonstrating that the amount of business experience and entrepreneurship experience are key proxies in predicting success in equity crowdfunding.

Moss et al (2015) considered how to capture signalling within the lending-based crowdfunding platform Kiva, utilising a text analysis approach, which examined the loan descriptions, identifying key aspects of virtuous orientation and entrepreneurial orientation of the project. Virtuous orientation considers the usage of positive rhetoric such as integrity, empathy, courage, zeal and can be utilised as a signal for a company quality in the presence of asymmetric information (Payne et al, 2013). While entrepreneurial orientation considers the specific entrepreneurial characteristics possessed by a firm, specifically the firms rate of innovation, willingness to take risk, proactiveness and aggressive competitive stance (Lumpkin and Dess, 1996). Moss et al (2015) utilised these concepts to consider, if these are functional signals within the Kiva market, however their results found that the projects which signalled virtuous orientation were actually less likely to be funded. While signalling entrepreneurial orientation were somewhat supported, with three out of the five terms considered, producing positive and significant results. One plausible reason why the text-based signalling did not support the virtual orientation hypothesis, is due to the consideration that there is no cost associated with adding virtuous textual terms to a loan description, leading to there being no difference in the cost of signalling between high quality and low quality campaigns, therefore a separating equilibrium cannot be observed and asymmetric information cannot be overcome utilising this signal (Riley, 1979; Cho and Kreps, 1987). Signalling theory has also been used as a general way of considering success within crowdfunding regardless of type (Boudreau et al, 2015; Vismara, 2018).

The author also considers that the signalling actions of the crowdfunding platform itself are not considered, the platform may require specific information to be sent by the creators and backers of campaigns. The platform can therefore be considered a third party involved in signalling, which can force either other party to send signals or act as a signalling agent itself. As demonstrated in the visualisation in Figure 2-10 below: the signal demanded refers to information that the crowdfunding platform must have from both the backers and the creators for them to participate in the platform. The forced signals refer to the information sent by the backers and creators in order to satisfy the signals demanded by the platform. The voluntary signals are additional signals that the creators and backers voluntarily send through the crowdfunding platform to future potential backers.

Figure 2-10 Visualisation enforced and voluntary signals



2.4.1.1.3 Utilising Signals as proxies for human capital

A key aspect of the utilisation of signalling theory within crowdfunding is the identification that human capital can be captured via using proxy variables within the crowdfunding platform. Moss et al (2015) usages of virtuous orientation and entrepreneurial orientation clearly link to established concepts of human capital. While Piva and Rossi-Lamastra (2017) work demonstrated the human capital signalling of experience via the past entrepreneurial activity. This identification that human capital can be identified as proxies via information from crowdfunding campaigns is one of the key points of the authors paper (Davies and Giovannetti, 2018), with the funding goal being used as a proxy for ambition and the number of previously created projects being used as a proxy for experience. This concept of capturing human capital via proxies is utilised within the creation of this thesis hypotheses.

2.4.1.2 Social capital

Social capital can be viewed as the ability to utilise goodwill generated within the fabric of social relations in order to facilitate actions from those social relations (Adler and Kwon, 2002). Social capital has been employed within the entrepreneurial finance literature, specifically in considering how entrepreneurs utilise their social capital in attracting funds for new ventures (Kim and Aldrich, 2005; Westlund and Bolton, 2003). In crowdfunding, social capital can be considered to impact how the backers and creators and the platform itself can encourage other potential backers to support their desired project. To capture the impact of social capital in crowdfunding, an examination of social networks is utilised.

2.4.1.2.1 Social Networks sites

Before considering social networks, it is necessary first to define what networks are and how these can be developed into social networks. A network is a set of nodes which represent a specific group of actors, these actors could be anything from individuals to firms or computers, each network specifies what each node represents (Borgatti and Halgrin, 2011). These nodes are then connected, or not connected, based on a specific condition and these connections can be either direction or non-directional, in a non-directional network two states are possible between nodes in the network. Either they are linked together, or they are not linked together. In a directional network links between nodes can be in one direction, thus four possible states are possible between two nodes in this network (Jackson, 2010). Consider two nodes, node A and node B the four possible state could be as follows. In the first state node A is connected to node B while node B is not connected to node A. The second state node A is connected to node B and node B is connected to node A. The third state node B is connected to node A, but node A is not connected to node B. In the fourth state node A is not connected to node B and node B is not connected to node A. Networks can be categorised into two major types: sociocentric networks and egocentric networks. Sociocentric networks capture all nodes and links within a specific network, for example a complete trade network could be expressed as a sociocentric network. Egocentric networks focus on the connections from a single node and the links between the connections of that node, for example egocentric networks have been utilised to examine the difference of support network of patients with and without dementia, showing that those with dementia were likely to have less friends within their support network and be more closely tied to family members (Perry et al, 2017). For the purpose of this thesis, sociocentric networks are considered.

Networks have been utilised across multiple disciplines from engineering to medicine due to their versatility and ability to represent complex systems (Boccaletti et al, 2006). Network can be considered via a macro or micro approach. The macro effect of the network considers the whole structure of the network, while the micro considers the individual characteristics of the nodes (Schweitzer et al, 2009; Wasserman and Faust, 1994).

One of the key networks utilised in the examination of social capital in crowdfunding are online social networks, for example Facebook, in which two people are connected if they are friends with each other (Ellison et al, 2007). Social networks sites specifically refer to online platforms which enable users to construct a public or semi-private profile within a system, which can be connected to other users based on a shared connection, these connections can be viewed within the system (Boyd and Ellison, 2007). The following section considers how to capture the impact of these sites on crowdfunding success.

2.4.1.2.2 Social networks site impact on crowdfunding: Capturing social capital in Facebook and Twitter

Lu et al (2014), considered how Twitter promotions are positively correlated with the number of supporters for the crowdfunding project. Utilising the Twitter API, they captured all Twitter promotions of crowdfunding project between November 2012 and April 2013, defining a promotion as a tweet which clearly provides the URL of the Kickstarter projects, or utilised Kickstarter inbuilt campaign share feature. They removed projects which had a low amount of funding or if they had less than five tweets. Their results showed positive correlation between log normalised number of promoters and number of backers within Kickstarter. Furthermore, Lu et al (2014) utilised the promoters to create a social network, with the nodes being a promoter, and links being drawn between promoters if two criteria were met: 1) that promoter A had promoted the project before promoter B and 2) promoter B followed or was mentioned by promoter A. Creating a directed social network based around the communication between promoters of specific crowdfunding projects on Twitter. This demonstrated a more sophisticated connection between promoters, with a higher number of edges being utilised as an indicator for interests among specific Twitter sub groups, leading to more support and thus an increase in the correlated ratio of funding goal achieved. Social media impact upon crowdfunding is thus clearly demonstrated, alongside utilising network analysis to capture this impact.

The effect of the social network on crowdfunding has been further demonstrated across multiple works specifically by (Mollick 2014; Giudici et al, 2014; Moisseyeve, 2013; Kromidha and Robson, 2016; Jarvinen and Nguyen, 2018; Beier and Wagner, 2015). However, there has not been consistent support for social media effects, with work from (Beier and Wagner, 2015; Colombo et al, 2015), not finding any significant support based on the number of Facebook friends or Twitter followers, while others still find significant support for social media (Mollick 2014; Moisseyev, 2013; Kromidha and Robson, 2016). The author considers that there is enough evidence in favour of including the impact of social network when studying success in crowdfunding. However, one of the major limitations of these social networks is that often the information utilised is not from the full social network, due to restrictions in both collecting and analysing the data. For example, Facebook has over 2 billion users and the relationships between these users is constantly changing every moment of the day (Statista, 2018), thus it is not currently plausible for an individual researcher to consider the full extent of the network effects, the exact limitations enforced will depend upon the study and the related social media. A more recent emerging problem is linked to the possible presence of fake social information within crowdfunding (Wessel et al, 2016).

2.4.1.2.3 Internal Social Capital: Transforming a crowdfunding platform into a network.

The previously discussed social networks can all be considered to be external social networks to the crowdfunding platform. Colombo et al (2015) considered that a crowdfunding project can generate their own *internal social capital*, based on establishing relationship with other backers and funders. They captured this via utilising the number of previously backed projects by the creator of the current project as a proxy. Butticè et al (2017), further built on this work by considering the impact of *internal social capital* could captured via examining the number of successfully backed projects by the creator within a specific timeframe, there results demonstrated that *internal social capital* has a limited duration and within a year and a half, *internal social capital* no longer had a significant impact on success. The author proposes that *internal social capital* of a crowdfunding network could be captured in a similar way as to how *external social capital* was captured by Lu et al (2014), in considering Twitter, specifically generating a social network based on patterns of connections from backers and creators. Focusing on exchange patterns between the two groups, to enable the development of a network which represents the evolving online community structure (Faraj and Johnson, 2011).

One method of identifying connections in crowdfunding can be extracted from past work into examining how networks forces affect the diffusion of innovations and adoption of new products. Coleman et al (1957), utilised network analysis in considering the innovation and adoption of new drugs for physicians within the American drug market. Specifically, they created a network which compared the rate at which doctors gave out a new drug based upon socioeconomic links between the doctors, suggesting that doctors who were socioeconomically linked were more likely to give out a drug at the same time. However, their results did not support this hypothesis and rather showed that linking within the socio-economic network had little impact in drug delivery timing. This work into network effects of adoption of innovations was continued by Rogers (1976) who considered the potential of network analysis built upon communication between agents and how weak links would reduce the effectiveness of the analysis. This work solidified the concept of utilising network analysis to consider adoption of innovations, whether the innovation was among farmers (Monge et al, 2008), young adults and the adoption of telephones (Taylor et al, 2011) or social media adoption (Mergel 2013). Highlighting the possibility of utilising network analysis to consider innovation within crowdfunding. To create a crowdfunding network, the method of connecting the actors (the links which build this network) has to be defined.

A method of defining these links could be utilising communication links between the actors, with the actors either being creators or backers. This builds from the concept that you can capture the effect of innovations by considering communication between the potential adopters (Monge et al, 2008; Rogers, 2010). If communication between backers and creators is observable, this can be utilised to create this network. For example, projects could be connected if they have joint backers, or if backers comment on both projects. Alternatively, projects could be connected based upon creators' activity, such as past created campaigns, or projects they have backed. Thus, if this data is viewable, then these networks can be developed. If communication between creators and backers within the crowdfunding platform is not directly observable, this communication could be inferred via the external social media activity of the creators and backers as utilised within the Twitter network created by Lu et al. (2014).

2.4.1.3 Social Network Analysis

Once the network has been established and defined, it can be examined via the utilisation of social network analysis techniques, this section introduces some of the core concepts of social network analysis.

Social network analysis can be traced back to Kent (1978) who captured the original dataset on the rise of the Medici family in Florence which was utilised in developing social network analysis by Padgett and Ansell (1993). They demonstrated how via creating and analysing a network based of marriage connections within the Italian Renaissance city of Florence the rise to success of the Medici family could be explained via their central position within the network.

One of the key tools within networks analysis is the concept of centrality. Centrality refers to how central the nodes are to the rest of the network. There are four main measurements of centrality, each capturing a different aspect of the concept and are utilised to represent different information flows and behaviour of the network (Jackson, 2010). Furthermore, centrality has been identified in past work as key to interpreting the effect of social networks (Freeman, 1978), thus four of the main centrality measures are considered below, the next sections 1.4.1.3 are based on definitions derived from the following sources; (Wasserman and Faust,1994; Jackson, 2010; Benedictis et al, 2014; Perry et al, 2018)

2.4.1.3.1 Degree centrality

This can be viewed as the simplest measure of centrality, in its unweighted form it considers the number of nodes that a node is connected to. It is often normalised by considering this amount relative to the total amount of nodes, within the network, the node could be connected to. The total number of nodes a node can be connected to is the total number of nodes in the network minus one, as the node cannot connected to itself. Thus, normalised *degree centrality* for a single node can be obtained by dividing the number of connections a node has by the number of nodes in the network minus 1. This can be represented in the following definition:

$$Normalised\ Degree(d_i) = \frac{\sum_{j \neq i}^{N} \mathcal{L}_{ij}}{N-1}$$

Where N is the number of nodes in the network, i considers the node being examined and $\mathcal{L}_{ij}$ is an indicator function that considers whether node i is connected to another node in the network, returning 1 if it is connected and 0 if it is not connected. Thus, the summation of these over all other nodes of the network, $j \neq i$, provides the total number of connection that the node has. If a network is directed, the notion of degree centrality can be expanded to consider separately a node's out-degree and in-degree. Out-degree considers the number of connections made from the node to other nodes, while in-degree considers the number of connections being received by the node, starting from other nodes.

Otte and Rousseau (2002) use *degree centrality* to demonstrate that authors who wrote on social network analysis were not closely connected. They constructed a network, where the agents were authors of papers on social network analysis and connected authors if the co-published together. They found the overall degree centrality of the network to be 11 percent and used this to argue that it showed that researchers were not closely working together in the area. *Degree centrality* has also been used to examine differences in trade outcomes in the global trade network (Benedictis et al, 2014).

2.4.1.3.2 Closeness centrality

This measure of centrality considers how close a node is relative to all other nodes in the network. It can be calculated by considering the geodesic distance between the single node and all other nodes in the network. In a network, a geodesic refers to the shortest path between two nodes, i.e. the lowest number of nodes that have to be travelled along to reach the other node. The smallest possible summed value of all geodesic for a node is the total number of nodes in the network minus 1. In this case the centrality measure for the node will be 1. The higher the geodesic of other nodes, the lower the *closeness centrality*. Which can be formally calculated using the following diagram.

$$Closeness(d_i) = \frac{N-1}{\sum_{j \neq i}^{N} \ell_{ij}}$$

Where i refers to the node being examined, N-1 captures the lowest possible closeness measure and ℓ_{ij} considers the path length between node i and another node in the network, $j \neq i$.

2.4.1.3.3 Eigenvector centrality

Eigenvector centrality considers that the centrality of a node is proportional to the sum of its neighbours. That is to say that the centrality of one node is based upon the centrality of the surrounding nodes, this creates an immediate problem as this becomes self-referential. Consider an increase in the centrality of the node will then increase the centrality of the surrounding nodes and thus increase the centrality of the node. In order to overcome this self-reference problem eigenvectors are utilised, a method originally suggested by (Bonacich, 1972). Eigenvectors are vectors of a linear transformation, which when the linear transformations are applied to themselves they only change by a scale factor. To consider how this can be applied to centrality measurements, let Ce(g) denote the eigenvector centrality from network g. Furthermore, the proportional factor can be represented as $\mathcal{L}$. Thus eigenvector centrality can be written as follows:

$$\mathcal{L}C_i\mathrm{e(g)} = \sum_j g_{ij}\, C_j e(g)$$

Which can then be represented in matrix notation as:

$$\mathcal{L}Ce(g) = gCe(g)$$

Thus $Ce(g)$, is an eigenvector of g, with $\mathcal{L}$ being the eigenvalue. There can be multiple *eigenvalues* and normally the highest *eigenvalue* is used (Jackson, 2010). This overcomes the self-reference problems and enables the effect of surrounding nodes to be considered when developing a centrality measurement. *Eigenvectors* are especially useful in capturing the effects of social capital within a network (Borgatti, 1998).

2.4.1.3.4 Betweenness centrality

Betweenness centrality considers how many paths utilise the nodes as part of a geodesic within the network. In other terms, it considers how many times the node has to be passed across in order for two other nodes to be connected as efficiently as possible. The maximum number of times a node can be passed through is based on the size of the network, specifically it can be calculated by (n-1)(n-2)/2. Therefore the centrality is simply the number of shortest paths which utilise the node divided by (n-1)(n-2)/2. More formally this can be written as:

$$Betwenness(d_i) = \frac{\sum_{k\neq j: i\notin[k.j]} p_{kj}}{(\mathrm{n}-1)(\mathrm{n}-2)/2}$$

Where p_{kj} represents the number of shortest paths which utilise node i within the network. *Betweenness centrality* can be used to examine scenarios where the position within the network enables or restricts access to other nodes. The examination of the rise of the Medici is a key example in which the *betweenness centrality* is key to identifying why they rose to power. As the Medici had the highest *betweenness centrality* of any family (Padgett and Ansell, 1993).

The specific meaning of the centrality is dependent upon the network they are examining as their interpretation can depend upon who the nodes are and how they have been linked together. For example, D'Ignazio and Giovannetti (2006) utilised *betweenness centrality* to examine the economic concept of partial essential facilities within the context of upstream internet access.

2.4.1.4 Competition within and outside the platform

The internal and external social networks consider how effective the creators and backers are at drawing in users into crowdfunding. However, this doesn’t consider the effect that the platform itself has in gathering backers to the platform. This is considered via examining competition within and outside of the network.

2.4.1.4.1 Increased Competition within a platform

Janku and Kucerova (2018) considered this concept in relation to reward-based crowdfunding, identifying the effects of competition on the success of funding projects on Kickstarter. They did so, by dividing the competition terms into three separate variables, the first being number of launched projects in the same month, the second being the number of projects launched within a specific federal state and the third considered whether the projects where launched at the weekend or a weekday. The first term demonstrates a temporal competition element within a crowdfunding platform that projects launched within the same month are competing for funds. However, utilising the launch month to judge this temporal competition seems flawed, due to how projects which are launched in the same month may not be competing for backers. If a project was launched on the first day of the month and had a duration of twenty days and another project was launched at the end of the month, there would be no overlap between these two projects. Instead of utilising a monthly separation, projects could be separated based upon their actual project activity, utilising the project start and end dates. Thus, the temporal competition would consider any project which was actively seeking funds at the same time.

The second competition variable demonstrates geographic competition within the platform, considering if the geographic position affects the success of the campaign. Building upon Agrawal et al (2014) and Mollick (2014) work into the effect of geography in successful crowdfunding projects this variable could also be focused more specifically to consider the impact of competition in cities and more generally to consider the impact of competition within a country. The last variable of weekend competition suggests that launching a project at the weekend decreases its chance of success due to there being a general trend of increased number of launches at the weekend. One could build upon this concept to consider if the number of launches each day affects the success of the project, removing the restriction of high number of projects launches only occurring on weekends. The next section expands upon how competition can be used to examine geographic differences in the platform.

2.4.1.4.2 Capturing geographic competition within a platform

In the previous section on social capital, the author considered how the internal social impact of crowdfunding can be examined via transforming the platform into a network, built on observable links between creators and backers. This section considers how the platform can also be considered by viewing the platform as an international trade network. This builds from the concept that world trade can be examined via the utilisation of networks (Benedictis et al, 2014; Amador and Cabral, 2017; Bhattacharya et al, 2008). The author considers that if a crowdfunding platform is occurring globally then a network could be developed akin to these global trade networks, where the global trade is replaced by the trade in funding.

For this network to be created two key pieces of information are required. Firstly, the geographical location of the project must be known and secondly the geographical locations of the backers who are supporting the project must be observable. If both of these pieces of information are available across multiple crowdfunding campaigns it is possible to create a trade network, which demonstrates how much funding from the crowdfunding platform each geographical area receive. Alongside how much funds each geographic area gives to other geographic areas.

This geographic approach would build upon the work of Agrawal et al (2014) which considered that greater geographic distance between backers and creators had a negative impact on the ability of creators to raise money on the crowdfunding platform Sellaband. Conversely Kang et al (2018) found the opposite: that increased levels of distance between creators and backers increased the likelihood of a project raising more funds. Geographic factors were further examined within Mollick (2014) and Kromidha and Robson (2016), both showing clear evidence that geography affects success in crowdfunding projects. This geographic network would thus enable geographic affect in crowdfunding to be captured and analysed via network analysis, utilising the centrality measurements discussed in the social capital section.

2.4.1.4.3 External competitive position of the platform.

Projects could be affected by the current popularity of the platform relative to other crowdfunding platforms. However, it is very difficult to observe this specific phenomenon. As in order to observe the competitive position of a platform, vis a vis all other platforms, one would have to capture, and compare, how successful each of the crowdfunding platforms was across the entire duration of any examined projects. If the data about the amount simultaneously raised on each platform could be captured then, the level of competition could be estimated through utilisation of the HHI index (Hirschman, 1980), a method suggested to be applicable in crowdfunding by Wessel et al (2017). However, it is very difficult for a researcher to estimate this effect as it would require capturing the amount raised across all crowdfunding platforms within a project's duration. Even if this information could be captured, it may still inaccurately estimate competition, as it makes the assumption that users of one platform are potential users of another platform. Without observing user behaviour this assumption may be flawed. Thus, this author focuses on the effects of internal competition, which can be observed through examining a single crowdfunding platform.

2.4.1.5 Backer motivations

This section considers a set of plausible motivations for backers to become involved in crowdfunding. One of the earlier identified motivations was that of altruism (Bretschneider and Knab, 2014), this can be most notably connected to donation-based crowdfunding, where the backer receives no incentive to participate. In incentive based crowdfunding Bretschneider and Leimeister (2017), identified six reasons why backers may be incentivised to participate, these six will be used as the framework for this section.

2.4.1.5.1 Recognition

Bretschneider and Leimeister (2017), suggested that backers could receive recognition on a crowdfunding platform when they are able to comment on the projects which they have backed. Considering recognition to be an acknowledgement of a user status, actions or achievements (Maslow, 1987). The author supports the notion that backers want to be recognised, however the author would disagree that it is through the comment mechanism which this would primarily occur. Instead, the author would suggest that recognition could be obtained by the sharing of their backing on social media. Sharing within social media would enable users to gain recognition and gratification from members of their own social network (Malik et al,2016). The comments section would not give lasting recognition as the comment could be pushed further back by future comments and it would thus give a very limited amount of recognition.

2.4.1.5.2 Desire to see project created, lobbying motivation

Bretschneider and Leimeister (2017), suggested that backers are motivated to support projects by the desire to see the project created. Arguing that backers developed their own personal need for a project existence based upon the content presented within a crowdfunding page, if this content was consistent with their value systems (Moysidou, 2017; Ordanini et al, 2011; Schwienbacher and Larralde, 2010).

However, this author would suggest that the lobbying motivation doesn’t have to be restricted to products which don’t exist within the market, instead lobbying could be utilised to increase the market availability of the product, or to encourage the continued existence of the project, or to create a variation of the product based upon the specific backer needs. Backers could be incentivised to increase the supply of the good within the market, as low supply of a product with high demand would lead to higher costs which could reduce access to the product. By lobbying through supporting projects on crowdfunding, backers could be able to increase supply and thus reduce the products costs, enabling more people to obtain the project which links with their personal need. Secondly, backers could also lobby to continue the existence of a product rather than simply creating it in the first, this can be shown via continuous crowdfunding platforms such as Patreon which enables backers to continually lobby for the existence of a project (Patreon, 2018a).

2.4.1.5.3 To build a specific online image

Bretschneider and Leimeister (2017), argued that backers are attempting to create a specific image through their actions within a crowdfunding platform. These actions are viewable on the user web page of crowdfunding platforms, which can then be linked to their personal social media, enabling them to create a specific online image from their actions on a crowdfunding platform. Utilising the concept that individuals value image in the virtual world as much as within the physical world (Jabr, 2013) and that this image can be generated by the purchase of digital goods (Kim et al, 2011). The author would argue, that is not a significantly different motivation compared to recognition, utilising a webpage seems to be a method for them to generate recognition utilising the creation of social imagery. Alternatively, recognition can be seen as part of the online social image, rather than a separate phenomenon. As public recognition is key to encouraging pro-social behaviour (Lacetera and Macis, 2010). These two motivations seem linked rather than separate, thus the author would consider them both together under the guise of generation of a specific online recognisable image.

2.4.1.5.4 Because they like the venture

Bretschneider and Leimeister (2017) suggested that backers may simply support a project because they like it, building from observations that in the field of start-ups, making an entrepreneur likeable is a key first step in receiving investment (Brettel, 2003; Feeney et al,1999; Mason and Stark, 2004). The author suggests that this likeability could be divided into two separate motivations. The likeability of the campaign and the likeability of the creator. As support for the individual may not necessarily be tied to support for the venture. This can be demonstrated by considering that early investors in start-ups are often made up of friends and family (Kotha and George,2012), who may be backing ventures due to liking the entrepreneur rather than the venture.

2.4.1.5.5 As anticipation of a reward

One clear motivation for backers is the reward/incentive they can receive; the type of reward will be dependent upon the crowdfunding platforms backer participation rights and the options chosen by the project creators. Rewards have been empirically demonstrated to be key motivators of success within crowdfunding platforms (Gerber and Hui, 2013; Hobbs et al, 2016; Bretschneider and Leimeister 2017).

2.4.1.5.6 As a function of herding behaviour.

Zhang and Liu (2012), considered the effect of herding within the micro-lending platform of Prosper, observing the phenomena that projects which are attracting a large number of backers will attract even more backers. Herzenstein et al (2011) considered that herding occurred due to backer's uncertainty of a project quality, as backers assumed that the other backers were able to identify high quality project, thus they followed the other backers regardless of whether the project was high quality or not. Herding has been extended from micro-lending to crowdfunding (Bretschneider and Leimeister, 2017; Kuppuswamy and Bayus, 2018)

These six categories show some of the possible motivations for backers on crowdfunding platforms, however this is undoubtedly a non-exhaustive list, as only an individual backer can ever fully know their own motivation. These six motivations can be utilised in creating a framework to consider what possible motivations can occur within a single crowdfunding platform. Certain motives may not be possible due to the crowdfunding platform design, the simplest example of that being that getting a reward on a donation-based platform is fundamentally impossible.

In conclusion this chapter has provided a definition which can be utilised to distinguish between crowdfunding and traditional financing, developed a clear subdivision method for a crowdfunding platform, highlighted key literature across the different subdivisions and, finally, developed a theoretical framework to be utilised in the methodology chapter in order to develop the hypothesis of this thesis.

3 Methodology

The structure of the methodology is as follows.

1) **Research philosophy and design**: This section discusses the theoretical underpinning of the methodology. Outlining why pragmatism was chosen as the research philosophy and the effects this decision had on the design of the study.

2) **Data collection management and analysis**: The aim of this section is to outline the specific software and techniques utilised in collecting, managing and analysing data across both crowdfunding platforms.

3) **Kickstarter dataset**: This section shows the exact process utilised in examining the crowdfunding platform Kickstarter. Firstly, the hypotheses are developed by utilising the theoretical framework developed in the literature review and expanding upon these theoretical underpinnings. Secondly, the data collection procedure is outlined including any data restrictions and ethical considerations. Finally, the data analysis procedure and models utilised to examine the dataset are outlined.

4) **Kiva dataset**: This section demonstrates the process utilised in examining the crowdfunding platform Kiva. Firstly, the hypotheses are developed through utilising the theoretical framework developed in the literature review and connecting and expanding to the theories introduced within the examination of the Kickstarter dataset. Secondly, the data collection procedure is outlined alongside any data restrictions and ethical considerations. Before the last subsection critically examines why truncated regression was utilised in the creation of the Kiva models.

3.1 Research philosophy and design

3.1.1 Pragmatism as a Research Paradigm:

The definition used for a research paradigm in this thesis is as follows: an organising structure or framework used throughout the research connecting the design to a philosophical position, thus directly affecting the design and contribution of the research. The choice of research paradigms is driven both by the research design and via the researchers own epistemological understanding of the world (Feilzer, 2010).

The research paradigm which will be utilised in this research is that of Pragmatism. Pragmatism considers that multiple different realities overlap in the world, some which can be interpreted via objective reasoning, others only by subjective reasoning, it states there is no consistent, correct way of viewing the epistemological design of the universe (Creswell and Clark, 2007; Dewey 1958). Research which utilises pragmatism is focused on providing a utility output, in general, this is achieved through the research having some direct application which can be utilised in the "*real world*" (Creswell and Clark, 2007). Pragmatism dictates that the specific approach used within the research should be chosen based on what is most suitable for that specific research, whether that approach is quantitative, qualitative or a combination of the two (Feilzer, 2010).

The author utilises pragmatism as a research paradigm to research crowdfunding for several reasons. Firstly, it aligns with the author's personal view of the state of the universe, that certain elements of reality have to be subjectively interpreted via considering an individual's perception (Jhangiani and Stangor, 2015). The author is of the view that one cannot perceive completely what another individual experienced, due to how an individual's perception and reaction to an event can be affected by the past actions and beliefs of the individual (Albarracin and Wyer, 2000). Thus, even with the same stimuli another person cannot experience the same understanding of the current experience as they have not had the same past experiences. Fundamentally meaning that elements of the universe are subjective and only possible to be understood by those who can subjectively view them. Conversely, the author takes the position that other aspects of the universe are objectively observable outside of the subjective reality. A key example of this is within the scientific method, although the objective elements depend upon the scientific process utilised (Dallaporta, 1993).

To best explain the author's fundamental underlying logic in deciding upon pragmatism an analogy of the structure of the universe is proposed. Consider the universe as a river, an analogy first introduced by the ancient philosopher Heraclitus (Kirk,1951), who considers how the universe was continually adapting and changing. The author expands upon this analogy by utilising it to examine the individual components of the river rather than the river as a whole.

Imagine a river flowing from the top of a mountain to a sea. Within this river, there are multiple flows of water running simultaneously to each other from the start to the end of the river. These flows may at times cross and become connected, while at other times they are completely independent. It is these flows which represent the subjective viewpoint of reality, whereby each flow represent how information can be divided across the universe which may not be perceivable from the position of the other flows. Making that version of reality only perceptible to those who are within those flows. However, all streams belong to the same river and are tied to forces affecting that river, for example, if the river starts to approach a waterfall then all flows will be affected. Objectivity is viewed as a factor which will affect all flows regardless of their position within the river. It could be considered the underlying rules which guide the river in this analogy are the underlying objective rules which guide the universe. For these objective rules to change, the entirety of the river must be altered, beyond the framework of the original. Due to this reasoning, the research aims to demonstrate, as accuratly as possible, what is occurring within the universe, while accepting that the universe is both objective and subjective in nature. Leading to the choice of pragmatism as a research philosophy as it aligns itself with accepting this structure of the universe.

Secondly, this approach is useful in examining crowdfunding, due to the broad variety of approaches which can be utilised in discussing this emerging phenomenon, the range of these is demonstrated within the literature review.

3.1.2 The reasoning behind using a quantitative approach:

The reasoning behind using a quantitative approach is linked to the aims of the study, to enable success to be measured across the entirety of a crowdfunding platform. It was noted through pre-data collection examination of Kickstarter that there were on average over 150 projects added each day, each project was hosted on its own webpage within Kickstarter, where the creator set the funding goal and provided key information about the venture, backers support the venture through the project page.

Thus to utilise qualitative methods, the timeframe examined would have to be greatly reduced or alternatively only a specific category on Kickstarter could be examined. While utilising a quantitative approach would require neither of these restrictions and maintain the generalisability of the result to similar forms of crowdfunding platforms. Similar forms of crowdfunding platforms refers to platforms which utilise the same backer participation rights and creator requirements.

Furthermore, through the examination of Kickstarter and Kiva, it became clear that the systematic structure of the crowdfunding platforms enabled key information to be consistently provided about the campaigns. For example, within Kickstarter every single project had to set a funding goal, enabling the funding goal to be compared across all projects. Kickstarter and Kiva both had a set of variables which were reported consistently across all projects, enabling a set of independent variables to be developed which were consistent across all projects. both platforms also provided consistent key information which could capture success in the platforms, enabling the dependent variable to be defined. For example, within Kickstarter, the all-or-nothing condition enabled successfully reaching the funding goal to be utilised as the dependent variable, enabling a consistent set of dependent and independent variables to be obtained across all projects within the crowdfunding platform which can then be tested utilising quantitative analysis techniques, and encouraging the choice of a quantitative approach.

For these reasons, a quantitative approach was utilised. The following sections outline the exact quantitative process utilised in developing the models to be tested for the thesis.

3.1.3 Outline of the Quantitative process

For each model, the following steps are used.

Step 1) Key hypotheses and conceptual framework are developed by utilising the theoretical framework outlined in the literature review.

Step 2) Data is collected from the crowdfunding platforms to obtain both the dependent and explanatory variables.

Step 3) A model of the data is proposed to be examined based upon the collected data and developed conceptual frameworks.

Step 4) The model is analysed using a quantitative approach, the exact approach is chosen based upon the nature of the dependent variable and underlying characteristics of the dataset.

Step 5) The hypotheses, derived from the research framework, are then tested based upon the model's estimations.

Step 6) Findings, recommendations and conclusions are developed and discussed based on the results and their impact within the framework and the existing literature.

3.1.4 Reasoning behind examining two distinct crowdfunding platforms.

Within this thesis, two separate platforms are examined Kickstarter and Kiva. Two separate datasets are collected from these platforms for the following reasons.

1) To demonstrate that the theoretical framework developed within the literature review could be utilised to examine multiple types of crowdfunding platforms, regardless of whether the platforms had the same backer participation rights and creator requirements.

2) Kiva was utilised specifically as it enabled the examination of the effects of the backer's past support within the platform, which was not observable in Kickstarter.

3) To enable comparison between both platforms, to identify if there were some specific underlying qualities across the crowdfunding platforms, which could be utilised as the basis for future research and more generalisable results.

3.2 Data collection/management techniques

The section considers the key data collection and management techniques used for both the Kickstarter and Kiva datasets. This section does not highlight the exact collection procedure used for each dataset but rather aims to demonstrate what techniques were used, why they were used, and the steps taken to address ethical issues and reliability issues.

3.2.1 Primary data collection

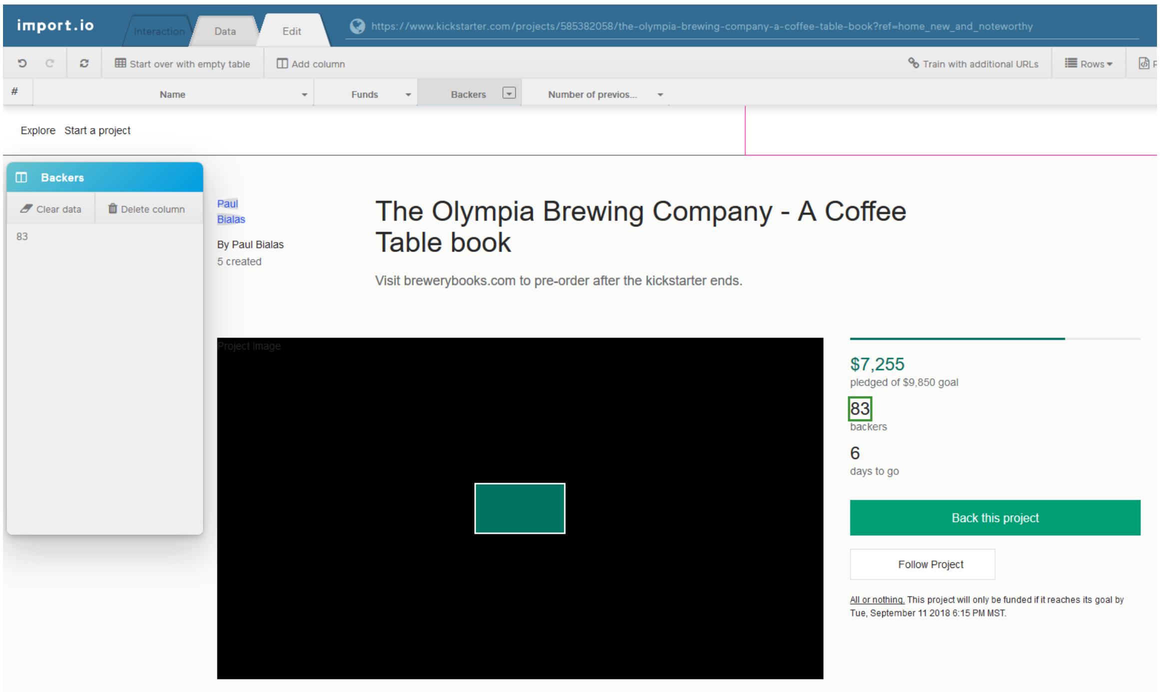
3.2.1.1 Utilising Import.io web crawler

A web crawler is a system for extracting specific information autonomously from the web or a specific website (Pant and Menczer, 2002). Web crawlers have been used extensively for the collection of crowdfunding data (Huhtamaki et al, 2015; Moqri and Bandyopadhyay, 2016; Thies et al, 2014). The specific web crawling software used for this thesis was Import.io. Import.io is a web crawling software/service, which enables the website to be extracted based on a point and click interface, which can be utilised to continually extract key pieces of data from the web (Import.io, 2018).

There are multiple elements to the crawler, for this thesis the most important aspect was the extraction tool. This tool works by first asking the user to input the website they wish to extract from. Once this is input, the page loads the webpage, with an extraction interface built over. The extractor has two key tabs the data tab and the edit tab. The edit tab shows the webpage you wish to extract from, and the data tab shows the data which would be extracted from that page. Data can be selected to be collected in the edit tab, and this is done by simply clicking the element in the webpage, this is demonstrated in Figure 3-1 below by the green square surrounding the number of backers. The data is arranged into multiple columns which can be viewed in the data tab. The process of selecting the elements one wishes to extract is known as training the extractor, and once the process has been done with one webpage, the crawler can then attempt to extract the same information from another webpage, if the data is not successfully extracted one can further train the extractor on the second webpage. There are multiple options built into the system such as disabling javascript and utilising manual x-path in the identification of specific elements, which can be used to train the extractor further improving its ability to collect the required information. This template can then be used across a list of other URLs, enabling mass extraction of data. Furthermore, the software has inbuilt scheduling, enabling the extraction of information at a specific time each day/week/month. Another feature which is useful is the ability to link extractors together if one extractor collects a URL, that URL can then be used as the target of another extractor

(Import.io, 2018). The specific way in which this tool was used will be discussed in further detail in the Kickstarter and Kiva sections.

Figure 3-1 Import.io extractor on a kickstarter page (Kickstarter 2019b)



3.2.1.2 Ethical usage and reliability of data within the use of web crawling techniques

Utilising web crawlers has specific ethical issues which must be taken into consideration. Thelwall and Stuart (2006), outlined four types of ethical issues surrounding web crawlers; cost, privacy, copyright and denial of services. Cost refers to how websites incur a cost for visitors visiting their website, and this will also be incurred by a web crawler. Thus the researcher by utilising a web crawler may increase costs to the business. These costs are not standard across time, and the temporal variance can be demonstrated by comparing the original costs outlined in Thelwall and Stuart (2006) paper. The websites hosting sites mentioned in the paper all had monthly bandwidth limits of between 0.25 gigabytes and 7 gigabytes with charges if these limits were exceeded. Compare this to Weebly, who in 2018 offer free websites with no limit on the bandwidth for UK users and no additional/hidden charges based on usage (Weebly 2018). Geographic differences can also occur with continents such as Australia having far more expensive bandwidth than Europe (Prince, 2014). Thus, the cost to a website of web crawlers is decreasing. However, this still highlights how the number of web crawls should be minimised, only crawling what is necessary to collect the data.

In order to reduce the cost of the crawlers on the sites for the thesis, two main steps were taken, one was to pick two large and established platforms, who were less likely to be affected by any bandwidth costs. Secondly, the crawlers were designed so that the minimum number of runs was utilised while still collecting the data. The exact crawling process utilised for each dataset is outlined in more detail later in the chapter.

Regarding privacy, although the internet is essentially in the public domain, researchers have to consider that by utilising web crawling there is the possibility of collecting personal data. The argument that the data is already in the public domain is not satisfactory when considering personal data. Zimmer (2010) paper examined the outcome of extracting data from a social media site; they identified how a 2008 study into Facebook accounts lead to the privacy of the users being at risk. What was notable was the study did take several steps in anonymising the information, it provided anonymous ids for both the students and the college they were attending and delayed the results of the research. However, based on the information of being a north eastern American university, the results were narrowed down to 13 universities, then to a single university and finally, the exact group of students were identified (Zimmer, 2008). This provides a perfect example of how simply relying on the data being accessible to the public is not enough to address privacy issues. And that releasing data that can be related to a single user can enable identification even when the name is anonymised. Web crawlers demonstrate why even anonymised information is so problematic, due to how they can be trained to look for these specific phrases and used to track down their source. This issue of extracting information specifically from social media sources is further discussed in Semenov (2013), considering both the legal and technical challenges, however as social media data is not extracted within the thesis further expansion on the topic is not carried out.

Furthermore article 17 of the General Data Protection Regulation (GDPR, 2018) sets out for individuals ‘a right to erasure’ so that they can request that personal data that is held should be deleted. This could represent a potential risk for researchers using web crawlers as individuals could request that copies of their personal data that has been obtained are removed. However, guidelines indicate that researchers can obtain exemptions under certain circumstances (GDPR, 2018).

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The issue of copyright and web crawling occurs due to how web crawling creates a copy of a website or specific information, which may be viewed as a breach of copyright in certain situations. O'Reilly (2006) gives a more detailed look at copyright and specific trademark challenges with the context of web crawlers and screen scrappers and the legal ramifications, which are outside the specific skill set of the researcher. In order to overcome any copyright issues, data is only reported at a platform level, with no specific information about each project released.

The last problem identified by Thelwall and Stuart (2006) was the problem of denial of service. Only a certain number of people can utilise a website at the same time based on the infrastructure of the website, and a crawler can reduce the capacity of the website and thus could lead to a denial of service of other users. To reduce the effect of crawlers on the users of the website, the runs were carried out at specific times in the day; the times were chosen by considering the userbase of the platform, which was observed via utilising Alexa. Alexa is an online database that can be used to identify which countries most actively use the website and thus what times should be chosen to minimise the effect of the web crawlers (Alexa, 2018).

3.2.1.3 Reliability and accuracy in web crawlers

A separate issue alongside ethical issues is the reliability of the data collected on web crawlers. Two main issues which can occur when utilising web crawlers is the problem of selective data and personalisation.

Selective data refers to how the website may retain only a selected sample of projects which best reflect the desired outcomes of the site. The crowdfunding platform Crowdcube is a perfect example of this in which data is available on the past campaigns which are successful but not the campaigns which are unsuccessful (Crowdcube, 2019). This makes perfect sense as the crowdfunding platforms themselves are incentivised to demonstrate they have delivered high-quality projects in the past, in order to attract high quality projects in the future (Agrawal et al 2014). However, this incentive means that if a crawler was run on Crowdcube and only captured the selective data, then the results are limited to examining factors in successful crowdfunding campaigns. If utilised to consider all campaigns, the result may be biased. This problem can be overcome by running crawlers' multiple times over a specific period. Enabling the capture of ongoing campaigns which may succeed or fail.

The second problem is that of personalisation. This is the concept that websites can be personalised to the specific user. A common example of this sort of personalisation can be seen within e-commerce applications, where the individual’s view of the website can be altered so that certain products are more prominent (Goy et al, 2007). This creates a unique problem when utilising web crawling that the specific webpage faced by each user may be different. Thus the webpage which is captured by the crawler may not be the webpage viewed by the user. To address this problem crawlers can disable specific scripts and utilise virtual private networks to access the website from different locations and with different metadata. For this specific thesis, personalisation was not a major issue as both of the examined crowdfunding platforms do not utilise personalisation.

3.2.1.4 Opportunity cost

In considering the feasibility of utilising web crawlers, an examination of the next best possible technique should be considered. In the case of crowdfunding one of the main alternative data collection technique utilised in the literature is surveys, as demonstrated in the following non-exhaustive list; (Marom et al, 2016; Sancak, 2016; Berglin and Strandberg, 2013). Therefore, the options of using surveys were considered as the next best alternative to web crawling. However, two main problems were identified with utilising surveys in this case. The first is that some campaigns creators had limited or no contact details, as demonstrated within the crowdfunding platform Kiva, where due to the structure of the platform the campaigns were run by partnership organisations representing each creator, instead of the creator themselves (Kiva, 2018a). This makes it problematic to contact the creator of the campaign in order to request the completion of a survey. The second is the scale of surveys which would have been necessary to capture the full ongoing campaigns at Kickstarter. The dataset collected for this thesis on Kickstarter, had over 50,000 campaigns within a single year, collecting this number of surveys as a single researcher was deemed to be unrealistic. As a result, utilising this method would have required a reduction in the scope of the research. For these reasons’ surveys were not seen as a viable alternative to utilising web crawlers in this research project.

3.2.2 Secondary data collection

Alongside collecting data directly from the crowdfunding platforms, secondary data sources were utilised to collect additional information about the crowdfunding platforms.

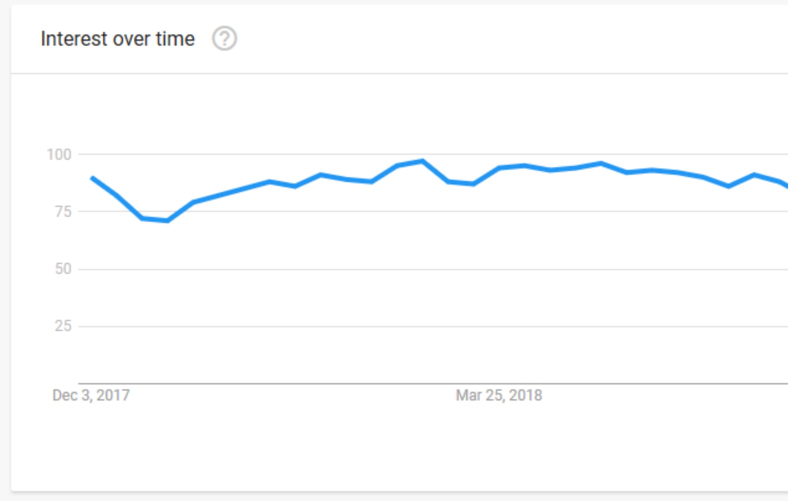
3.2.2.1 *Shared Count*

Shared Count is an online website which can be used to track the number of times a specific URL has been shared upon social media. Shared Count captures how many times a URL has been shared, commented on, or reacted to on Facebook, as well as how many times it has been pinned on Pinterest. Shared Count was utilised within the Kickstarter model, to demonstrate how many times the crowdfunding projects on Kickstarter had been shared on Facebook (Shared Count, 2018).

3.2.2.2 Google Trends website data

Google Trends is an online tool which can be used to identify the popularity of search terms within the google search engine. The results can be tailored to specific search terms at a specific time and within a specific region. The result is in an index, where 100 represents the highest search frequency for the website in that specific time period. This data is presented as a graph on the website and can be downloaded in CSV format (Google Trends, 2018a). Preis et al (2013) noted that you can utilise Google trends in tracking shocks to financial markets. Multiple past authors have identified that google trends plays a role in identifying the impact of online media (Rech, 2007; Nghiem et al, 2016). Within crowdfunding specifically, Geva et al (2017) used Google trend data to highlight how a large supply side shock can be considered as responsible for helping crowdfunding low-quality actors. They considered the somewhat infamous example of Zack Danger Brown and his crowdfunding project funding *potato salad* (Kickstarter, 2014), noting that the interest in the search term Kickstarter had dramatically increased during his project. Their work highlighted how the success of a project can be impacted by the external media inputs and, thus, that this should be captured as a key covariate within models examining crowdfunding success. The temporal profile of the interest in Kickstarter, between 2017 and 2019, is displayed in figure 3-2 below.

Figure 3-2 Interest in Kickstarter over time (Google Trends, 2018b)



3.2.3 Software utilised in data management and analysis

This section considers how the data was managed and analysed, highlighting the specific software and techniques utilised by the author.

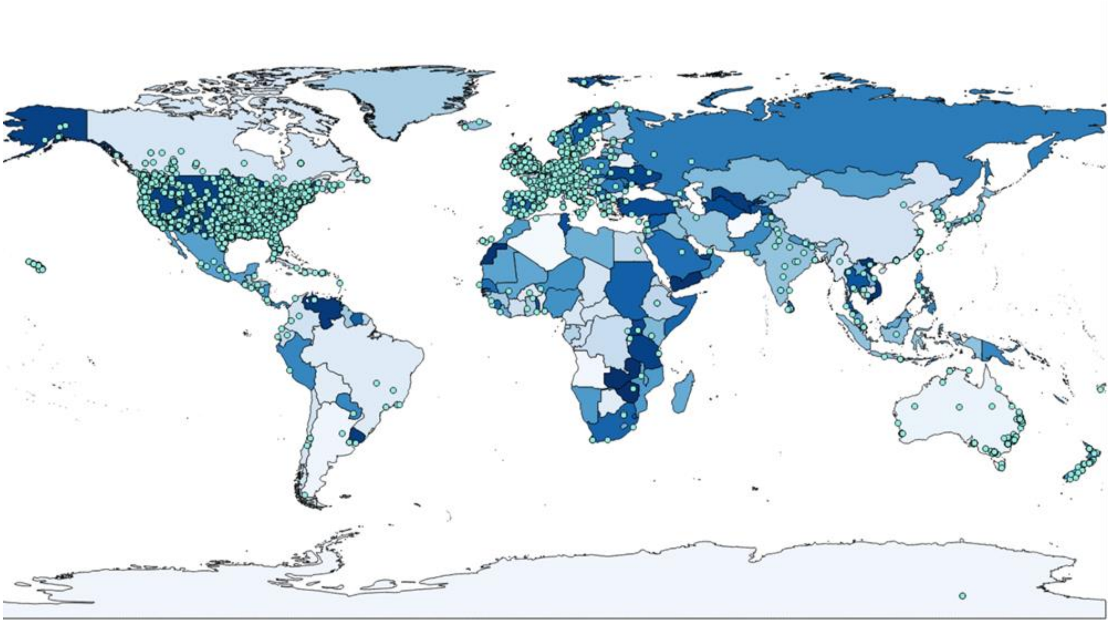
3.2.3.1 Excel

The main data management tool utilised in the thesis was Microsoft Excel. Data extracted utilising Import.io and from Google Trends was extracted in csv format which can be directly opened and manipulated in Excel. The main Excel commands which were utilised in organising the data are outlined in detail within the data appendix (section 7.1).

3.2.3.2 QGIS: Mapping software

QGIS is a data mapping software which can be utilised to compare geographic variables and to plot these variables on a map of the authors choosing. The software was utilised within the Kickstarter dataset to plot the location of crowdfunding campaigns. For further documentation on the general usage of the software, please refer to the software website (QGIS, 2018).

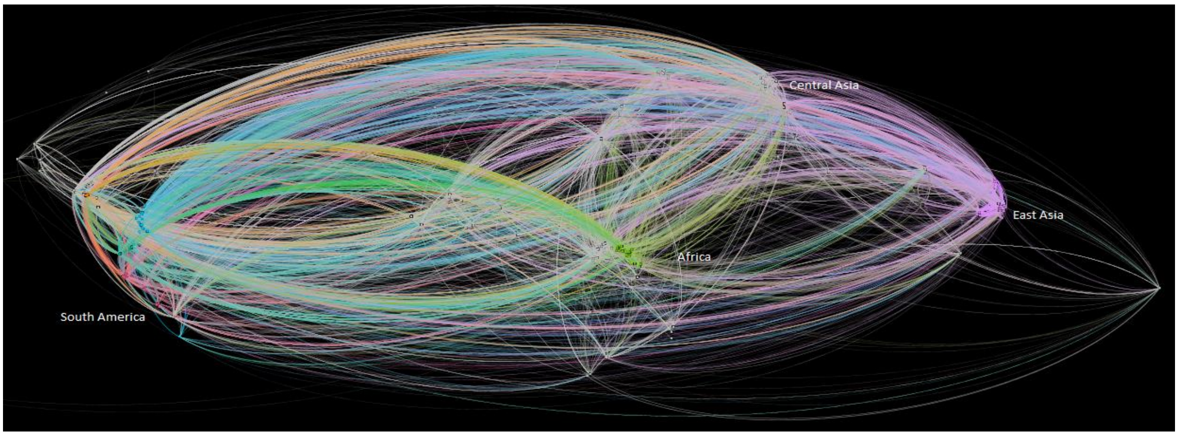
Figure 3-3 Geographic positions of all collected Kickstarter projects



3.2.3.3 Gephi

Gephi is a network analysis and visualisation tool, which can be used to visually display networks and obtain network statistics concerning said network. The software can build a network from multiple different data formats, the simplest requiring three columns of data, one column with the source of the link, one column with the target of the link and one column with the weight of the link. Gephi was utilised in the network development for the kiva dataset as shown in Figure 3-4, the specific network characteristics extracted is considered within the Kiva model. For more information, please refer to the software website (Gephi, 2018).

Figure 3-4 Example of Gephi usage, geographic network from Kiva dataset.



3.2.3.4 Stata

Stata was utilised in the econometric analysis of the data. It was used to carry out a logistic regression on the Kickstarter dataset, and truncated regression analysis on the Kiva dataset alongside further statistical robustness tests on both datasets. For in-detail records of the exact processes used, please refer to the syntax files recorded within Appendix sections **Error! Reference source not found.** and 7.6.

3.2.3.5 Postman

Postman was utilised when collecting data on the partnership organisation on Kiva. Postman defines itself as a complete API development environment, whereby an API (application programming interface) allows applications to communicate with each other in order to enable the applications to be used together. API have many usages, the specific usage within this thesis was to collect data on Kiva partnership organisation by utilising an API to access Kiva's database on partnership organisations (Postman, 2019).

3.3 Kickstarter Model

Kickstarter is a reward-based crowdfunding platform which was founded on the 28th April 2009. Since then it has raised over 4.2 billion dollars in funds and supported 159,000 projects as of the 23rd of March 2019 (Kickstarter, 2019a). The process for obtaining funds on Kickstarter is as follows:

Step 1) The creator sets up a project page, which contains key information about the campaign. The page must contain the projects funding goal, the project location, the project duration, the different reward levels, the project category and specialism, past number of projects created by the creator and past number of projects backed by the creator. Additionally, the creator is free to add images, videos and text to persuade users to back the projects.

Step 2) After the project page is created, the creator then decides when they want to launch the project, this becomes the project start date.

Step 3) The project start date is reached, and the project becomes live, potential backers can now visit the project and back the project. At this point, the project starts to display the number of backers supporting the project and the amount of money raised towards the goal as well as the time left before that goal must be reached. The maximum difference between the start and end date is sixty days.

Step 4) The creators are free to adjust their project during the campaign, they can add additional reward levels, remove unused reward levels, add updates or more videos and texts. The backers are also free to comment but only after they have backed the project. This campaigning process continues until the end date.

Step 5) By the end date of the project and if the funding goal has been reached or exceeded, the project gets to keep all of the funds. If the project has not reached its funding goal the money is returned to the backers.

Step 6) The rewards are given to the backers, this step may occur at any point, some rewards can be given instantaneously and thus will occur during the campaign, however in other cases rewards will be sent at a future point in time.

Examining this step by step process utilising the expanded subdivision method outlined in the literature review enables Kickstarter to be further defined as a reward-based all-or-nothing limited generalised traditional crowdfunding platform (see section 2.2.7 for detail on the expanded subdivision method).

It is reward-based as all projects must offer different rewards levels in return for the backing they receive. Reward levels differ slightly from the concept of a reward, as reward levels can combine multiple rewards into a single funding level. For example, a project could set two reward levels, one at 5 dollars where backers receive a hat and one at 20 dollars where backers receive a hat and a signed shirt. The platform is all-or-nothing as projects must reach their funding goals to receive any funds. It can be considered limited as this is referring to the project duration, and projects on Kickstart must finish between 1-60 days. It is generalised as although projects must be legal there are no other specific requirements for what can be raised. And finally, it is traditional as it does not utilise cryptocurrency.

Success on Kickstarter is measured depending upon a crowdfunding project reaching its funding goal. If the project reaches the funding goal then it will be considered a success, if the project doesn't reach the funding goal, it will be considered a failure, utilising the same measure of success as Mollick (2014) and Janku and Kucerova (2018). Additionally, if the project is cancelled by the creator it will also be considered a failure. However, if Kickstarter suspended a project, then this observation would not be considered a success or failure, but instead was removed from the dataset. This is due to how a suspended project could have already reached their funding goal but was suspended based upon breaking Kickstarter internal ruleset. Therefore, these projects cannot be viewed as successful or unsuccessful and thus were removed from the dataset.

3.3.1 Hypotheses and conceptual framework development

The next four sections create the main hypotheses for the Kickstarter model, separating these hypotheses into separate sections based upon the theoretical framework developed in section 2.

3.3.2 Creators Signals

This section considers the development of the hypotheses focussing on how signals sent by the creators might affect the outcome of the crowdfunding projects. As mentioned in the literature review three qualities are required for signals between two groups to be effective; they must be observable, manipulatable and their cost should be positive correlated with the quality of the sending group (Spence 1978), in this case, costlier for high-quality projects versus low-quality projects. Within Kickstarter, all of the signals are observable, due firstly, to how the platform requires specific information to be delivered and, secondly, to the fact that this information is freely available on the crowdfunding page. However, assessing whether the signal is manipulatable and costlier will have to be considered on a signal by signal basis. Signals have been used as a proxy, to capture the human capital of a project's creator, the reasoning behind the usage of each proxy for that specific aspect of human capital is justified within each section.

3.3.2.1 Over-confidence

The specific signal examined in this sub-section is the relative funding goal within the specialism of the creator, or the amount of money a project declares it wants to reach by the end of their campaign on Kickstarter relative (taking differences) to other projects active within the specialism over the duration of the Kickstarter project. The funding goal and thus the relative funding goal can be set at any level by the creator and this level of funding can also be exceeded.

The relative funding goal can be considered as a signal for the level of confidence of the creator of the crowdfunding project. With the reasoning being that: the greater the confidence the creator has in the project, the more likely that the creator will consider their project to be better than other projects within the same specialism (smallest sub-division in Kickstarter) and thus that they are able to set a higher funding goal. If the creators lack this confidence then they would be more likely to consider their project to be worse than other projects within the platform, thus setting a lower relative funding goal.

To examine the impact of confidence, the author considered if this level of confidence was justified or if it was likely to be overestimated by the creators of the crowdfunding projects. In examining the performance of start-ups it was considered that traditional entrepreneurs tend to be overconfident (Astebro et al, 2014), therefore it could be argued that creators in crowdfunding which includes entrepreneurs (Bruton et al, 2015) could also be viewed as overconfident. This argument is supported by work specifically on crowdfunding which finds creators to be overconfident (Miglo, 2018). Therefore, the author argues that the creators in crowdfunding on average might tend to exhibit overconfidence.

In examining the impact of overconfidence Moore and Healy (2008) divided overconfidence into three distinct concepts; overestimation, over placement and over precision. Overestimation considers individuals assessing their ability or performance too greatly, over placement considers that the individual rates its ability above that of others.

Finally, over precision considers that individuals believe that they are more accurate in the predictions of their ability than they actually are. All of these three different features of overeconfidence can be captured by creators setting a higher relative funding goal in their crowdfunding campaigns.

Malmendier and Tate (2005a) argued how over placement and overestimation can both be linked to the concept that individuals overestimate their ability when comparing their ability to other people, a key concept within the social psychology literature (Larwood and Whittaker, 1977; Svenson, 1981; Alicke, 1985; Camerer and Lovallo,1999). Kruger and Dunning (1999), further considered that it was those with the lowest level of competence that were the most likely to overestimate their relative abilities. Testing individuals with separate tests on humour, grammar and logic, they found that individuals who scored lowest were the most likely to overestimate their results. For example, the results showed those who performed poorest in the test, scoring within the lowest 12 percent of all participants estimated themselves to be above average, predicting they would score in the top 38 percent of the test. Relating these results to crowdfunding indicates that projects with the lowest quality may greatly overestimate their ability, by comparing themselves to high-quality projects which occurred in the past and believing they can also achieve this level of success. As a result, creators overestimate their projects ability to raise funds, which leads the creator to set an unrealistic high relative funding goal.

Overpredicting can also be directly related to crowdfunding as the relative funding goal can be seen as a direct outcome of the prediction of how much money the campaign will be able to raise. Malmendier and Tate (2005b) demonstrated that CEOs overpredicted results by finding high levels of variance in stock trading, they utilised the calibration literature in explaining how individuals tend to overestimate the accuracy of their knowledge (Lichtenstein et al, 1977; Alpert et al, 1982; Koriat et al, 1980; Einhorn and Hogarth,1978). Furthermore, this literature even points out that experience, is not able to prevent inaccurate predicting. Einhorn and Hogarth (1978), considered three plausible reasons for this: the lack of evidence against their original viewpoint, the inability of the individual to identify environmental effects which impact the outcome of the event and finally that outcomes were not accurately recorded or coded so that outcomes cannot be referred to when assessing future events. Applying these ideas to crowdfunding, suggests that creators are unlikely to be able to successful gauge the potential of their project, even if they have past experience on the platform, which may lead to an unachievable relative funding goal being set.

As previously discussed, it is necessary to consider if the relative funding goal, intended as a signal, respects the three critical conditions of being manipulatable, costlier for low-quality projects and observable. Clearly, the relative funding goal is manipulatable and observable, as any funding goal can be set for a project and the backers are free to view the funding goal. This signal can also be considered costlier for low-quality projects as, usually, more backers will be needed to support a project with a higher funding goal. Thus, with an increased number of backers, there will be an increased amount of scrutiny placed upon the project, not only as a result of the direct knowledge of each backer but as a function of the combined knowledge of the backers in the form of crowd wisdom (Sadiku et al, 2017). Low-quality projects would be less likely to withstand this increased level of scrutiny, therefore incurring a higher cost for setting a higher relative funding goal. Hence, the relative funding goal can be seen as an effective signal and can be used as a proxy for the level of confidence of the creators. Thus, the author proposes that in general creators signalling through their relative funding goals, might be overconfident in the quality of their projects, unintentionally leading this signal to have a negative impact on the success of the crowdfunding project. This is captured by stating the following hypothesis:

H1a: Creators' overconfidence has a negative impact on the probability of the project's success.

3.3.2.2 Experience

The signal examined in this sub-section consists of the past number of projects that the creators have created on the crowdfunding platform. Past created campaigns are considered as a proxy for the creator's experience, as if they have carried out previous projects on Kickstarter, by definition they are more experienced, than creators who have carried out less or no previous projects on Kickstarter. The concept of utilising experience as a key measure of success stems from key contributions in the entrepreneurship literature. Gompers et al (2010), examined how experience impacted entrepreneurs' ability to go public with their start-ups. They found that entrepreneurs who have successfully gone public in the past had a 30 per cent chance of going public in contrast to the 18 per cent chance for first-time ventures. The reasoning suggested for this evidence is that many aspects of being an entrepreneur can only be learnt through experience and by doing entrepreneurship. Thus entrepreneurs who have experienced past projects have learnt specific skills which make future start-ups more successful (Packalen 2007). One of the possible advantages these specific skills could give is to enable entrepreneurs to adapt to the changing business environment surrounding the start-up. Alternatively it could provide them with knowledge of technology key to the success of the new venture (Shepherd et al, 2000). Thus, this concept can be transferred to examine crowdfunding, arguing that creators develop specific skills by carrying out past crowdfunding campaigns and that these specific skills will enable them to be more successful in the future.

The same concept can be tackled from an economic perspective, utilising the consumer experience perspective. Shapiro (1983) considers that if observations of a product attributes are difficult for consumers, they can use the last produced product as an indicator of past quality. Furthermore, this past quality can then be used to moderate their future consumption of a good (Peña et al, 2013). Therefore, within the context of crowdfunding, the past campaigns carried out by the creator can be utilised by backers as indicators of past quality, enabling them to moderate there future backing based upon the past quality provided by the creator.

Utilising the creators previously backed campaigns as past experience to predict success within crowdfunding has been common across the crowdfunding literature. However, the literature is divided other whether the past experience has any significant effect. Marelli and Ordanini (2016) alongside Koch and Siering (2015), both found that the past creators experience did not have a significant effect on the level of success, even when only past successful projects were considered. Conversely, Buttice et al (2017), Janku and Kucerova (2018), and Kuppuswamy and Bayus (2018), all found that the past creator's experience did have a positive effect on the likelihood of success. Janku and Kucerova (2018) suggested that it was the sample sizes of the projects which were affecting the results, with the work of Marelli and Ordanini (2016) and Koch and Siering (2015), who respectively had sample sizes of 500 and 1000 observations. Compared to Buttice et al (2017), Janku and Kucerova (2018) and Kuppuswamy and Bayus (2018), who respectively had samples of, 31,389, 202,272 and 25,508 observations.

Furthermore, higher levels of experience within the crowdfunding platform could also impact the other variables utilised to examine the success of projects. For example, Koch and Siering (2015), included the project description, graphical accompaniment and the provision of video materials, as additional independent variables, finding that all three of these did have a significant effect on success. These authors argue that these could be considered as an outcome of the experience of the creators, whereby more experienced creators utilise these techniques more than less experienced ones. A further example of this is in Marelli and Ordanini (2016) study which included variables on text length and video inclusion. These two variables could also be demonstrating the creator's experience as utilising the optimum text length and the ability to include a video could be seen as skills derived from previous attempts.

As previously discussed, it is necessary to consider if the experience, as a signal, is manipulatable and costlier for low-cost projects. The past number of campaigns are manipulatable, as creators can create more campaigns to increase this variable over time, the variable can also be manipulated downwards by not linking the past accounts to the new project, resetting the number to zero. The signal has higher costs for low quality campaigns, as the only way to increase this signal is to run additional campaigns, in contrast projects with past experience will not need to run any campaigns. Therefore, low-quality projects regarding experience have to endure a higher cost to appear as high-quality projects.

Therefore, creator experience can be adopted as an effective signal and can be assessed in its potential to impact success on Kickstarter. Increased experience is seen as a positive signal of project quality, and thus the following hypothesis is proposed:

H1b: Signalling increased experience has a positive impact on the probability of the project’s success.

3.3.2.3 Trustworthiness

The signal examined in this sub-section consists of the number of updates provided by the creators during their campaign, Log values for updates were utilised to normalise these values. The author argues that updates can be seen to represent trustworthiness, due to how updates provide new information to the backers, answering questions on possible flaws and providing greater details about the project. They provide an ability for creators to reassure the backers on the reliability of the project and that the desired outcomes can be achieved, while the funding of the project is ongoing. Thus, demonstrating how trustworthy the creator is.

The impact of trustworthiness on success can be examined by considering the entrepreneurship literature, where trustworthiness is a key aspect of successful entrepreneurs (Rauch and Frese, 2007; Abdullah, 2013). Highly competent entrepreneurs are better at gaining trust and confidence from their investors or consumers (Baron and Markman, 2003). Furthermore, the ability of entrepreneurs to signal trustworthiness can be a crucial impactor in securing supply from other businesses (Venkataraman, 1997).

As discussed previously it is necessary to consider if the number of updates, seen as a signal, is manipulatable and costlier for low-cost projects. This signal can be manipulated as the creators have the ability to send as many or as few updates during the duration of the project. At first glance, it seems that there is little ability to distinguish between high quality and low-quality campaigns for this signal as there is no direct higher cost in posting an update to the project page for the low-quality projects. However, it could be proposed that lower quality projects will incur a higher cost when posting updates, as the more updates that are posted, the more information is available for the crowd to scrutinise the higher the likelihood that the low quality of the project will be revealed, leading to an increased signalling cost for the lower-quality campaigns. Therefore, trustworthiness, as a signal, can be considered to be effective, and the following hypothesis is developed.

H1c: Increased levels of trustworthiness have a positive impact on the probability of a project's success.

3.3.2.4 Impatience

The signal examined in this sub-section is the duration of the crowdfunding project. The duration of the crowdfunding project is considered as a proxy for the level of patience of the creator. The shorter the duration, the more impatient the creator is in acquiring their funds, the longer the duration, the more patient a creator is. The most impatient creators create campaigns which last a single day, conversly the most patient creators will create 60 days campaign, as Kickstarter allows projects to last a minimum of 1 day and a maximum of 60 days.

Patience has been identified as a necessary element of success within entrepreneurship (Kirby, 2004). As often to succeed entrepreneur need to defer their consumption, enabling them to make further investments with the aim of providing benefit to them in the future (Doepke and Zilbotti, 2014). Furthermore, over 75 per cent of Start-ups fail to return their original investment (Gage, 2012) and therefore an entrepreneur may need to run several start-ups before receiving any return on their investment. Requiring a large amount of patience by the entrepreneurs, while they continuously aim to create their successful start-up.

Conversely, alongside patience being desirable, impatience is undesirable. Cadena and Keys (2015), examine the impact of impatience and its effect on income across the lifetime of members of the public. They utilised surveys which identified impatient individuals based on a specific set of questions, then compared these to specific outcomes. The paper demonstrated that impatient users had less money, were more likely to have smoked and drunk to the point of having a hangover, compared to there patient counterparts. Furthermore, they examined the relationship between how impatient someone was, and their level of education obtained, with impatient people 10.2 per cent more likely to drop out of high school. The cumulative effect of these decisions was that the impatient participants were earning 13 per cent less than their cohorts by the time they were 46 years old. Therefore, impatience seems to be an undesirable trait for entrepreneurs, while patience emerges as a desirable one.

As previously discussed, it is necessary to consider if the duration of the project is a signal that is both manipulatable and costlier for low-cost projects. Duration is manipulatable, as the creator can set the duration between 1 and 60 days. However, there is no clear higher cost to low-quality campaigns compared to high-quality campaigns. The author would argue that if the duration was far longer than the 60-day limit imposed by Kickstarter than an increased cost of low-quality campaigns could be argued. Consider a duration limit of 365 days; the far longer funding period would enable far greater scrutiny of their product, giving the potential for weakness in low-quality projects to be identified. Thus a higher duration would incur higher costs to low-quality projects. However, in such a restricted time limit as sixty days, the author would propose that there would be no way to distinguish between high-quality campaigns versus low-quality campaigns. Therefore, even though patience is desirable this signal is not likely to be effective. Thus, as patience would be seen as having a positive impact the following hypotheses is proposed, however it is considered that it is likely that the hypotheses will be rejected due to the inability for high quality project to distinguish themselves from low-quality projects:

H1d: Increased level of patience have a positive impact on the probability of a project's success.

3.3.2.5 Ambition

The specific signal examined in this sub-section is the funding goal, or the amount of money a project declares it must reach by the end of their campaign on Kickstarter. From an operational point of view, a logarithmic transformation of the funding goals values was introduced to help comparison across projects and reduce the effect of outliers. The set funding goal is considered as a proxy of the ambition of the creator. As this author argues that creators with more ambitious projects would require higher amounts of funding than projects with less ambition. This is especially likely due to how Kickstarter is organised as an all-or nothing platform and thus, projects must reach their funding goal to receive any funding and thus creators are not incentivised to set funding goals above their ambition level.

In order to interpret whether signalling a higher level of ambition would have a positive or negative effect on the project's success, the effect of ambition within entrepreneurship was initially considered. Within the entrepreneurship literature, higher levels of entrepreneurial ambition are seen as a positive element, driving start-ups ability to grow and expand (Davidsson, 2003 and Bosma, 2009). However, excessive amounts of entrepreneurial ambitious have been considered to have negative effects on the overall macro level of the economy, leading to economic inefficiency (Cieślik et al, 2018). Additionally, within the crowdfunding literature, ambition has been identified as having a negative effect. Wells (2013) identified that ambitious crowdfunding project success can be hampered, due to how it can enable bad actors to steal trademarks and patents. However, we somewhat disagree with this argument as it suggests that the company is unable to file patents or copyrights before they run the crowdfunding campaign. Furthermore, within crowdfunding campaigns key information for new products does not need to be revealed. For example, one could state that he is building a new type of 3-D printer, however one would not need to state the specific technology used in this printer. However, Mollick (2018) suggests a far simpler reason why ambitious projects are more likely to get less support: that they are in general more complicated, thus more likely to fail in development and thus less likely to receive funding. This effect will be reinforced by the all-or-nothing condition which requires all projects to reach their funding goal to receive funds. Moreover, since by their very nature more ambitious projects require higher goals, this decreases their likelihood of succeeding. Thus this author argues that if Ambition is an effective signal, it will exert a negative impact on the probability of a project's success.

As with other signals, one must consider whether the funding goal is manipulatable, observable and costlier for low quality projects. The funding goal is manipulatable and observable, as any funding goal can be set for a project and the backers are free to view the funding goal. This signal can also be considered costlier for low-quality projects as, usually, more backers will be needed to support a project with a higher funding goal. Thus, with an increased number of backers, there will be an increased amount of scrutiny placed upon the project, not only as a result of the direct knowledge of each backer but as a function of the combined knowledge of the backers (Sadiku et al, 2017). Low-quality projects would be less likely to withstand this increased level of scrutiny, therefore incurring a higher cost for setting a higher funding goal. Hence, the funding goal can be seen as an effective signal and can be used as a proxy for the level of ambition of the creator.

The author proposes that, in general, creators signalling greater level of ambition will have a negative impact on success and that it will be an effective signal. This is captured by the following hypothesis:

H1E: Creators' Ambition has a negative impact on the probability of a project's success.

3.3.3 Backers Signals

The reason that backers have to engage in signalling behaviour within Kickstarter is due to the link between the utility gained by an individual backer and the support of other backers, a typical case of direct network externalities. One backer, in the majority of cases, will not be solely responsible for funding a project. Instead, they will be offering a portion of the required funds, based upon the level of backing they give to the project. However, if the project does not reach its funding goal, the creators will receive no money, and thus the backers are not going to receive their rewards and their expected utility gain. Therefore, a backer is incentivised to signal, to other backers, to increase the probability that the project will reach its funding goal. Moreover, even after the project has reached its funding goal, the backer may still be incentivised to encourage further support for the project, under the assumption that this will increase the likelihood of successfully delivering the project's rewards.

The signals sent by the backers are fundamentally different to the signals sent by the creators, the reason for this is that each backer is communicating their desires and therefore the signals sent can be seen as a combination of all backer's desires, but not a direct reflection of any single backer. Therefore, it is not possible to examine these signals as proxies for the human capital of the backers due to the collective nature of these signals. Instead, the signals are considered as specific strategies by the backers.

The backers have three primary ways to signal support in crowdfunding campaigns, through making comments on the crowdfunding page, by the act of backing a project and by choosing the level of backing they provide. In backing the project, the backers signal both support for the project and how strong that support is via the amount of money that the backer provided. Therefore, these can be considered as two separate signals, the first solely based on the desire to back the project and the second based on how much money they are willing to give. Furthermore, after supporting the project backers can directly leave comments on the crowdfunding page, both positive and negative comments. However, to be able to post comments, they must first back the project, suggesting an increased number of comments can be viewed as a signal of support for the project. Log values of the number of posted comments were utilised within the model to capture the positive but decreasing marginal impact of additional comments. As within a crowdfunding page there is a set limit of how many comments can be viewed on the front page of the community page of the Kickstarter project. When this limit is reached the comment is pushed further back, and for someone to view the comments, they have to click another link, thus for each additional comment renders older comments less likely to be read, and to a decrease in their impact.

In order to capture the signalling effects of backing, the early funding period was examined, following Colombo et al (2015), the initial funding period examined was a 1/6th of the duration of the project[1]. Colombo et al (2015) utilised the early funding period to examine the effects of *internal social capital* within crowdfunding. Conversely, the author utilises this early funding period, to examine the impact of signalling behaviour of the backers. Arguing that the early signalling sent by the backers are key to success for the project, due to how they can be viewed as the early adopters of the crowdfunding project. The concept of early adopters is outlined within the theory of diffusion of innovation. Rogers (2010) argued that each innovation is initially supported by a set of early adopters before being supported by other users and without these early adopters other future groups of adopters will not support the innovation. The author argues this phenomenon would also occur within Crowdfunding and that these early adopters are key to success on the platform. Thus the signals sent by backing in the early funding period is expected to positively affect the success of the project. The early backing period is captured, in the model, by three separate variables, the number of backers, the amount of funds raised and the pledge per backer. The first two variables are simply those reported by Kickstarter. The third variable of pledge per backer was originally suggested as a measure by Kromidha and Robson (2016). The author argues that this measure can be utilised in the early funding period. It captures the average amount of money pledged

[1] This specific length of the time period was tested for goodness of fit in the model, please see appendix item Item 3: Models testing early funding period for the results of the goodness of fit.

per backer, which can be interpreted as a measure of how effective the campaign is at persuading each individual backer to provide more money. Log values were utilised as a measure of normalising effect for this variable, and this is necessary due to how within the dataset some campaigns have a very small number of backers with a very high amount of backing.

As with the creator's signals, to be effective also the set of backers' signals must be observable, manipulatable and costlier for low-quality projects. They are observable as the information is freely available on the crowdfunding page, they are manipulatable as the backers can increase both the comments and the amount of early backing provided to the campaign. As backing has a cost, backing low-quality campaigns is costlier than backing high quality ones as they have lower probabilities of success. Therefore, the signal can be considered to be effective, leading to the creation of the following hypothesis:

H2: Increased number of signals sent by the backers has a positive impact on the probability of a project's success.

3.3.4 Backer incentives: Rewards

Rewards are the primary incentives of backer participation in reward-based crowdfunding (Bretschneider and Leimeister, 2017). The specific incentive mechanism provided by rewards can be considered as based on the characteristics of the reward. Thürridl and Kamleitner (2016) identified eight different dimensions in which rewards can be allocated; these are: purpose, tangibility, scarcity, geographical limitation, monetary value, recognition, level of collaboration and core features. Further arguing that, by leveraging these dimensions, rewards can be utilised as strategic assets in securing funding on a crowdfunding platform. Thus, these elements are particularly relevant in capturing the value of rewards. However, capturing these elements can be difficult, due to how each specific reward could display different values for each of these dimensions and how some of these dimensions are subjective, such as the level of collaboration. Thus, while these dimensions can be utilised to examine a specific project, it is far more difficult to use them across projects. Therefore, to assess how rewards can be used within Kickstarter, one must first consider how rewards are offered on Kickstarter.

On Kickstarter every single crowdfunding campaign must offer at least one reward level, the creator can then choose to add additional reward levels. The rewards levels can contain multiple rewards and backers are free to support as many different reward levels as they wish, they can also support the same reward level multiple times. Zhang and Chan (2019) suggested that the number of rewards should be examined rather than the reward level. However, the author disagrees with this suggestion for two reasons. Firstly this would require the researcher to be able to identify what counts as a reward within every reward level, for example, consider if one reward level contains a box of goods, does that reward level contain one reward, or is every item in the box a reward. Or, consider another reward level, which is spending a day visiting the creators, is this a singular reward or is every activity in that day a reward. Fundementally, this is thus a problem as it creates uncertainty in the estimation of the number of rewards. Secondly, backers can only back projects at a reward level, they cannot pick a single reward and make a customised reward level. Therefore it is assumed that it is the effects of reward levels which should be investigated, not the number of rewards. For these two reasons, the author examines reward levels, instead of the number of rewards.

The number of reward levels is considered to demonstrate the variety of options given to the backers, with the assumption made that projects which give a higher number of reward levels are more varied and thus more likely to fulfil backer motivation (Frydrych et al, 2014). Past empirical research into Kickstarter supports that the number of reward levels impact success on Kickstarter (Frydrych et al, 2014; An et al, 2014). Xu et al (2014), further identified that adding reward levels to an ongoing campaign was a more successful way to increase the chance of success compared to changing the textual context of the campaign. Thus, the author proposes:

H3a: Increased number of reward levels within a campaign will have a positive impact on the probability of the project success.

Further developing alongside this hypothesis, the author suggests two sub-hypotheses based upon additional information surrounding the reward levels, specifically, the average time a backer has to wait for the reward to be delivered and whether the reward is global or local.

3.3.4.1 Average wait time to reward

This variable captures the amount of time backers have to wait on average until the predicted reward delivery date. This is collected from the projects at the end of the campaign and weighted by the number of backers for each reward, and their respective delivery dates.

These are only predicted date values as the time needed to facilitate reward delivery is often underestimated by creators. As Mollick (2014) work demonstrated by showing that only 24.9 percent of design and technology projects on Kickstarter delivered on time out of a sample of 389 projects.

Joenssen et al (2014) study on Kickstarter, found empirical evidence that higher waiting times negatively impacted the likelihood of crowdfunding success. They argued that this was due to how wait time could be seen as a proxy for examining how far along a product was within its development cycle and projects further along in their development cycle would be more likely to succeed. However, this explanation thus requires crowdfunding to be for something which has a clear-cut development cycle, as Joenssen et al (2014) were examining only the technology category within Kickstarter this could be justified, however as this thesis examines all categories on Kickstarter, this explanation is not satisfactory.

The author argues that in understanding why longer wait times for rewards may impact the success of the crowdfunding project on Kickstarter, the concept of the personal discount rate can be utilised. In the economic literature, the personal discount rate reflects the rate at which consumers trade future consumption in favour of present consumption (Hausman, 1979). The higher the discount rate, the more the individual prefers to consume in the present rather than consume in the future, the specific rate will depend on the individual, but it has also been linked to socioeconomic factors, such as, their level of education and age (Warner and Pleeter, 2001). If a user on a crowdfunding platform chooses to back a project, she/he is setting aside a given amount of money at present to be rewarded at a future time. If the amount of time a backer has to wait until she/he received the rewards is short, then this backer will not be greatly affected by their personal discount rate and would be more likely to back the product. However, if the waiting time is long, backers will be affected by their discount rates and thus less likely to back the products, leading to the formulation of the following hypothesis:

H3b: Increased expected delivery times of reward levels will have a negative impact on the probability of project success.

3.3.4.2 Global or local rewards

This variable considers whether the rewards are global or local. Rewards can either be shipped to anywhere in the world or restricted to specific regions, this variable considers the number of globally shipped rewards and can be used to explore whether consumers prefer rewards to be local or global. Digital rewards were grouped alongside local rewards as their delivery time could be considered instantaneous making them more alike to local rewards.

The author proposes that backers would prefer local rewards versus global rewards, for the following reasons. Firstly, global rewards have an increased delivery time, which will impact the backers discount rate as discussed above. Secondly, they inherently have an increased cost to the backers as shipping costs have to be paid alongside any taxes or duties which may be imposed as part of the import process. Thirdly, there could be a desire for backers to consume locally rather than globally. Their motivation for local consumption could be a perception of increased quality or considered as a socially responsible action in supporting the local economy (Jenkins, 2006; Onozaka, 2010; Sims, 2009).

For these reasons, the number of global reward levels is considered to have a negative impact on the success of the crowdfunding project, leading to the formulation of the following hypothesis:

H3c: An increased number of global rewards will have a negative impact on the probability of the project success.

3.3.5 Social capital

The definition of social capital utilised in this thesis is as follows: the ability to utilise goodwill generated within the fabric of social relations in order to facilitate actions from those social relations (Adler and Kwon, 2002). The impact of social capital on success within crowdfunding has been separated between its external and internal effects. The concept of *internal social capital* in relation to crowdfunding, stems from Colombo et al (2015), who argued that crowdfunding platforms could generate their own *internal social capital* through the social interactions between creators. The expected impact on the campaigns' success of external and *internal social capital* are examined separately in the following two subsections.

3.3.5.1 External Social capital

The effect of *external social capital* is captured through considering the level of presence of a campaign on external social networks. Specifically, the author utilises the number of times the project was shared on Facebook. A share on Facebook refers to a user of Facebook sharing a link to the project to their Facebook network, with their Facebook network consisting of anyone who is friends with them or follows them. The higher number of shares is considered to represent a higher amount of social capital as each share displays another user on the social network being linked to their project

As discussed previously, in the development of the theoretical framework, within the literature on crowdfunding, there is a lack of consensus about the actual effect that increased social media presence has on success in crowdfunding. However, many of the studies which reached a differing conclusion, simply utilised the number of Facebook friends or Twitter followers as a measure of the social capital (Beier and Wagner, 2015; Colombo et al, 2015; Mollick 2014; Moisseyev, 2013; Kromidha and Robson, 2016). The author argues that measuring social capital effects in this way is flawed, because it does not fully capture the activity of the network and instead only captures the *potential* activity of the network. Utilising network analysis literature, one can consider that the number of Facebook Friends can be seen to represent the number of paths with length one to the original node. Therefore, if the impact of social capital is greater than the first jump within the social network, then only utilising the number of Facebook friends will underestimate its impact. As discussed within the eigenvector centrality section of the literature review, other surrounding nodes may also impact on the project, and this will not be captured when using Facebook friends. Secondly, it does not demonstrate whether the creator utilised those connections, it only demonstrates that they can utilise them. Compare this to the number of times a project is shared on Facebook; this measure captures the number of nodes within the Facebook network which have received a link to the crowdfunding project, regardless of the path lengths between the two nodes. Demonstrating that backers are actively utilising the Facebook network to support the crowdfunding project. However, this measure has one major flaw, it cannot distinguish between creator shares and backers shares and therefore can only be used to consider the impact of the combined social capital of creators and backers.

The impact of social capital on crowdfunding success is considered to be positive as social capital has been shown to increase the amount of donations to charities (Brown and Ferris, 2007), widely important for the success of start-ups (Pirolo and Presutti, 2010) and demonstrated to be vital to knowledge sharing within virtual communities (Chiu and Wang 2006). Therefore, the following hypothesis is developed.

H4a: Increased levels of combined creator and backer *external social capital* has a positive impact on the probability of the project's success.

3.3.5.2 Internal social capital of creators

The *internal social capital* of the creators is captured via the number of other creators' projects backed by the creator, up to the current date. This metric shows how active the creators have been within the crowdfunding platform and thus how much *internal social capital* they might have generated. The measure can be captured within Kickstarter as users can be “playing both sides”, a term coined within Zvilichovsky et al (2015). The term refers to the ability of backers to become creators and creators to become backers. Zvilichovsky et al (2015) identified that within Kickstarter this two-sided activity is recorded within the project page of the crowdfunding campaign, providing access to the past platform backing activities of the creator and thus enabling the consideration of whether this past backing activity can support the *internal social capital* of the creator and, eventually, positively affecting the likelihood of success of its own campaigns.

Past work has empirically shown that this backing is repaid within the creators' community (Koch and Siering, 2015; Kunz et al, 2017; Marelli and Ordanini, 2016). The positive effect of *internal social capital* can be captured as the occurrence of reciprocity within the platform. Therefore, examining the reasons of why reciprocity may occur within the platforms, is relevant in developing testable hypotheses about the impact of *internal social capital* on campaigns success.

One way of explaining the effect of reciprocity within an online network is through network exchange theory. This considers configurations and distributions of social power within networks connections and the effects of the ability to utilise this power (Walker et al, 2000). Faraj and Johnson (2011) utilised this approach in relation to reciprocity, suggesting that although individuals have differing intrinsic motivations, reciprocity within an online network occurs at an aggregate level. These authors also identified that reciprocity was present across each one of the different examined online networks, however, the magnitude of these effect varied across each community, leading to the suggestion of differing social norms and network structures (Faraj and Johnson, 2011). In the specific context of crowdfunding, if the creator of one project backs another project, that project is likely to get backed in return even if this reciprocal backing is not coming from the creator who benefited from the backing. Zvilichovsky et al (2015) expanded upon this approach, classifying reciprocity into: direct and indirect reciprocity, with direct reciprocity considering interactions between two individuals and indirect reciprocity considering the interaction between an individual and a group. They capture both direct and indirect reciprocity in regard to Kickstarter, with the results supporting the concept that reciprocity increases the likelihood of projects reaching their funding goals. Colombo et al (2015) support these results showing that project creators are more likely to support other project creators, when compared to normal backers, providing further evidence of direct reciprocity. Johnson et al (2014) describe how indirect reciprocity can be seen as an individual interacting with an entire social group. With members of the social groups supporting an individual who they themselves don't interact with but are encouraged to support via the individual participation within the group. In the case of crowdfunding, this could suggest that by backing other projects they will be rewarded by individuals in the community who supported the original campaign.

Therefore, whether direct or indirect, reciprocity is considered to have a positive effect on crowdfunding success and thus that internal capital which creates reciprocity should have a positive impact on success in crowdfunding, leading to the creation of the following hypothesis:

H4b: Increased amount of creator internal social capital have a positive impact on the probability of the project's success.

3.3.6 Competition effects

In the same way that social capital can be examined internally and externally to the crowdfunding platform, competition can also be decomposed into the same two categories, as internal and external competition, with internal competition considering the impact that other projects within the platform have on the current project seeking funds, while external competition considers how successfully Kickstarter is at competing at attracting potential backers with other crowdfunding platforms.

3.3.6.1 Competition within the platform

Higher levels of competition within a platform can have either a positive or negative effect on the likelihood of a project reaching its funding goal due to the strength of the positive and negative externality effects (Economides, 1996). Positive externality effects can occur due to an additional project within the platform increases the attractiveness of the platform and thus increases the number of users of the platforms and thus benefits all project which utilises on the platform. Conversely, negative externality effects occur as an additional project will be competing over the same resources within the platform, with each additional project there will be fewer resources to go around and thus decreases the likelihood of other projects succeeding (Lee, 2014). Therefore, the entry of a new project can either have a net negative or positive effect on the chances of other projects succeeding based upon whether the positive or negative externality effects were stronger. In identifying whether positive or negative externalities effects would be stronger within crowdfunding, the author argues that this would depend upon the position of the new project relative to the position of the examined project within the crowdfunding platform.

The author argues that additional competition within the projects speciality and category will have a significant and negative externality effect, while, competition in the rest of the platform will lead to a significant and positive externality effect. This arises because projects within the same specialism and category can be considered to be substitutes with each other and thus compete over backers in Kickstarter. Porter (1989), showed that the threat of substitution played a key role in driving competition within an industry. Conversely, projects which don't share the same category are unlikely to be substitutes for each other. Therefore both projects benefit from the increased number of users drawn by the additional project, while not directly competing over these backers. This assumes that each backer looks beyond the original project which they were attracted to, an assumption that is supported by considering that users on average will visit 2.76 pages on Kickstarter (Alexa, 2018).

The next step in the analysis of these externality effects, requires defining the set of projects the current project is, internally, competing with. Janku and Kucerova (2018) showed that competition within Kickstarter could be divided into smaller subsections based on temporal and geographical information. The first measure of temporal competition utilised was the number of projects launched in the same month. This author proposes improving this measure by considering the number of projects active at the same time as the crowdfunding project, rather than utilising the number of projects within a month. Arguing that projects within the same month may not be competing with each other, if one project has a duration of 10 days and starts at the beginning of the month then it will not compete with another project which starts at the end of the month.

The second temporal measurement suggested by Janku and Kucerova (2018) considered whether projects were launched on a weekend or on a weekday. They argued that projects launched on a weekend would lead to it being more competitive as, on average, more projects were launched on the weekend. Within this thesis, this idea is captured by measuring the number of competing projects on launch day, regardless of whether the project was at the weekend or not. Geographic competition, instead, will be measured by examining the impact of the project's city and country on the likelihood of success. This measurement will also be weighted by the number of backers obtained by projects within the city or country during the duration of the project.

Additionally, each measure of the degree of intra-platform competition will be weighted by the number of backers obtained by the project with either its full duration or on the launch day based upon the competition measure. The competition measures utilised to examine the entire funding period will be converted into an index form utilising the Herfindahl–Hirschman Index (Hirschman, 1964). This index is given by the sum of the squares of the market shares of each individual firm within the market, to capture the overall level of competition within the relevant market. This index is often used both as a measure of the level of competition and of market structure (Rhoades, 1993; Caves 1974). The specific market will be defined as composed by all projects which were active at the same time as the examined project. Thus, based upon the arguments outlined in this section, the following two hypothesis are proposed:

H5a: Increased competition within the category has a negative impact on the probability of the project's success.

H5b: Increased competition outside the project's category but on the same platform has a positive impact on the probability of the project's success.

3.3.6.2 Geographic competition within Kickstarter

Utilising competition measures enables the geographic impact on success to be captured via the creation of a competition index whereby competition is categorised based on country. This index thus captures all of the projects which are competing against each other within the same country. Mollick's (2014) work showed that there was clustering between projects of the same category within Kickstarter. As mentioned in the previous subsection, products of the same category were considered to be more likely to be substitutes of each other leading to a negative impact on the success of the project of additional projects being added. Thus, an increased number of companies in a small geographical area such as a city can be expected to decrease the chances of success. Conversely, an increase in the number of projects within a large geographic region can be seen to demonstrate an increase in the general level of success and thus is expected to have a positive impact on success, utilising the logic that projects outside of the local area are less likely to be substitutes of each other.

H5d: Increased geographical competition at a city level will decrease the likelihood of a project succeeding.

H5e: Increased geographical competition at a country level will increase the likelihood of a project succeeding.

3.3.7 Kickstarter Conceptual framework

Drawing together the predicted outcomes of the hypotheses from the previous sections leads to the creation of the following conceptual framework displayed in Figure 3-5, based upon the theoretical framework developed in section 2.4 of the literature review.

Figure 3-5 Kickstarter conceptual framework

Positive	Internal and external social capital Reward levels Early funding Early backing	Competition outside the category	Internal and external social capital Experience Trustworthiness
	Backers	Platform	Creators
Negative	Global rewards Wait time to rewards	Competition within the category	Impatience Overconfidence

The conceptual framework utilises the developed hypotheses to consider the expected impact of the different factors on the success of crowdfunding projects within Kickstarter. For example, increased amounts of competition outside of the category which the project is based in is considered to have a positive impact on the success of the examined project.

3.3.8 Additional covariates collected for Kickstarter

Alongside the variables identified in the conceptual framework, an additional covariate was captured, the google trend value for the search term Kickstarter, further restricted to the category of the project. As discussed previously in section 3.2.2.2, google trend information captures the popularity of a specific search term, in the form of an index value between 0 and 100, where 100 represents the search term being most popular and 0 being least popular (Google Trends, 2018a). Thus, this covariate captures shifts in the overall popularity of the category of the examined projects on Kickstarter. As popularity may be shifted by factors outside of the examined variables, this thus stops the overestimation of the impact of other variables.

3.3.9 Data collection procedure for Kickstarter

Data was collected from Kickstarter between 11th November 2015 and 11th January 2017 utilising the Import.io web crawling software previously outlined in section 3.2.1.1. The timeframe enabled the capture of an entire years' worth of Kickstarter projects, the extraction lasted over a year due to the full completion of all projects only completing sixty days after the 11th November 2016. The data collected is expressed as a cross-sectional dataset. Data was extracted from Kickstarter utilising crawlers which were run every day for this duration at 08.00 Greenwich Mean Time (GMT). This specific time was chosen to take into account that the largest user base for Kickstarter is American, this was identified utilising Alexa (Alexa, 2018). Thus, a time was chosen when many of the users would be asleep, as 08.00 GMT translates to 04.00 Eastern Standard Time (EST) and 01.00 Pacific Standard Time (PST). Therefore, limiting the effect that the crawler would have on the users and owners of Kickstarter. Four crawlers were necessary to extract all information from Kickstarter.

3.3.9.1 Crawler 1: URL extractor:

The first step was to capture the URLs of new projects launched on the Kickstarter platform. This was achieved utilising Kickstarter's inbuilt explore feature, which can be used to sort projects by when they were added to the site. The URL for this explore feature is as follows;

https://www.kickstarter.com/discover/advanced?woe_id=0&sort=newest&seed=2560961&page=1

This page had 12 results per page. And could be easily altered to extract additional pages of results, utilising the concatenate function in excel, as the only necessary change to extract from the second group of 12 is to alter page=1 to page=2 in the URL. Therefore the URLs for the crawler were as follows.

https://www.kickstarter.com/discover/advanced?woe_id=0&sort=newest&seed=2560961&page=1

https://www.kickstarter.com/discover/advanced?woe_id=0&sort=newest&seed=2560961&page=2

The number of pages that it was necessary to extract was based on the number of new projects which were added each day. Early days of data collection observed that between 200-300 projects were added each day. Thus 30 URLs were collected, giving 360 of the most recently started campaigns. These were checked against already existing URLs within the dataset by utilising the VLOOKUP command. With each new URL being added to the dataset to be used with the main crawler. Before the first day of the full extraction, a list of the past day's project was collected, ensuring that the first day contained only projects which started on the 11th November 2015. This crawler was run every morning at 8.00 a.m., in order to capture new projects before running the main extractor.

3.3.9.2 Crawler 2: Main crawler

After obtaining a list of URLs for ongoing campaigns, the main extractor was run, this extractor was scheduled to run at 8.30 a.m., 30 mins after the first extractor to ensure there was sufficient time to upload the updated list of URLs. This specific extractor collected all information from the main page of the crowdfunding project on Kickstarter. Capturing the following variables: funding goal, duration, past number of created campaigns, past number of backed campaigns, the location of the project, category of the project, specialism of the project, start date, end date, number of Facebook friends. Alongside these variables, the number of backers and the amount backed was also collected for that specific day. This crawler was run each day to capture the changes between backers and funds across the entire funding period. A separate crawler was needed to capture the last day of backing and funding as Kickstarter changes the format of the crowdfunding page when it reaches its conclusion.

3.3.9.3 Crawler 3: End day crawler

The final crawler was carried out on the last day of the campaign, this captured the results of the campaign. Specifically it captured the following variables, the outcome of the campaign, the number of updates and the number of comments, alongside the final day backers and the final day funds.

Utilising all three crawlers across the span of a year enabled all projects on Kickstarter to be captured across an entire year.

3.3.9.4 Dataset characteristics

The following section provides a brief overview of the dataset. Table 3.1 below displays key statistics of projects from the Kickstarter dataset.

Table 3.1 Key statistics from the Kickstarter dataset

Category	**Number of projects**	**Percentage of total**	**Number of successful campaigns**	**Percentage successful**	**Rank (based on percentage**	**Average amount pledged**	**Average Funding Goal**

					successf ul)		
Art	3,517	6.48	1234	35.09%	7	2595.489	15686.04
Comics	1,884	3.47	1089	57.80%	2	4979.81	7902.744
Crafts	1,775	3.27	383	21.58%	12	1501.595	9477.257
Dance	376	0.69	235	62.50%	1	2396.61	10214.35
Design	5,529	10.19	1942	35.12%	6	15291.68	27585
Fashion	4,041	7.45	901	22.30%	11	4807.722	16119.79
Film and Video	6,281	11.58	2114	33.66%	8	4940.633	29861.34
Food	3,940	7.26	795	20.18%	13	4426.321	36840.85
Games	6,369	11.74	2313	36.32%	5	15041.96	25090
Journalism	1,425	2.63	180	12.63%	15	2119.825	32541.44
Music	5,601	10.32	2413	43.08%	4	2119.825	12769.14
Photography	1,341	2.47	449	33.48%	9	2829.119	12024.2
Publishing	5,418	9.99	1688	31.16%	10	3810.035	11666.61
Technology	5,583	10.29	1083	19.40%	14	3560.716	55198.57
Theatre	1,180	2.17	650	55.08%	3	18045.23	13101.46
Total	54,260						

The following map, in *Figure 3-6* below, shows how projects were located across every continent in the world and how they were most heavily concentrated in Europe and North America. The exact number of results from each region can be more clearly seen in

Table 3.2 located below the map.

Figure 3-6 Spread of Kickstarter projects across the world

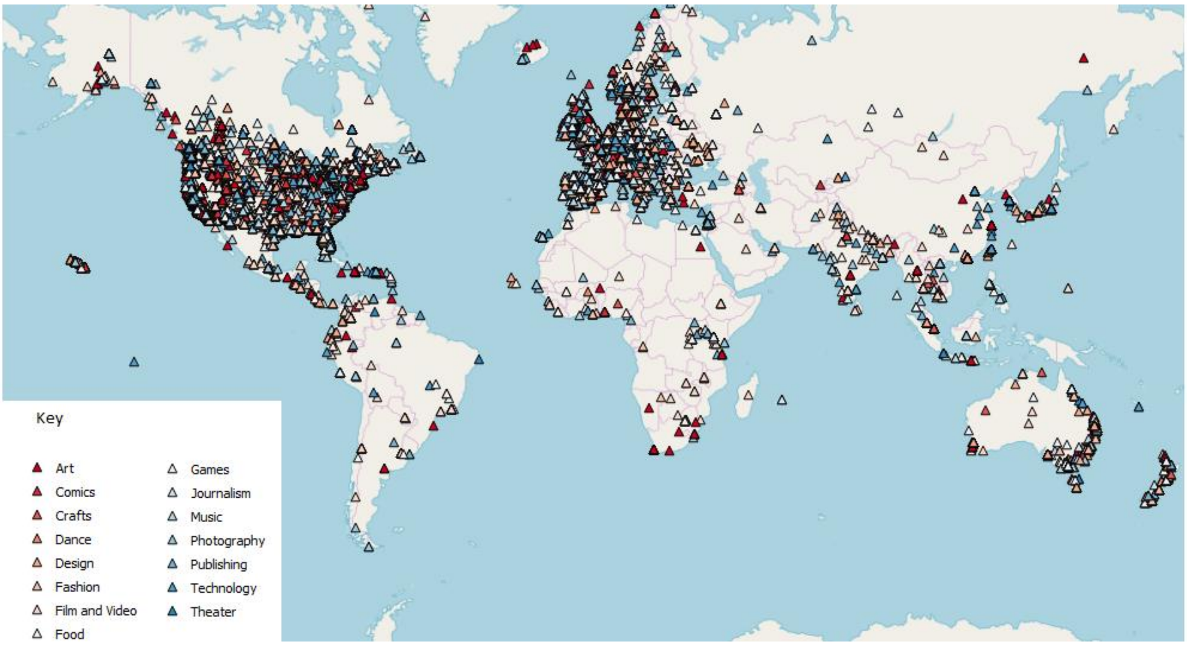


Table 3.2 Summary of projects by continent for Kickstarter model

Continent	Number of projects	Percentage	Number of successful projects	Percentage successful	Rank (based on percentage successful)	Average amount pledged	Average funding goal
Africa	166	0.31	56	33.73%	3	6088.618	23511.05
Antarctica	3	0.01	2	66.67%	1	7564.44	1798
Asia	876	1.61	318	36.30%	2	10265.91	23177.65

Europe	9,433	17.38	2589	27.45%	6	8636.492	15686.04
North America	41,883	77.19	13950	33.31%	4	7299.022	24411.61
Oceania	1,767	3.26	521	29.49%	5	7383.757	23345.49
South America	130	0.24	33	25.38%	7	2004.551	17468.3
Seven seas (open ocean)	2	0.00004	0	0.00%	8	1564	6000

3.3.9.5 Data restriction

Only projects with a funding goal of less than 1 million dollars were utilised. Projects above this funding goal were considered to be unrealistic. This restriction aligned itself with restrictions utilised within the literature, specifically by (Mollick 2014) and (Janku and Kucerova 2018).

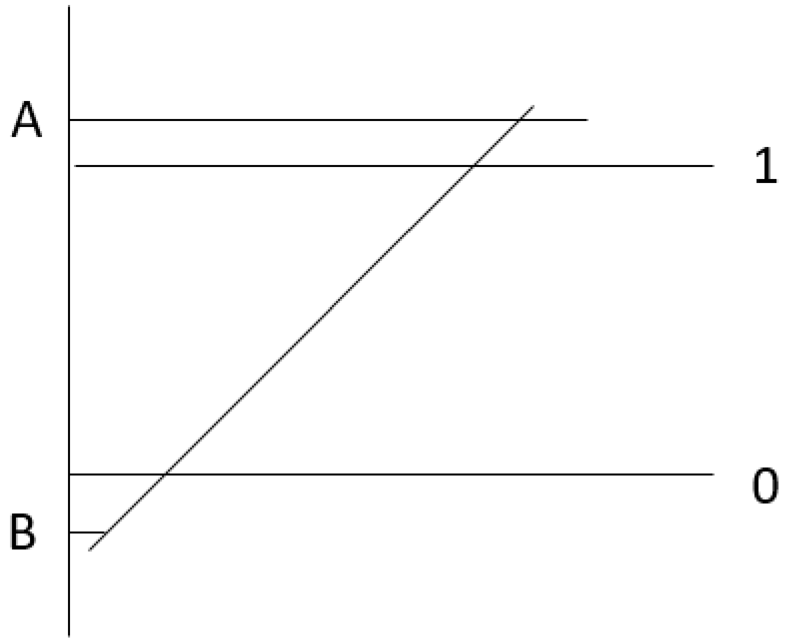
3.3.10 Data analysis and econometric specification

The following sections examine the specific econometric techniques utilised to examine this data set. This information was adapted from the following sources: (Asteriou and Hall, 2015; Greene, 1997; Gill, 2000; Hahn and Soyer, 2005; Hayashi 2000).

3.3.10.1 Logit model

In the following, since the dependent variables, success or failure, is dichotomous, either being 1 or zero, the logit model will be used as the more appropriate specification, due the limitations of adopting a linear probability model, for dichotomous dependent variables, in particular that the variance of the error term is a function of the regressors, demonstrating that heteroscedasticity is inherent within the model. Additional problems associated with the linear probability model include that predications can lie outside of the (0,1) intervals. This problem is highlighted in Figure 3-7 below:

Figure 3-7 Dichotomous regression errors, Adapted from (Asteriou and Hall, 2015, p.256



The diagram demonstrates that by utilising a normal regression line where the predicted value is greater than 0, or less than 1, shown at points A and B, both of these points don't have a defined meaning as they fall out of the 0 to 1 valid range for probabilities. Furthermore, the distribution of the error term is not normal and instead follows a binomial distribution (Asteriou and Hall, 2015).

To overcome these problems a logit or probit model can be utilised. Hahn and Soyer (2005) argued that there was a persuasive view in the literature that there was a limited difference within the application of probit versus logit models. With authors such as Greene (1997) and Gill (2000) concluding that in most scenarios it made little difference in the choice between probit and logit.

To choose between the two in this specific case, an abductive approach was used, with both logit and probit considered and compared within the dataset. Logit was then chosen by comparing the results between probit and logit version of the models. Probit was unable to calculate the main model, thus the restricted model was used as a comparision, with the consideration that if probit was a better fit than alteration to the main model would have been necessary. However utilising the fitstat command in stata, demonstratated that probit was a worse fit for the model in comparision to logit, as shown in appendix section 7.4.

The logit function, estimated via the maximum likelihood estimator, and is defined as:

$$f(x) = logit(x) = \log\left(\frac{f(x)}{1-f(x)}\right) \qquad (2)$$

(For full information on the derivation of the logit function please see appendix item 7.2)

As discussed above, the dependent variable in the logistic function must be dichotomous in nature, i.e. either 1 or zero. One of the advantages of the model is that the coefficient derived from the logistic model can be directly interpreted to represent the odds ratio of the event occurring. The odds ratio represents the likelihood of an event to occur. So, for example if an event is likely to occur 1 in every 5 time then the odds ratio can be expressed as 1/5. This has to be taken into account when considering the impact of the coefficient as they are not demonstrating positive or negative impacts on the likelihood of the event occurring but rather demonstrating positive or negative impact on the odds ratio of the event occurring.

3.3.11 Model definitions:

In the following models the dependent variable of success is defined as follows:

$$Y_i = \begin{cases} 1\ If\ a\ project\ successfully\ reaches\ its\ funding\ goal \\ 0\ If\ \ a\ project\ does\ fails\ to\ reach\ its\ funding\ goal \end{cases}$$

The models are constructed in order to reflect each aspect of the conceptual framework outlined in the previous section. Each section was added as a separate part of an overall model to enable the consideration of the impact of that specific group of variables. To reduce observations which set unreasonable funding goal, projects within funding goals of over 1,000,000 were removed from the models, reducing the number of observations within the dataset from 54,260 to 54,193.

Across all models, dummy variables for category and geographical region were originally considered, however their usage was problematic, as it was either causing very high levels of multicollinearity, increasing standard errors leading to statistically insignificant parameters. In order to still capture some of these effects, dummies for geographical and sector were integrated into the competition measures, where the effect of a category was captured in the *category index*, which examined the effect of differing levels of competition within a Kickstarter category. While the effects of geographical location where captured though the city and country competition indexes.

3.3.11.1 Model 1 Creator Signals

The first model only considers the signals sent out by the creator of the crowdfunding campaign. This is represented in the following model form:

$$P(Y_i) = 1 =$$

$$\alpha + \beta_1 logAmbition + \beta_2 logConfidence + \beta_3 Experience + \beta_4 LogTrustworthiness + \beta_5 Impatience \ + \ \varepsilon_i$$

This equation will then be referred to as [Creators Signals].

3.3.11.2 Model 2 Creators and Backers Signals

The second model includes all the previous variables while also introducing the variables based on the backers' signalling behaviour, leading to the formation of the following model:

$$P(Y_i) = 1 =$$

$$\alpha + [Creators\ Signals] \ldots + \beta_6 LogCampaign\_Comments + \beta_7 Early\_Funding + \beta_8 Early\_Backing + \beta_9 Early\_Average\_Pledge \ + \ \varepsilon_i$$

The additional variables introduced in this equation will then be referred to as *[Creators and Backers Signals].*

3.3.11.3 Model 3 Creators and Backers Signals and Backers incentives

The third model utilised the variables from the previous models while introducing variables focused on exploring the impact of the backer's incentives, leading to the formation of the following model:

$$P(Y_i) = 1 =$$

$$\alpha + [Creators\ Signals] + [Backers\ Signals] + \beta_{10} Reward\ Levels + \beta_{11} Global\ Rewards + \beta_{12} Average\ wait\ term \ + \ \varepsilon_i$$

The additional variables introduced in this equation will then be referred to as [Creators and Backers Signals and Backers incentives]

3.3.11.4 Model 4 Addition of external and internal social capital

The fourth model considers the additional impact of social capital on success in Kickstarter. Both *internal* and *external social capital* effects are captured leading to the creation of the following model:

$$P(Y_i) = 1 =$$

$$\alpha + [Creators\ Signals] + [Backers\ Signals] + [Backer\ Incentives] + \beta_{13} Facebook\_Shares + \beta_{14} Reciprocity + \varepsilon_i$$

The additional variables introduced in this equation will then be referred to as [Social Capital]

3.3.11.5 Model 5 Main Model

This model considers all variables excluding a specific set of competition variables. This is due to some competition variables only be accurately calculated in a restricted version of the dataset. The main model captures the competition variables which are unrestricted, specifically those which are based around considering the impact of competition on the launch of the project. leading to the creation of the following model:

$$P(Y_i) = 1 =$$

$$\alpha + [Creators\ Signals] + [Backers\ Signals] + [Backer\ Incentives] + [Social\ Capital] + \beta_{15} LaunchCompetition + \beta_{16} Launch\ Comp\ Category + \beta_{17} Google\ trend\ of\ category + \varepsilon_i$$

The additional variables introduced in this equation will then be referred to as [Launch Competition]

3.3.11.6 Model 6 Restricted Model

The last model identified for the Kickstarter platform considers the competitions variables which are restricted within the dataset. Due to the nature of the variables, they will be underestimated in the first 60 days and last 60 days of the dataset. Within this timeframe projects are competing against projects which were not captured within the dataset. Therefore the number of competing projects would be underestimated. Therefore, the following restricted model is considered.

$$P(Y_i) = 1 =$$

$$\alpha + [Creators\ Signals] + [Backers\ Signals] + [Backer\ Incentives] + [Social\ Capital] + [\text{Launch Competition}] + \beta_{18} City\ index + \beta_{19}\ Country\ index + \beta_{20} Category\ index + \beta_{21} Kick\ index + \varepsilon_i$$

The additional variables introduced in this equation will then be referred to as [Platform Competition].

Therefore, this model can be expressed as

$$P(Y_i) = 1 =$$

$\alpha + [Creators\ Signals] + [Backers\ Signals] + [Backer\ Incentives] +$ $[Social\ Capital]$+[Launch Competition]+ [Platform Competition] $+\ \varepsilon_i$.

However, due to the restriction of platform competition requiring the last 60 and first 60 days to be omitted, this model will only be used to examine the addition of platform competition.

Interpreting scale of log results in a logit mode.

3.3.12 List of all variables in Kickstarter

All variables in the table were directly collected from Kickstarter using web crawling, with the exceptions of Facebook shares, collected on shared count and google trend of category, collected via google trend.

Table 3.3 List of all variables utilised in Kickstarter,

Variable	Variable Output	Variable description
Success or failure	Success or failure	The dependent variable, recorded as 1 if the project reaches its funding goal and 0 in all other cases, including the project funding being cancelled
Ambition	Funding goal (log values)	The log value of the funding goal of the project.
Confidence	Relative Funding goal	The difference between the funding goal of the project and the average funding goal in Kickstarter while the project was running within that specific specialism.
Trustworthiness	Number of Creator Updates (Log values)	The log value of the number of posted updates on the crowdfunding project page by the creator of the campaign.
Experience	The number of previously created campaigns	The number of previously created projects on Kickstarter by the creator of the current project.
Reciprocity	The number of previously backed campaigns.	The number of previously backed projects on Kickstarter by the creator of the current project.
Impatience	The duration of the project.	The number of days which the project is raising funds on Kickstarter.

Reward levels	The number of reward levels.	The number of different rewards levels that the backers can support for the project.
Global rewards	Global rewards	The number of reward levels which can be shipped globally.
Average wait time	Average time backers have to wait for rewards.	The average (mean) difference between the amount of time that backers ordered rewards and when they were received, this was weighted by the number of backers who chose each reward level.
Campaign Comments	Comments	The log value of the number of comments made on the project by the backers of the project.
Early Average Pledge	Pledge per backer	The log value of the average amount of money each backer provided to the project by the early funding period ($1/6^{th}$ of the duration).
Early Backing	Early backing	The number of backers reached by the project by the early funding period ($1/6^{th}$ of the duration)
Early Funding	Early funds	The number of funds reached by the project by the early funding period ($1/6^{th}$ of the duration)
Facebook Shares	Facebook Shares	The log value of the number of Facebook shares of the project.
Launch Competition	Launch Competition from the rest of Kickstarter	The number of projects which are launched on Kickstarter on the same day as the current project outside of the project's category. Weighted by the number of backers those projects obtain on that first day.
Launch competition category	Launch competition within the specific category of the creator.	The number of projects which are launched on Kickstarter on the same day as the current project and within the same category. Weighted by the number of backers those projects obtain on that first day.
Google trend of category	Google trend index value for the category of the project.	An index value measuring search interest of Kickstarter category on google trends. Index values are between 0 and 100, with a 100 showing greatest interest in the category and 0 showing the lowest interest.
City index	Competition index value based upon competition between projects within the same city and occurring at the same time.	An index value measuring competition between projects on Kickstarter within the same city. Index values are between 0 and 10000, with higher index values showing lower levels of competition.
Country index	Competition index value based upon competition	An index value measuring competition between projects on Kickstarter within

	between projects within the same country and occurring at the same time.	the same country. Index values are between 0 and 10000, with higher index values showing lower levels of competition.
Category index	Competition index value based upon competition between projects within the same category, whose campaigns overlap.	An index value measuring competition between projects on Kickstarter, restricted to projects within the same category. Index values are between 0 and 10000, with higher index values showing lower levels of competition.
Kick index	Competition index value based upon competition between projects across the entirety of Kickstarter, whose campaigns overlap.	An index value measuring competition between projects on Kickstarter, from any project whose was raising funds at the same time. Index values are between 0 and 10000, with higher index values showing lower levels of competition.

3.3.13 Kickstarter summary statistics

Table 3.4 and Table 3.5 report summary statistics for variables utilised in the examination of the hypotheses in the results section. Table 3.6 shows the marginal impact of each of the variables for both models at the mean maximum and minimum.

Table 3.4 Summary statistics from main model

variable	mean	sd	min	max
Average wait time	130.1454	137.0995	0	2129
Average google trend	48.77506	19.86891	0	100
Campaign comments	0.912814	1.380342	0	11.27634
Ambition	8.751633	1.717377	0	13.81551
Early Average Pledge	2.281858	2.812328	-2.30259	9.21035
Early Backing	49.37754	440.197	0	50311
Early Funding	4245.817	50461.37	0	9570510
Experience	0.571292	2.247201	0	74
Facebook Shares	3.078752	2.332112	0	12.71055
Impatience	33.33816	11.40492	1	60
Launch competition	4904.628	5528.548	27	50761
Launch competition in category	647.4876	2060.199	0	42605
Reciprocity	3.759563	18.03081	0	890
Reward levels	7.388242	5.819252	1	179
Trustworthiness	0.990633	1.269777	0	11.37094
Global Rewards	3.687063	5.129691	0	179

Table 3.5 Summary statistics from restricted model

variable	*mean*	*sd*	*min*	*max*
Category index	326.8946	405.8768	19.77083	6644.796
City index	3986.172	3599.66	0	10000
kick index	671.8295	649.2174	39.99643	6320.38

Table 3.6 Marginal impact of Kickstarter models

	margin at mean	*margin at min*	*margin at max*
Ambition	0.2850013	0.9780455	0.0206466
Confidence	3.18E-01	0.3751364	0.0220859
Experience	0.3220047	0.3204058	0.5190883
Trustworthiness	0.2926114	0.2156681	0.8817697
Impatience	0.3250969	0.3250961	0.3197559
Campaign Comments	0.302652	0.2481619	0.7905069
Early Funding	3.22E-01	0.3223705	0.1074527
Early Backing	0.3230296	0.3193789	1
Early Average pledge	0.2578631	0.0895198	0.6029852
Reward levels	0.3173777	0.2956814	0.8043709
Global rewards	0.3241267	0.3352736	0.0130849
Average wait time	0.3201795	0.3347502	0.1169387
Facebook Shares	0.3225444	0.0942488	0.8414072
Reciprocity	0.2475301	0.3243246	0.030497
Launch Competition	0.3219999	0.3151286	0.3856989
Launch competition category	3.86E-01	0.326637	0.0737503
Average Trend Category	0.3220606	0.3085438	0.336231
Kick index	671.8295	0.330186	0.3963209
City index	3986.172	0.3508533	0.3163448
Country index	447.8236	0.3370555	0.3478277
Category index	326.8946	0.3435704	0.2003869

3.4 Kiva model

Kiva is a lending-based crowdfunding platform, which focuses on funding loans to support projects across 83 different countries, it has raised 1.10 billion dollars supporting 2.7 million borrowers since being founded in 2005 (Kiva, 2019a). Kiva provides backers with the option to obtain funds in two ways: firstly, by directly backing individuals and secondly by individuals working in tandem with partnership organisations who assist in the facilitation of the loans. In the second scenario the creators of the project can be viewed as both the partnership organisation and the individuals seeking the loan. Under the definition of crowdfunding proposed within the literature review (section 2.3), this can still be viewed as crowdfunding, as long as the partnership organisation does not choose how the funding from the crowd is allocated.

Partner organisations assisting the original loan seeking individuals play a necessary role due to the nature of the loans markets within the emerging world (Kiva, 2019a), where there is less access to the internet and individuals may not have the required skills' set to set up an online crowdfunding campaign, although, this being said, the gap in internet usage between the developed and emerging economies is declining in part due to the increasing usage of smart-phones (Poushter, 2016). Only projects which utilise partnership organisation will be considered within this analyis, due to an examination of the collected data, demonstrating that over 99 percent of the project utilised partnership organisations. Table 3.7 below provides summary statistics from the partnership organisations within the dataset. The number of sectors refers to the number of categories within Kiva which are represented by the partnership organisation, with an example of a sector being argiculture.

Table 3.7 Summary statistics of Partner organisations

Number of partners in data set	Average cost to borrower	Average time on Kiva	Number of countries represented	Number of sectors represented
73	35% APR	78.5 months	43	13

Kiva can be further defined as a lending-based all-or-nothing limited generalist traditional crowdfunding platform utilising the subdivision methodology outlined in (section 2.2.7). It is a lending-based platform as any money provided to the project must be returned to the backers at a future date. Kiva is an all-or-nothing as projects need to reach their funding goal in order to directly receive the money they raise from the backers. The project funding period lasts for exactly thirty days; thus, it is a limited platform. The projects are generalised as they are not restricted to raising funds for one specific product or purpose. Finally, Kiva can be considered as *traditional* as it does not utilise crypto-currency. The exact funding process for Kiva is described in Figure 3-8 below:

Figure 3-8 Structure of Kiva adapted from (Kiva, 2019b)

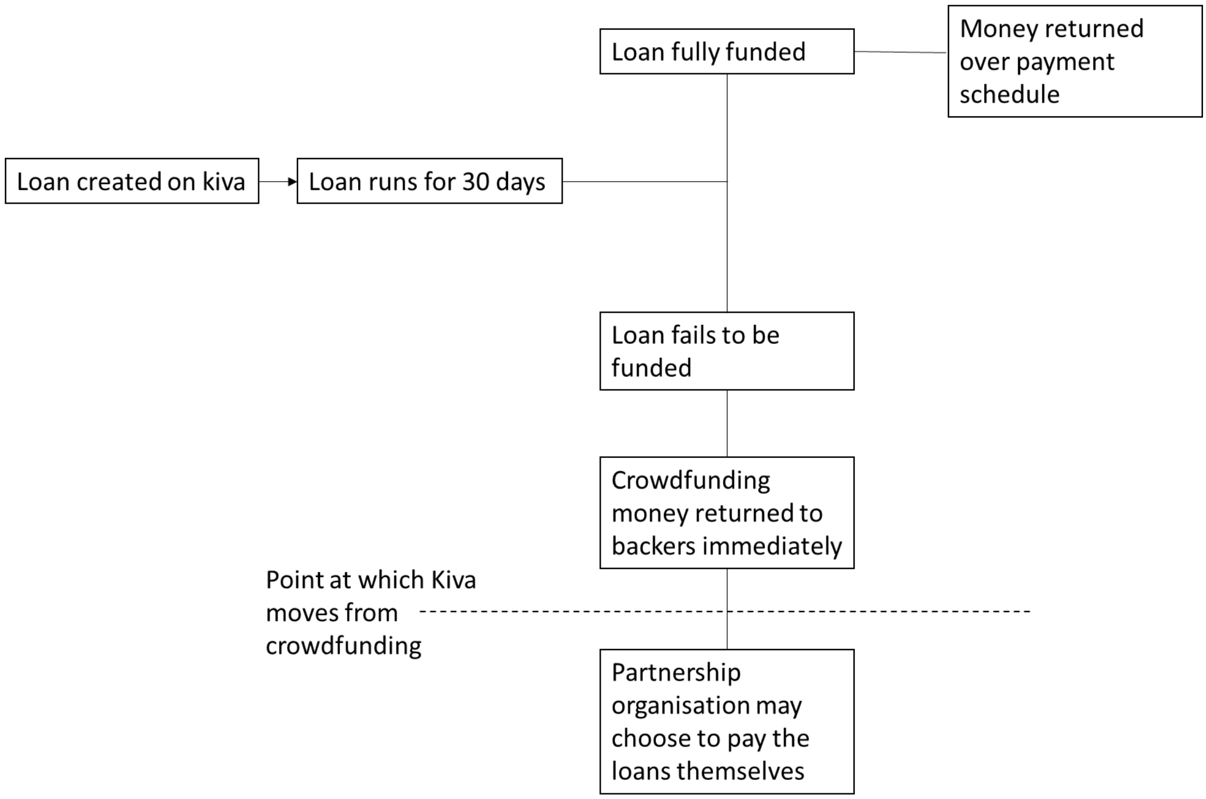


Figure 3-8 highlights a key issue with Kiva, that is the platform enables both crowdfunding and traditional financing to occur. If a project successfully reaches its funding goal, then crowdfunding is utilised to fund the project. However, if a project does not reach its funding goal the partnership organisation may choose to fund the project regardless of the outcome of the crowdfunding project. The partnership organisation uses their own funds to support projects, thus this is entirely separate from the crowdfunding process, thus it can be considered that Kiva enables two processes to occur, crowdfunding and traditional financing. For the purposes of this thesis we are only interested in the crowdfunding portion of Kiva.

This structure also encourages using the amount of money raised as the measure of success within Kiva for two reasons. Firstly, due to how failure to reach the funding goal may not equate failure in receiving funds, which reduces the effect of using this cut off point. Secondly due to how the outcome for backers in the event of failure is very similar to the outcome in success, in failure backers receive their funds immediately, in success backers receive their funds slowly over time, thus making the only effect of success on backers as receiving their funds more slowly.

3.4.1 Hypothesis and conceptual framework development for the Kiva model:

Utilising the theoretical framework developed within the literature review, the following hypotheses are developed, addressing, some of the previously highlighted key factors such as: creators signalling, backers social capital and competition within the platform.

3.4.2 Creators Signals

This section considers the different set of signals sent out by the partner organisation of the crowdfunding campaign. As previously stated, for the signal to be effective they must be observable, manipulatable and costlier for low-quality creators versus high-quality creators. The signals are all observable as they are freely visible on the Kiva website. However the other factors must be considered in a signal by signal case. Creators in Kiva refers to both the partnership organisations which facilitate the loan and the recipient of the loan, however for purposes of the development of the hypotheses the creator refers to the partnership organisation. As the creators signals identified within the dataset all relate to the signalling the quality of the partnership organisation, not the participant.

3.4.2.1 Experience

Two separate signals are examined in this sub-section both utilised as proxies for the level of experience of the creators (partnership organisation). The first signal considered is the amount of time the partnership organisation has been listed on Kiva. The second signal is the number of previously facilitated loans the partner organisation has carried out on Kiva. The first metric captures experience as expressed by the amount of time which has passed since the organization was listed on Kiva, this will be referred to as *temporal experience*. While the second expresses experience by the amount of past activity done on the platform, and this metric will be referred to as *capacity experience*. The impact of *temporal experience* is considered to have a positive impact on the success of creators on Kiva, utilising the arguments outlined within the experience section of the Kickstarter conceptual framework development (section 3.3.1).

The impact of the *capacity experience* is also considered to exert a positive impact on the success of creators on Kiva, expresed as the total amount of funds raised in each project. As the creators can utilise supporters from their past projects in subsequent campaigns (Skirnevskiy et al 2017), the initial connection on a crowdfunding platform between the creators and backer creates a linkage between both parties (Nahapiet and Sumantra, 1998). This connection can then be activated by the creator in support of their current campaign. Activation could occur through emails, direct messages or backer surveys (Skirnevskiy et al 2017). These links can be activated before the campaigns have begun and thus be used as early supporters of the next campaign (Zheng et al, 2014).

The two signals, discussed above, are both manipulatable. Temporal experience can be increased by spending additional time on the platform, capacity experience can be increased by running additional projects. These signals are also both costlier for low-quality projects, as more time and effort would be required to make them appear to be high quality projects. Therefore, these two experience signals can both be considered as effective and the following hypothesis on the proxy of experience is developed:

A1: Creators signalling increased experience has a positive impact on the amount of money raised in kiva.

3.4.2.2 Generosity

The element of human capital considered in this section is that of generosity of the partnership organisation captured via a proxy calculated on the average cost that the partnership organisation charges the loan participant for acting as its intermediary in Kiva, averaged across all participants a partnership organisation has assisted in securing funds. A lower average cost is considered to display a higher level of generosity by the partnership organisation, as the loan recipients on average will be charged a lower rate of interest.

The level of generosity is considered to have a positive impact on the success of a project. Rastogi (2000), considered how the value of generosity can be considered a component of a person's orientation of *pronoia*. Orientation towards *pronoia* enables effective collaboration within the members of the organisation and increases social capital generation outside the organisation. Thus, the increased functionality within the organisation and increased amount of social capital generation can both be assumed to increase the likelihood of a project succeeding in generating a larger amount of funding. Additionally, generosity can also be considered as exerting a positive impact by encouraging reciprocity from within a community (Gurven et al, 2000).

Generosity, as a signal, is manipulatable as it can be modulated by increasing or decreasing the interest rate received from the recipient of the loan. However, the signal may not be costlier for low quality partnerships versus high quality partnerships, as low-quality partnership organisation are free to set lower interest rates. In fact, low quality partnership organisation may find it easier to set lower interest rates than high quality partnerships, as high-quality partnership organisations may have increased cost ensuring the validity of their participants, leading to a required higher interest rate. Upon saying this, the author considered that the signal may not be effective, however the following hypothesis is still proposed, to test the validity of requiring lower cost signals:

A2: Signalling an increased level of generosity, by the partnership organisation, exerts a positive impact on the amount of funds raised, by the final project.

3.4.2.3 Signals Sent by the platform about the creator

One of the unique aspects of the crowdfunding platform Kiva, is that the platform itself sends a signal regarding the quality of the creator (partnership organisation). The signal is sent through the rating system, whereby the creator is rated between 0 and 5 stars by Kiva. With 5 stars demonstrating a highly trusted creator and zero stars demonstrating an untrustworthy creator. This signal is created by the platform and placed on the project page, thus the platform itself is engaging in signalling behaviour with the backers. In regard to the impact of the signal, the signal is expected to have a positive impact on success, due to how the stars can be seen as positive reviews left by the platform, positive reviews have been identified to increase online consumption (Cheng and Ho, 2015).

Furthermore, the reviews can be seen as effective signals as firstly, they are manipulatable as the platform can change the number of stars whenever they wish. Secondly, there are higher cost for low quality projects as there is no direct way for them to pay to increase their star count and can thus only achieve this through increased performance. For this reason, the signal can be seen as effective and thus the following hypothesis is proposed:

A3: The platform signalling increased level of support on the creator, exerts a positive impact on the final amount of funds raised, by the project.

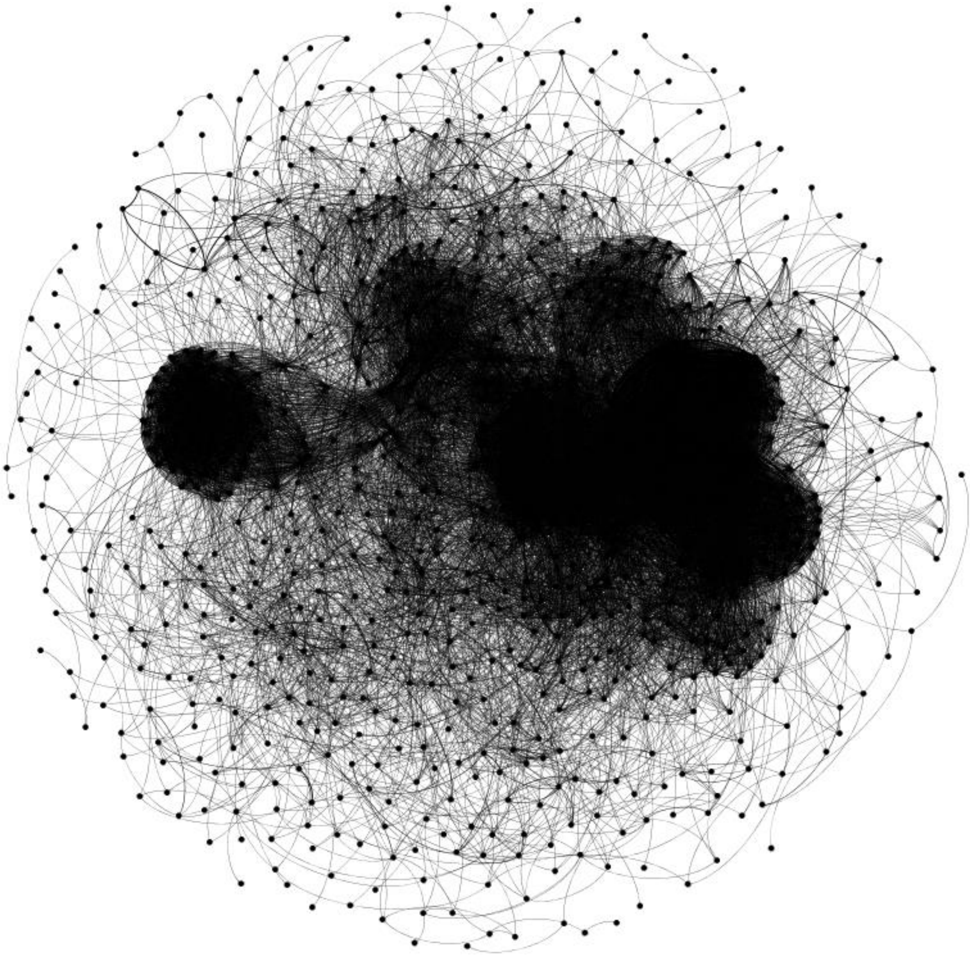
3.4.3 Social capital hypotheses

The following two hypotheses considers how social capital will be examined within the Kiva model. Looking at social capital within the platform itself and generated at a geographic level.

3.4.3.1 Social capital captured via latent projects links from shared backers

The impact of *internal social capital* of a project in Kiva is examined by considering the past behaviour of backers supporting the current project. Within Kiva, backers past behaviour can be identified within each project page. The past backing behaviour for each project was utilised to create a latent network of the crowdfunding platform. With the nodes of the network being the projects on Kiva, and the edges being formed when two nodes (projects) are being supported by the same backer. Therefore, if two projects were supported by the same backers, they would be linked within this latent network. If more than one backer supported both projects the weight of this link would be increased, so that the anlaysis will consider a weighted network of latent links between otherwise disconnected projects-nodes. The full network developed on the base of these above assumptions, linking any two projects if and only if they have joint backers, is displayed in Figure 3-9 below.

Figure 3-9 Network of Kiva project based on joint connections



This network enables the examination of the role of latent social capital of the backers; social capital that can then be utilised as a predictor for collective action (Burt, 2009). Increased capital within a network has been shown to increase the participation rate for the users of the network (Wasko and Faraj, 2005). Furthermore, the greater the number of times individuals interact within the network, the greater the likelihood that they begin to act in coordination with each other to achieve specific tasks (Marwell and Oliver, 1993). The latent social capital generated by the backers within the network, requires a specific way of capturing it, that goes beyond simple direct measures of, latent, connectivity.

For this specific latent network three separate centrality measures are captured *eigenvector centrality*, *betweenness centrality* and *closeness centrality*, three of the measures discussed in section 2.4.1.3. In this dissertation the latent social capital associated with each node-project, will be examined through its *eigenvector centrality*, in line with past usage outlined in (Borgatti et al, 1998). *Eigenvector centrality* was used as a measure of social capital at it captures the full impact of the co-operation among backers within the platform, as it includes not only the direct, one-hop, connections in the latent network that backers create among projects, but it also considers the indirect connections that each link carries, and the indirect connections of these indirections and so on. As each link in the network represents a backer who is shared between two projects, thus if two projects have multiple links, this can be seen to represent a group of backers who are jointly supporting those two projects and demonstrates that these group of backers must be interacting within the platform. The more interactions between these groups the more they are likely to coordinate together and thus have an increased impact on the success of the project (Marwell and Oliver, 1993). These backers will also be interacting in the surrounding projects, as both backers must be present in at least one of the surrounding projects. Thus, since the *eigenvector centrality* captures the impact of this interaction between the examined node and the surrounding nodes it can capture the impact of this co-operation and was utilised to measure the social capital of the project, as identified through the direct and indirect linkages created by the presence of shared backers. Therefore, increased levels of *eigenvector centrality* are considered to demonstrate increased levels of backer's interaction and thus increased *internal social capital* for the examined project both from the creator and from backers. In turns, *internal social capital* is considered to have a positive impact as discussed in section 3.3.5. Leading to the formulation of the following hypothesis:

B1: Higher levels of internal social capital within Kiva have a positive impact on the amount of funds raised.

Furthermore, Freeman (1978) identified that a different notion of centrality, *closeness centrality* can be seen as exerting two separate effects: that of the ability of the node to be independent of other nodes or that of the efficiency of the node to control access to other nodes. In line with other empirical work (Brandes et al, 2016; Powell et al, 1996; Rowley, 1997), a project's *closeness centrality* will be considered to represent the independence of the node within the Kiva latent network. A project with low *closeness centrality* has low levels of independence as the connection the the rest of the network will be restricted through a few other projects, while projects with high *closeness centrality* are far more independent as they have many nodes to access the network through. With nodes of *closeness centrality* of 1 being able to directly access all other nodes in the network and thus be completely independent of other nodes. The third notion of network centrality discussed above in section

2.4.1.3, *betweenness centrality* can be used to represent whether a node's ability to influence the spread of information through the network is important (Newman, 2005; Brandes et al, 2016). Thus if one can empirically find a positive impact between a project's *betweenness centrality* and the amount of money raised, it can be argued that a control of information within the network can affect the success of projects in raising loans on the Kiva platform.

3.4.3.2 Creators joint internal social capital with a region

This section considers if the past creation of internal social capital within a platform by other creators can positively impact on the success of the current project. It explores whether the creator of the current project utilises social capital generated by previous creators in supporting their project. This idea stems from how social capital can be tied to a specific organisation (Tillie, 2004), rather than a specific individual. Suggesting that this social capital can be utilised by different individuals by joining said organisation, so that, within the context of crowdfunding the creators may be able to benefit from the amount of social capital generated by past creators in support of their current project. In lieu of joining an organisation, instead it is considered as if creators in Kiva propose their loan within a specific geographic region and that they can benefit from the past social capital generated, within Kiva, for this specific region in support of their own current project. This is possible due to how a current loan records the number of previously created loans within the region, a metric this dissertation uses as a proxy for the total sum amount of social capital generated by all creators within a project's region. As increased localised social capital is considered to have a positive impact on success, this measure will also be considered to have a positive impact on success leading to the creation of the following hypothesis:

B2: Higher levels of social capital generated by previous creators within a geographic region have a positive impact on the amount of funds raised by projects located in the region.

3.4.4 Competition hypotheses: Competition within the platform

As previously discussed, increased competition is considered to have a positive or negative impact based upon the relative size of the positive and negative network externalities. In the case of Kiva, however, the author argues that the negative externalies are likely to be far larger than the positive ones. This is due to how on Kiva the partnership organisations (identified in this model as the creators) are rarely new participants to the platform and are, instead, participants regularly returning to the platform. Thus partnership organisations have already drawn additional participants to the platform and any extra positive network externality effect they have will be limited. This is further strengthened as Kiva has limited *external social capital* links, as projects don't have any direct links to social media, compared to Kickstarter which lets projects actively link in their Facebook connections. For these reasons, increased levels of competition are predicted to negatively impact the amount of funds in Kiva and the following hypothesis is proposed

C1: Increased amount of internal competition within the platform has a negative impact on the amount of money raised by a project.

In order to test this hypothesis, different variables are developed to capture the effects of increased competition. Firstly, competition can be measured utilising the number of competing firms on launch day, a measure suggested to be used in crowdfunding by Janku and Kucerova (2018). Alternatively, competition can be captured by utilising the HHI index values (Hirschman, 1980), a method suggested to be applicable in crowdfunding by Wessel et al (2017). Two separate competition indexes are developed: one based on competition in the sector, whereby the sector is selected by the partnership organisations when creating the project, and the second, based on competition from other projects launched by the partnership organisation. Finally, success can also have a spatial element in crowdfunding as argued in Gallemore et al (2019), as such competition can also be expressed in a geographic form, captured in the model by the number of competing loans within the same country of the project. All four of these measures are expected to exert a negative impact on the amount of money raised by a project on Kiva, in line with proposed hypothesis C1.

3.4.5 Kiva Conceptual framework

A unified consideration of the above hypotheses leads to the development of the Kiva conceptual framework, represented in the Figure 3-10 below.

Figure 3-10 Kiva conceptual framework

Positive	Social capital captured via centrality measures	Rating of project Provided by Kiva	Temporal Experience Capacity Experience Sustainability Generosity
	Backers	Platform	Creator's (partnership organisation)
Negative		Increased country, sector and launch competition	Increased competition from partners projects

This framework represents the expected effects of the different factors used to examine Kiva. For example, an increased level of generosity within the platform by the partnerships organizations is expected to have a positive impact on the amount of money raised by the project this organization is presenting. While increased level of competition is considered to exert a negative impact on the amount of money raised.

3.4.6 Data collection procedure

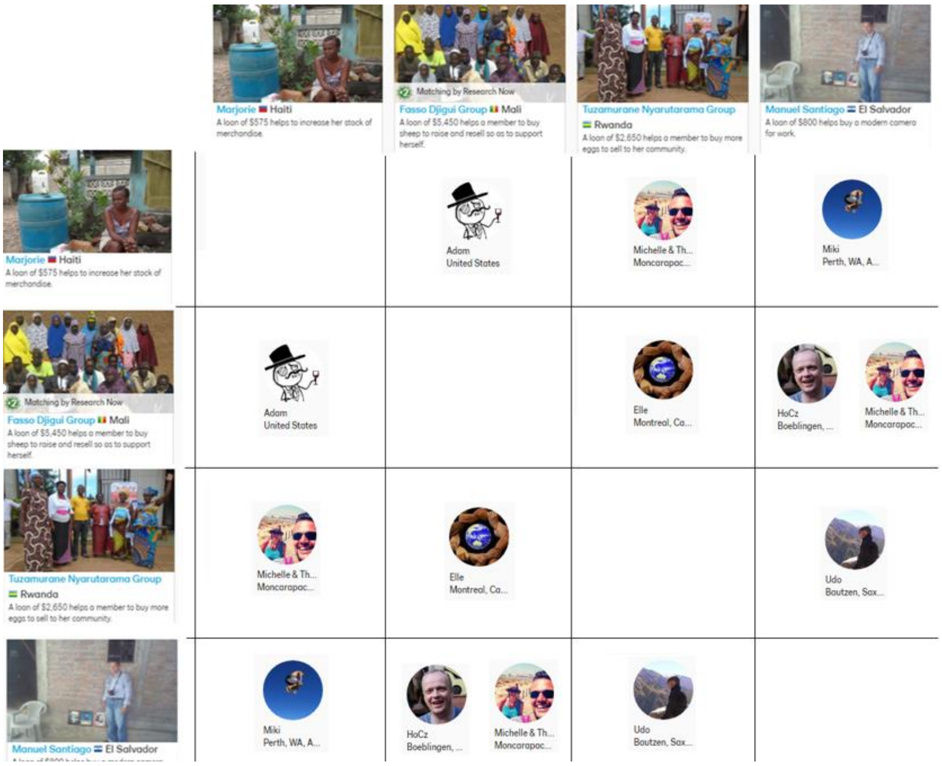
The data collection for the Kiva platform was carried out on the 16/05/2017, unlike Kickstarter, the entire data was collected in a single day, as the temporal funding pattern was not considered for this model. At the point of collection, projects had already concluded. The first step was in identifying a project which was recently completed on Kiva, and then in designing a selection process to capture projects which were completed within the month before the first examined project. This restriction was utilised to capture the impact of backers' interaction within a small timeframe. The first project was selected manually by utilising the previously completed projects and then moving to the most recent project which was also completed. Then, additional projects which had finished before the project were also identified and selected. This is possible as Kiva has an Identifier (ID) for each project contained within its URL, to find the project which occurred before the last project the ID simply had to be changed by 1 digit for example if the ID was 1400, the project before that would have the ID 1399. Therefore, utilising Excel and the Concatenate command enabled the URL of the past 1000 project to be created, over 1000 specific projects URLs were created. Due to restrictions in Import.io crawler projects with over 50 backers could not be accurately captured, and some projects had already been removed from Kiva. Hence, from the 1173 project originally captured only 1000 observation were retained and examined. Once the final list of URLs had been obtained, Import.io was utilised to obtain additional project's specific information from the actual project page. Additional secondary data was also collected on the partnership organisations through the utilisation of Postman and the Kiva API (Postman, 2019; Kiva, 2019c).

3.4.6.1 Adjacency matrix creation

The creation of the backers' latent network discussed in section 2.4.1.2.3, requires the creation of an adjacency matrix. In order to create an adjacency matrix of backers funding patterns, a specific crawler was designed to extract the group of backers who supported each campaign. These backers had the choice to keep their identity anonymous or to openly back the campaign. The crawler did not extract backers who had chosen to keep their identity anonymous. It extracted up to 50 non-anonymous backers from each campaign, the key to achieving this was the use of manual x-path, this a system for identifying key elements of a web within the Import.io framework. After they were extracted an adjacency matrix was constructed of all 1000 projects. Projects were then connected or not connected based upon if they shared a joint backer.

A multi-step process utilising Countifs functions within Excel was used to create an adjacency matrix which showed which projects shared joint backers. Then the links in the adjacency matrix were weighted by the number of joint backers between any two projects. The data was transformed into three columns of source target and weight and transferred to Gephi for the generation of the network and to calculate the *eigenvector centrality*. Figure 3-11 below shows an example of how projects could be connected in an adjacency matrix, where columns and rows are identified by a project page's snapshot and their links by the avatar of one or multiple shared backers.

Figure 3-11 Adjacency matrices of kiva projects



3.4.6.2 Data restriction

Only projects with funding goals of over 50 dollars were utilised in the examination of the results, which lead to 15 projects being deleted from the model. This restriction aligned itself with restrictions utilised within the literature, specifically by Mollick (2014) and Janku and Kucerova (2018).

3.4.7 Kiva econometric analysis

The logistic regression previously utilised to analyse the Kickstarter data would not have been appropriate for analysis in the Kiva model. In the Kickstarter's model the dependent variable, success or failure, was dicotomic, while in the Kiva case there is no such restriction as the amount raised by a project can take any positive value, being the amount of funding raised necessarily above or equal to 0. Therefore, an alternative approach has to be considered which is more suitable for this specific set of dependent and explanatory variables. OLS was initially considered through examination of the dataset and discovering that the models which would be generated would satisfy the Gauss-Markov assumptions and thus provide the best linear unbiased estimators. Furthermore, a truncated regression was considered to avoid misspecification due to the actual observations of the dependent variable, amount of money raised within Kiva, being necessarily truncated at zero.

Ordinary least squares (OLS) estimator can be utilised to obtain estimates, $\hat{\beta}$, of the true parameters of a linear regression. For example, if the dependent variable y_i is a liner function of the explanatory variables x_i, with some unobserved error terms, the unknown true relation can possibly be expressed in the following equation.

$$y_i = \alpha + \beta_1 x_{1i} + \beta_2 x_{i2} \dots . + \varepsilon_i$$

Ordinary least squares can then be utilised to calculate estimators $\hat{\beta}$ of the population parameters capturing the scalar impact of the explanatory variables on the dependent variable.

The Gauss-Markov assumptions are a set of assumptions for the linear regression model, such that under the condition that they are satisfied, OLS will provide the best linear unbiased estimators. These assumptions are as follows:

1) $E[\varepsilon_i] = 0$.

2) [$\varepsilon_1, \dots, \varepsilon_n$] and [$x_1, \dots, x_n$] are independent

3) Var(ε_i) $= \sigma^2$

4) cov($\varepsilon_i, \varepsilon_j$) $= 0: i \neq j$

5) No perfect Multicollinearity

Therefore, if one can show that these 5 Gauss Markov assumptions are satisfied, then ordinary least squares would produce BLUE estimators of the true unknown population parameters. The following sections considers the specific procedures which were utilised to test whether the Gauss-Markov assumptions were satisfied relative to the specific conditions which could be problematic for this model.

3.4.7.1 Testing for multicollinearity

Multicollinearity is a problem which occurs whereby the correlation between two explanatory variables is too high, thus making it impossible to distinguish the influence of either variable upon the dependent variable. Non-perfect multicollinearity itself does not violate the Gauss-Markov but should be reduced as it may increase the variance of the estimators. Multicollinearity was tested for using the Vector Inflation Factor (VIF) Stata command and is reported for the models utilised.

3.4.7.2 Dealing with possible Heteroscedasticity

Heteroscedasticity considers the problem that can occur if the variation of the error terms varies across the observations. With heteroscedasticity, the OLS estimator will be inefficient. As with heteroscedasticity, only the standard errors are biased, not the coefficients, if alternate standard errors can be found, heteroscedasticity no longer impact the efficiency of the estimator. Therefore, to address this potential problem, robust standard errors are utilised, a method suggested by White (1980). This is carried out in Stata by using the `robust` option while carrying out the regression options. For its implementation in Stata, please refer to the syntax document for Kiva appendix item 7.6.

3.4.7.3 Omitted Variable Bias

An omitted variable bias can occur if a relevant explanatory variable correlated both with the dependent variable and one or more included independent variables, is not included in the model which leads to the estimators of the included correlated dependent variables becoming biased. In order to test for this within the Kiva Regression, the Ramsey RESET test was utilised, which runs an F-test under the null hypothesis that there is omitted variable bias. This test is run in Stata using the `ovtest` command after the regression has been carried out. For its implementation in Stata, please refer to the syntax document in section (7.6).

3.4.7.4 Truncated regression

Allison et al (2014) have previously used OLS to examine Kiva. They utilised OLS to examine how factors impacted upon the amount of time it took for projects on Kiva to reach their funding goal. Moreover, OLS has also been utilised within the wider crowdfunding literature (Calic and Mosakowski, 2016; Mollick and Nanda, 2015).

However, the problem with utilising OLS in our analysis of the determinants of the amount raised by the projects, is that Kiva projects cannot raise negative amounts of money. Thus, the dependent variable of the models is truncated at 0 and if this is not adapted for, this could cause a critical model misspecification error (Heckman, 1979). To overcome this problem a truncated regression approach can be carried out which overcomes this misspecification error, by restricting the sample and the residuals to values which are positive. As log values are utilised this restricts all values of amount raised to being above 1 dollar.

3.4.8 Kiva model definition:

The Kiva dataset is examined in four different models, all of the models utilised logarithms (natural logarithms) as weights in order to overcome omitted variable bias. The details of the models are as follows:

3.4.8.1 Model 1: Signals only model

This model considers all of the variables which can be identified as signals sent between the backers, the creators and the platform itself.

The dependent variable is:

Yi= Amount of money raised for project i

$$\mathrm{Log\ Yi} = \alpha + \beta_1 \mathrm{logGenerosity} + \beta_2 \mathrm{logTemporal\ Experience} + \beta_3 \mathrm{Capacity\ Experience} + \beta_4 \mathrm{LogRating} + \varepsilon_i$$

3.4.8.2 Model 2: Signals and social capital:

The second model adds the network centrality measurements which capture the impact of social capital in the model.

$$\begin{aligned}\mathrm{Log\ Yi} = \ & \alpha + \beta_1 \mathrm{logGenerosity} + \beta_2 \mathrm{logTemporal\ Experience} \\ & + \beta_3 \mathrm{logCapacity\ Experience} + \beta_4 \mathrm{logRating} + \beta_5 \mathrm{logEigen\ Centrality} \\ & + \beta_6 \mathrm{logBetweeness\ Centrality} + \beta_7 \mathrm{Closeness\ Centrality} + \varepsilon_i\end{aligned}$$

3.4.8.3 Model 3: Complete OLS Model

The third model introduces the competition variables and thus the model contains all examined variables.

$$\begin{aligned}Log\ Yi = \ & \alpha + \beta_1 logGenerosity + \beta_2 logTemporal\ Experience \\ & + \beta_3 logCapacity\ Experience + \beta_4 logRating + \beta_5 logEigen\ Centrality \\ & + \beta_6 logBetweeness\ Centrality + \beta_7 Closeness\ Centrality \\ & + \beta_8 logActive\ Loans + \beta_9 logLaunch\ Competition \\ & + \beta_{10} logSector\ index + \beta_{11} logPartner\ index + \varepsilon_i\end{aligned}$$

3.4.8.4 *Model 4: Kiva Truncated regression*

The fourth model uses all of the variables from the complete model, this truncates the model when the dependant value is 0. Thus, as the dependant variable is the natural log of the amount raised this thus captures all positive values of above 1. And thus the model is defined as follows:

$$Log\ Yi = \alpha + \beta_1 logGenerosity + \beta_2 logTemporal\ Experience + \beta_3 logCapacity\ Experience + \beta_4 logRating + \beta_5 logEigen\ Centrality + \beta_6 logBetweeness\ Centrality + \beta_7 Closeness\ Centrality + \beta_8 logActive\ Loans + \beta_9 logLaunch\ Competition + \beta_{10} logSector\ index + \beta_{11} logPartner\ index + \varepsilon_i$$

With the restriction $Log\ Yi > 1$ and $Log\ \bar{y}i > 1$

3.4.9 List of all variables in Kiva

The following table, provides a full list of all variables utilised in the Kiva models.

Table 3.8 List of all Kiva Variables

Variable	Variable Output	Variable description
Amount raised	Natural logarithm of the amount raised by the end of the project	The natural logarithm of the total amount of money raised by crowdfunding for the examined projects. This is the dependent variable for all of the Kiva models.
Generosity	Natural logarithm of the average interest rate charged to the individual seeking the loan by the partnership organisation.	The natural logarithm of the average interest rate charged by the partnership organisation to the individual seeking loans. This variable is based of all past loans from the organisation and not just the loans within the dataset.
Temporal Experience	Natural logarithm of the time that the partnership organisation has spent on Kiva.	The natural logarithm of the amount of time in months which a partnership organisation has spent on Kiva.
Capacity Experience	Natural logarithm of the number of projects that the partnership organisation has previously funded on Kiva.	The natural logarithm of the number of successfully provided loans which a partnership organisation has facilitated within Kiva, since the creation of the partnership organisation.
Country Funds	Natural logarithm of the amount of funds lent within the country on Kiva.	The natural logarithm of the amount of funds that have been lent by Kiva within the country of the individual seeking funds.
Active Loans	Natural logarithm of the number of active loans within the country.	The natural logarithm of the amount of active loans, loans which have been funded and are currently being repaid within the specific country of the individual seeking funds.
Rating	Natural logarithm of the rating provided by Kiva to the partnership organisation.	The rating is between 0-5 stars and is provided by Kiva to all partnership organisation.

Eigen vector Centrality	The Eigen vector centrality of the project node within the latent network of Kiva.	Captured via considering the Eigen vector centrality of the project in the latent network formed by joint backers. Eigen vector centrality is used to examine the effects of internal social capital within the model.
Betweenness centrality	The natural logarithm of the Betweenness centrality of the project node within the latent network of Kiva.	Captured via considering the Betweenness centrality of the project in the latent network formed by joint backers. Betweenness centrality is utilised as a covariate within the mode.
Closeness centrality	The natural logarithm of the Closeness centrality of the project node within the latent network of Kiva.	Captured via considering the Closeness centrality of the project in the latent network formed by joint backers. Closeness centrality is utilised as a covariate within the mode.
launch comp	The natural logarithm of the level of competition on launch day.	Launch competition was captured via the number of other projects which were launched within the same day as the examined project.
sector index	The natural logarithm of the level of competition within the sector.	An index value measuring competition between projects on Kiva within the same sector as chosen by the individual seeking the loan. Index values are between 0 and 10000, with higher index values showing lower levels of competition.
partner index	The natural logarithm of the level of competition for each partnership organisation.	An index value measuring competition between projects on Kiva within the same partnership organisation. As each partnership organisation is funding multiple projects, these can be seen to compete with each other. Index values are between 0 and 10000, with higher index values showing lower levels of competition.

3.4.10 Kiva summary statistics

The table below provides summary statistics for the variables utilised within the Kiva models.

Table 3.9 Summary statistics for Kiva variables

	Mean	*Std.*	*Min*	*Max*
Amount raised	5.998845	0.758075	4.317488	8.517193
Generosity	-1.09146	0.362618	-2.99573	-0.41552
Temporal Experience	4.212621	0.455956	2.302585	4.875197
Capacity Experience	9.922996	1.292193	3.828641	12.05235

Country Funds	17.04178	1.206516	12.79504	18.30839
Active Loans	4.559813	1.508066	0	6.586172
Rating	1.033783	0.379592	0	1.504077
Eigen vector Centrality	-3.28645	2.171032	-9.26463	-.0498581
Betweenness centrality	1.808549	6.735709	-9.21034	9.287293
Closeness centrality	-0.91877	0.266306	-1.5976	-.6319214
launch comp	4.886813	1.048697	0	5.666427
sector index	4.862394	0.757686	4.208949	8.19849
partner index	6.225386	0.999128	4.698356	9.21034

3.5 Methodology conclusion

This chapter has outlined the data collection and analysis procedure for both platforms examined within this thesis. This is summarised in Table 3.10 below:

Table 3.10 Summary of the two models

	Kickstarter	*Kiva*
Subdivide type	Reward-based	Lending-based
Data-type	Cross sectional	Cross Sectional
Observations	54193	1000
Measure of Success	Reaching the funding goal	Amount of funds raised
Analysis method	Logistic regression model	Truncated Regression

4 Empirical Results

This chapter explores the results of the models and their impact on the proposed hypotheses developed in this thesis, enabling the main findings to be discussed in the following chapter, the structure of the chapter as follows:

1) Kickstarter model's results: Explores the results of the key different Kickstarter logistic models, focussing on the full model results for both the main and restricted models, while providing a summary of all other examined models. The goodness of fit for both the main and restricted model are also considered in this section.

2) Kickstarter's results by hypothesis: Examines the impact of the results of the econometric model upon the hypotheses proposed for the Kickstarter model. Illustrating whether the hypotheses are supported by the empirical evidence. Moreover, this section begins to highlight the potential findings of the thesis for further discussion in the findings and recommendations section.

3) Kiva model's results: Provides the results of the two key ordinary least squares regressions utilised to examine the Kiva crowdfunding platform. Examining the goodness of fit of the models and considering if multicollinearity or omitted variable bias was problematic within the models.

4) Kiva results by hypothesis: Examines the impact of the results of the models based upon each of the hypotheses developed in the methodology chapter 3. Beginning to highlight the potential implications of these results and comparing them with the results from the Kickstarter model, leading into further discussion within the findings and recommendations section of the thesis.

4.1 Kickstarter model results

This section considers all the results from the logistic model examining Kickstarter. Before considering the specific impact on the relevant hypotheses, a general analysis is carried out on the main and restricted models. The main model is used for examining the majority of the hypotheses. While the restricted model is utilised in examining the impact of multiple competition measures which required a reduction in the dataset to create unbiased results.

4.1.1 Main Model results

The main model considers all variables except the competition variables which require a restricted version of the dataset. It is thus defined as follows:

$$Y_i = \begin{cases} 1 \; if \; a \; project \; successfully \; reaches \; its \; funding \; goal \\ 0 \; if \; a \; project \; does \; fails \; to \; reach \; its \; funding \; goal \end{cases}$$

$$P(Y_i) = 1 =$$

$$\alpha + \beta_1 logAmbition + \beta_2 Confidence + \beta_3 Experience + \beta_4 LogTrustworthiness + \beta_5 Impatience + \beta_6 LogCampaign\_Comments + \beta_7 Early\_Funding + \beta_8 Early\_Backing + \beta_9 Early\_Average\_Pledge + \beta_{10} Reward\ Levels + \beta_{11} Global\ Rewards + \beta_{12} Average\ wait\ term + \beta_{13} Facebook\_Shares + \beta_{14} Reciprocity + \beta_{15} LaunchCompetition + \beta_{16} Launch\_Comp\_Category + \varepsilon_i$$

With the model results presented on the following page:

Table 4.1 Kickstarter Main Model Logistic regression

Success or failure	Coef.	St.Err.	t-value	p-value	[95% Confidence Interval]		Sig
Ambition	-1.382	0.018	-75.10	0.000	-1.418	-1.346	***
Confidence	-0.00000649	0.000	-8.01	0.000	0.000	0.000	***
Experience	0.0393	0.007	5.44	0.000	0.025	0.054	***
Trustworthiness	0.893	0.018	49.49	0.000	0.857	0.928	***
Impatience	-0.00128	0.002	-0.80	0.425	-0.004	0.002	
Campaign Comments	0.707	0.017	41.80	0.000	0.674	0.741	***
Early funding	-3.5E-07	0.000	-0.17	0.867	0.000	0.000	
Early backing	0.00103	0.000	3.91	0.000	0.001	0.002	***
Early average pledge	0.615	0.015	40.59	0.000	0.586	0.645	***
Reward levels	0.0469	0.004	11.94	0.000	0.039	0.055	***
Global rewards	-0.0433	0.004	-10.32	0.000	-0.052	-0.035	***
Average wait time	-0.00158	0.000	-8.47	0.000	-0.002	-0.001	***
Facebook shares	0.784	0.013	61.27	0.000	0.759	0.809	***
Reciprocity	-0.00673	0.001	-8.21	0.000	-0.008	-0.005	***
Launch competition	2E-05	0.000	6.88	0.000	0.000	0.000	***
Launch competition in Category	-1e-04	0.000	-11.59	0.000	0.000	0.000	***
Google trend in category	0.00391	0.001	4.82	0.000	0.002	0.005	***
Constant	3.449	0.121	28.58	0.000	3.212	3.685	***

Mean dependent var	0.322	SD dependent var	0.467
Pseudo r-squared	0.638	Number of obs	54193.000
Chi-square	43500.800	Prob > chi2	0.000
Akaike crit. (AIC)	24665.063	Bayesian crit. (BIC)	-565895.07

*** *p<0.01, ** p<0.05, * p<0.1*

From Table 4.1 it can be seen that the majority of the variables are significant with only Impatience and Early funding not having a significant effect on the probability of successful funding a campaign. Secondly, the Pseudo R-Squared value of 0.6385 can be deemed as a good fit for the model, as Domencich and McFadden (1975) argued that any value larger than or between 0.2-0.4 could be deemed as excellent fit for a logit model.

Thirdly the chi-squared probability of zero demonstrates that the variables are jointly significant in impacting the success and failure of a Kickstarter project. The possibility of multicollinearity was then considered, of note you cannot directly carry out a variance inflation factor (VIF) analysis of a logit model in Stata, therefore, to utilise this test a standard Ordinary least squares regression was carried out on the variables, before the VIF command was utilised, which will provide accurate testing of multicollinearity between the variables.

Table 4.2 Kickstarter main model variance inflation factor

	VIF	1/VIF
Early Backing	2.589	.386
Early Funding	2.506	.399
Reward levels	2.3	.435
Facebook Shares	2.181	.458
Trustworthiness	2.132	.469
Global rewards	2.11	.474
Campaign comments	2.068	.484
Early Average Pledge	1.632	.613
Ambition	1.476	.677
Confidence	1.322	.757
Experience	1.19	.841
Reciprocity	1.177	.849
Average wait time	1.12	.893
Launch competition category	1.084	.923
Impatience	1.081	.925
Google trend in category	1.035	.966
Launch competition	1.023	.978
Mean VIF	1.649	.

Table 4.2 above shows the VIF of the main model. VIF is the ratio of the variance of an explanatory variable i.e. $\widehat{\beta_\iota}$ fitted against the full model to the variance of the same explanatory variables $\widehat{\beta_\iota}$ fitted only by itself. Therefore, the smallest value that VIF can take is one, demonstrating no collinearity between any of the explanatory variables. However, in practice there tends to always exist some levels of collinearity between the variables, only values of 5 or greater are considered to be problematic (James et al, 2013). Therefore, as none of the values exceed 2.59 multicollinearity is not a problem within this model.

The presence of significant outliers in the data was addressed through the removal of any project which had a funding goal of over 1 million dollars, as these were seen as unrealistic. However, it is possible that other variables may contain outliers affecting the results, thus in order to consider if this was true a winsorization approach of limiting the top 99 and 95 percent of all variables was utilised. This process enables outliers to be addressed by setting those specific values down to a specific outlier, without having to reduce the number of observations within the dataset (Ghosh and Vogt, 2012). Two tables, using these procedures, can be seen in appendix section 7.7. Although altering some coefficients, using these procedures do not alter the significance or signs of the relevant coefficients. Thus, reducing/ removing the outliers by this process would not greatly affect the analysis of the hypotheses.

Table 4.3: Predicting the accuracy of the main model

	TRUE		
Classified	D	~D	Total
+	15147	2565	17712
-	2319	34162	36481
Total	17466	36727	54193
Sensitivity		Pr(+| D)	86.72%
Specificity		Pr(-|~D)	93.02%
Positive predictive value		Pr(D| +)	85.52%
Negative predictive value		Pr(~D| -)	93.64%
False + rate for true ~D		Pr(+|~D)	6.98%
False - rate for true D		Pr(-| D)	13.28%
False + rate for classified		Pr(~D| +)	14.48%
False - rate for classified		Pr(D| -)	6.36%
Correctly classified		90.99%	

Table 4.3 above shows the predicting accuracy of the main model, with the overall percentage of correctly predicted outcomes being 90.99 percent, as denoted by the “correctly

classified" row at the bottom of the table. This can be calculated by summing the number of correctly predicted successes and the number of correctly predicted failures over the total number of predictions. The model's predictive ability is decomposed further into multiple prediction categories.

Within the table "D" refers to projects which were observed to be successful, while "~D" refers to projects which were observed to be unsuccessful. The first section of the table demonstrates the amount of correctly classified results, with the second row, denoted by "+", demonstrating that 15147 successes were correctly predicted as successes, while 2565 failures were incorrectly predicted as success. Therefore 15147 projects out of the 17712 predicted to be successful by the model were in fact successful. Thus, there is a *positive predictive value* of 85.52 percent as donated further down the table. Conversely, the third row, denoted by "-", provides the ability of the model at predicting failure, it correctly predicts 34162 failures as failures, while incorrectly predicting 2319 successes as failures. Thus, leading to a *negative predictive value* of 93.64 percent as donated further down the table. Additionally, the *sensitivity* and *specificity* can also be calculated. With *sensitivity* referring to the percentage of successful projects which are successfully predicted to be successful, in this case 86.72 percent, as 15147 successes were predicted as successes and 2319 were successes predicted as failures. While *specificity* refers to the percentage of failures which were correctly predicted, in this case 93.02, as 34162 failed projects were successful predicted as failures and 2565 failure were predicted as successes. These results taken together, show that the model is better at predicting failures correctly than it is at predicting successes, as shown by the higher level of *specificity*.

Additionally, Table 4.3 can also be utilised to examine the probability of predicting successes and failures based upon the result being failures or successes. For example, the probability of a product being predicted as a success when it is a failure is 6.98 percent. Conversely the probability of a product being predicted as a failure when it is successful is 13.28 percent. Demonstrating that the model is more likely to incorrectly predict a failure as a success than a success as a failure. These values can be utilised both in examining an individual model and in comparison, across models.

4.1.2 Comparison between the Main model and social capital model.

In order to consider whether the main model should be utilised in determining success and failure on Kickstarter, the model was compared to alternative model specifications. The first specification compared to the main model was the social capital model which did not include the launch competition explanatory variables and was defined as:

$$Y_i = \begin{cases} 1\ if\ \ a\ project\ successfully\ reaches\ its\ funding\ goal \\ 0\ if\ \ \ a\ project\ does\ fails\ to\ reach\ its\ funding\ goal \end{cases}$$

$$P(Y_i) = 1 =$$

$$\alpha + \beta_1 logAmbition + \beta_2 Confidence + \beta_3 Experience + \beta_4 LogTrustworthiness + \beta_5 Impatience + \beta_6 LogCampaign\_Comments + \beta_7 Early\_Funding + \beta_8 Early\_Backing + \beta_9 Early\_Average\_Pledge\ + \beta_{10} Reward\ Levels + \beta_{11} Global\ Rewards + \beta_{12} Average\ wait\ term + \beta_{13} Facebook\_Shares + \beta_{14} Reciprocity + \ \varepsilon_i$$

Table 4.4 below demonstrates the differences between the main model and the social capital model, providing different measures of pseudo R squared measures which can be utilised to consider the goodness of fit of the logit models. Additionally, the Bayesian information criterion (BIC) is provided, this measure developed by Gideon E. Schwarz can be utilised in model selection, with the lower BIC value being preferred between the two models (Schwarz, 1978). The formula for BIC is as follows:

$$BIC \equiv -2ln\mathcal{L}_{\max} + klnN$$

Whereby $\mathcal{L}_{\max}$ is the maximum likelihood possible to be achieved in the model, k is the number of parameters and N is the number of datapoints used in the fit (Liddle 2007). Furthermore, the Akaike information criterion (AIC), is also included, this is a similar measure to BIC, with a lower AIC value demonstrating a preferred model (Akaike, 1974). The Formula for AIC is as follows:

$$AIC \equiv -2ln\mathcal{L}_{\max} + 2k$$

Similar to BIC $\mathcal{L}_{\max}$ is the maximum likelihood possible to be achieved in the model and k is the number of parameters (Liddle 2007).

Table 4.4 Comparing the main model to social capital model

	Main model	*Social capital model*	*Difference*
N	54193	54193	0
Log-Lik Intercept Only	-34064.931	-34064.931	0
Log-Lik Full Model	-12314.531	-12412.446	97.914
D	24629.063(54175)	24824.891(54178)	-195.829(-3)
LR	43500.800(17)	43304.972(14)	195.829(3)
Prob > LR	0	0	0

McFadden's R2	0.638	0.636	0.003
McFadden's Adj R2	0.638	0.635	0.003
Maximum Likelihood R2	0.552	0.55	0.002
Cragg & Uhler's R2	0.771	0.769	0.002
McKelvey and Zavoina's R2	0.891	0.891	0
Efron's R2	0.693	0.69	0.003
*Variance of y**	30.261	30.171	0.09
Variance of error	3.29	3.29	0
Count R2	0.91	0.908	0.001
Adj Count R2	0.72	0.716	0.005
AIC	0.455	0.459	-0.004
*AIC*n*	24665.063	24854.891	-189.829
BIC	-565895.071	-565731.943	-163.128
BIC'	-43315.495	-43152.368	-163.128

Difference of 163.128 in BIC' provides very strong support for the main model.

Table 4.4 above demonstrates that across all pseudo R Squared measures the pseudo R squared of the main model is higher than the pseudo R squared of the Social capital model. Additionally, both the AIC and the BIC measures are lower indicating support for utilising the main model over the usage of the social capital model.

Furthermore, the utilisation of the main model is supported through an examination of the predictive ability of the social capital model as shown in Table 4.5 below.

Table 4.5 Predictive ability of social capital model

	TRUE		
Classified	D	~D	Total
+	15111	2608	17719
-	2355	34119	36474
Total	17466	36727	54193
Sensitivity		Pr(+| D)	86.52%
Specificity		Pr(-|~D)	92.90%
Positive predictive value		Pr(D| +)	85.28%
Negative predictive value		Pr(~D| -)	93.54%
False + rate for true ~D		Pr(+|~D)	7.10%
False - rate for true D		Pr(-| D)	13.48%

False + rate for classified +	Pr(~D| +)	14.72%
False - rate for classified -	Pr(D| -)	6.46%
Correctly classified 90.84%		

Comparing Table 4.5 and Table 4.3 demonstrates that in every single aspect of predictive ability the main model is better at predicting than the social capital model. Further supporting that the main model should be utilised in the examination of the proposed hypotheses.

4.1.3 Restricted model results

The following section considers the restricted model, which had reduced observations due to how the competition indexes would be underestimated if the first or last sixty days of the dataset was included reducing the observations from 54193 to 42277. This is necessary due to how projects have a maximum duration of sixty days, thus a project which was launched on the first day could be competing with projects from before the start of the dataset, thus by dropping the first and last sixty days of observations competition effects are not underestimated. The restricted model was defined as the following:

$$Y_i = \begin{cases} 1\ if\ a\ project\ successfully\ reaches\ its\ funding\ goal \\ 0\ if\ a\ project\ does\ fails\ to\ reach\ its\ funding\ goal \end{cases}$$

$$P(Y_i) = 1 =$$

$$\alpha + \beta_1 logAmbition + \beta_2 logConfidence + \beta_3 Experience + \beta_4 LogTrustworthiness + \beta_5 Impatience + \beta_6 LogCampaign\ Comments + \beta_7 Early\ Funding + \beta_8 Early\ Backing + \beta_9 Early\ Average\ Pledge\ + \beta_{10} Reward\ Levels + \beta_{11} Global\ Rewards + \beta_{12} Average\ wait\ term + \beta_{13} Facebook\ Shares\ + \beta_{14} Reciprocity + \beta_{15} LaunchCompetition + \beta_{16} Launch\ Competition\ Category + \beta_{17} Google\ trend\ of\ category + \beta_{18} City\ index + \beta_{19}\ Country\ index + \beta_{20} Category\ index + \beta_{21} Kick\ index + \varepsilon_i$$

Table 4.6: Restricted model results

Success or Failure	Coef.	St.Err.	t-value	p-value	[95% Confidence Interval]		Sig
Ambition	-1.431	0.022	-66.46	0.000	-1.473	-1.388	***
Confidence	-0.00000658	0.000	-7.10	0.000	0.000	0.000	***
Experience	0.0469	0.008	5.55	0.000	0.030	0.063	***

Trustworthiness	0.945	0.021	45.26	0.000	0.904	0.986	***
Impatience	-0.00624	0.002	-3.28	0.001	-0.010	-0.003	***
Campaign Comments	0.748	0.019	38.74	0.000	0.711	0.786	***
Early Funding	2.07E-06	0.000	0.95	0.343	0.000	0.000	
Early Backing	0.00044	0.000	1.72	0.086	0.000	0.001	*
Early Average Pledge	0.594	0.017	34.37	0.000	0.560	0.628	***
Reward levels	0.0445	0.004	10.09	0.000	0.036	0.053	***
Global rewards	-0.0406	0.005	-8.43	0.000	-0.050	-0.031	***
Average wait time	-0.00201	0.000	-9.35	0.000	-0.002	-0.002	***
Facebook Shares	0.804	0.015	54.38	0.000	0.775	0.833	***
Reciprocity	-0.00773	0.001	-8.20	0.000	-0.010	-0.006	***
Launch Competition	1E-05	0.000	4.25	0.000	0.000	0.000	***
Launch Competition Category	-0.000106	0.000	-11.42	0.000	0.000	0.000	***
Google trend of category	0.00739	0.001	7.49	0.000	0.005	0.009	***
City index	-5E-05	0.000	-9.24	0.000	0.000	0.000	***
Country index	1.87E-05	0.000	0.88	0.380	0.000	0.000	
Category index	-0.000249	0.000	-5.71	0.000	0.000	0.000	***
Kick index	0.000178	0.000	5.92	0.000	0.000	0.000	***
Constant	4.438	0.137	32.43	0.000	4.170	4.706	***

Mean dependent var	0.338	SD dependent var	0.473
Pseudo r-squared	0.652	Number of observations	42277.000
Chi-square	35222.516	Prob > chi2	0.000
Akaike crit. (AIC)	18882.900	Bayesian crit. (BIC)	-431261.296

*** *p<0.01, ** p<0.05, * p<0.1*

From Table 4.6 multiple factors can be considered. Firstly, the majority of the variables are significant with only Early backing, Early funding and country index not having a significant effect on the probability of successful funding a campaign. Secondly, the Pseudo Squared value of 0.652 can be deemed as a good fit for the model and is larger than the 0.6385 value of the main model. Thirdly the chi-squared probability of zero demonstrates that the variables are jointly significant in impacting the success and failure of a crowdfunding project. The possibility of multicollinearity in the additional variables was then considered.

Table 4.7 Restricted model VIF test

	VIF	1/VIF
Early Backing	2.679	.373
Early Funding	2.6	.385
Reward levels	2.318	.431
Facebook Shares	2.222	.45
Global rewards	2.155	.464
Trustworthiness	2.146	.466
Campaign Comments	2.079	.481
Early Average Pledge	1.678	.596
Ambition	1.488	.672
Confidence	1.322	.756
Experience	1.195	.837
Reciprocity	1.185	.844
Average wait time	1.127	.888
Category index	1.111	.9
Impatience	1.107	.903
Kick index	1.103	.907
Launch Comp Category	1.085	.922
Google trend of category	1.069	.936
City index	1.05	.952
Country index	1.046	.956
Launch competition	1.015	.985
Mean VIF	1.561	.

As the VIF value of the explanatory variables does not exceed the boundary level of 5 multicollinearity is not observed within the restricted model (James et al, 2013), furthermore, the predictive ability of the model is also considered in Table 4.8 below.

Table 4.8 Restricted model predictive ability

	TRUE		
Classified	D	~D	Total
+	12508	2022	14516
-	1761	26006	27761
Total	14269	28008	42277

Sensitivity	Pr(+ D)	87.66%
Specificity	Pr(-~D)	92.85%
Positive predictive value	Pr(D +)	86.20%
Negative predictive value	Pr(~D -)	93.66%
False + rate for true ~D	Pr(+~D)	7.15%
False - rate for true D	Pr(- D)	12.34%
False + rate for classified +	Pr(~D +)	13.80%
False - rate for classified -	Pr(D -)	6.34%
Correctly classified 91.02 %		

In comparison to the main model the restricted model is better at overall prediction with a rate of correctly classified of 91.02 to 90.99. However, it has a higher rate of falsely predicting success when actual failure occurred at 7.22 compared to 6.98 of the main model. Overall the predictive ability is very similar to the main model. The following table shows a summary of all models Table 4.9.

Table 4.9 Summary of all Kickstarter models

	Creator signals	*Backers signals*	*Backer incentives*	*Social capital*	*main model*	*Restricted model*
Ambition	-0.538***	-0.946***	-0.992***	-1.393***	-1.382***	-1.431***
	(-56.93)	(-71.11)	(-70.21)	(-75.89)	(-75.10)	(-66.46)
Confidence	-0.00000181 ***	-0.00000323 ***	-0.00000304 ***	-0.00000617 ***	-0.00000649 ***	-0.00000658 ***
	(-3.94)	(-5.18)	(-4.73)	(-7.72)	(-8.01)	(-7.10)
Experience	0.0136*	-0.0438***	-0.0375***	0.0379***	0.0393***	0.0469***
	(2.38)	(-6.96)	(-5.89)	(5.27)	(5.44)	(5.55)
Trustworthine ss	1.579***	1.017***	0.994***	0.869***	0.893***	0.945***
	(114.71)	(63.03)	(60.12)	(48.74)	(49.49)	(45.26)
Impatience	-0.00909***	-0.00757***	-0.00457**	-0.00166	-0.00128	-0.00624**
	(-7.60)	(-5.45)	(-3.20)	(-1.04)	(-0.80)	(-3.28)
Campaign Comments		0.734***	0.732***	0.685***	0.707***	0.748***
		(47.82)	(46.84)	(-41.03)	(41.79)	(38.74)
Early Funding		-0.00000418***	-0.00000405**	-4.8E-07	-3.5E-07	2.07E-06
		(-3.49)	(-3.18)	(-0.23)	(-0.17)	(0.95)
Early Backing		0.00157***	0.00164***	0.000873***	0.00103***	0.00044
		(6.7)	(6.87)	(3.35)	(3.91)	(1.72)
Early Average Pledge		0.694***	0.690***	0.617***	0.615***	0.594***
		(52.5)	(51.13)	(40.68)	(40.59)	(34.37)
Reward levels			0.0911***	0.0495***	0.0469***	0.0445***
			(24.57)	(12.68)	(11.94)	(10.09)
			-0.0630***	-0.0441***	-0.0433***	-0.0406***

Global rewards			(-16.28)	(-10.61)	(-10.32)	(-8.43)
Average wait time			-0.00138***	-0.00153***	-0.00158***	-0.00201***
			(-8.52)	(-8.31)	(-8.47)	(-9.35)
Facebook Shares				0.800***	0.784***	0.804***
				(62.8)	(61.28)	(54.38)
Reciprocity				-0.00696***	-0.00673***	-0.00773***
				(-8.57)	(-8.21)	(-8.20)
Launch Competition					2E-05***	1E-05***
					(6.88)	(4.25)
Launch Competition Category					-1e-04***	-0.000106***
					(-11.59)	(-11.42)
Google trend in category					0.00391***	0.00739***
					(4.82)	(7.49)
City index						-5E-05 ***
						(-9.42)
Country index						1.87E-05
						(-1.05)
Category index						-0.000249***
						(-4.51)
Kick Index						0.000178***
						(6.79)
Constant	2.311***	3.145***	3.108***	3.753***	3.449***	4.032***
	(-28.48)	(-32.22)	(-31.34)	(-33.53)	(-28.58)	(-27.50)
Observations	54193	54193	54193	54193	54193	42277
Pseudo r-squared	0.4071	0.5452	0.5559	0.6356	0.638	0.652
Chi-square	27738.18	37145.23	37871.61	43304.97	43500.800	35222.516
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.000	0.000
*AIC*n*	40403.687	31004.630	30284.252	24854.891	24665.063	18882.900
BIC	-550263.250	-559626.706	-560320.383	-565731.943	-565895.07	-431261.296

t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001

4.2 Kickstarter results by hypothesis:

This section considers the implications of the results on the research hypotheses both for the main and the restricted models. Across this section, numeric values are reported in 3 significant figures or 2 decimal places whichever is more appropriate in recording accuracy. The section is split into sub-sections based upon the specific areas which each hypothesis is considering.

4.2.1 Creators signals

This sub-section considers signals sent by the creators of the crowdfunding campaigns.

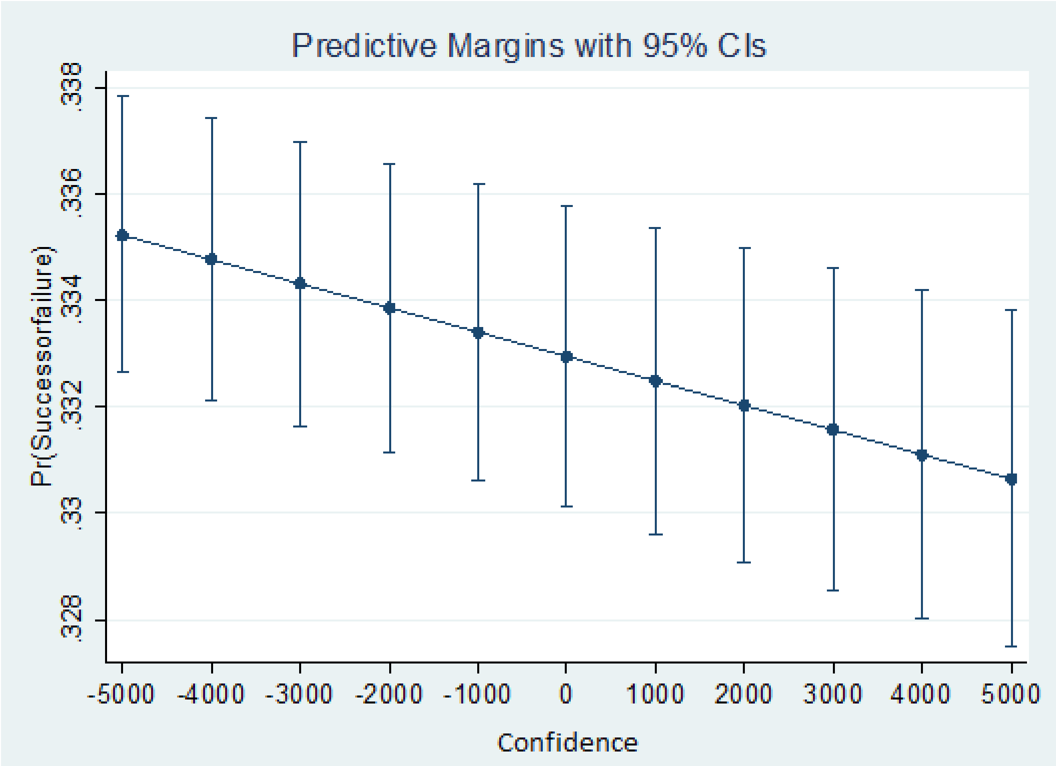
4.2.1.1 Confidence

Hypothesis 1a addressed the role that overconfidence played in crowdfunding project success on Kickstarter, stating H1a: *Creators' overconfidence has a negative impact on the probability of the project's success.*

The hypothesis was developed based upon the concept that, on average, creators are overconfident in their projects' ability to obtain funds, a concept developed in section 3.3.2.1. The platform forces the creators to set their funding goal at the beginning of the campaign, and this is utilised as the predictor of the confidence level of the project, natural log values of the relative funding goal were utilised to normalise the result and reduce the impact of abnormally high or low relative funding goals. The results shown in Table 4.1, indicate that the confidence had a negative and significant impact on the success of the project to above a 99.99 percent confidence level, supporting H1a.

This hypothesis can also be examined by considering the relative level of confidence of the project compared to other projects within the same specialism on Kickstarter, captured through the relative funding goal variable. The results shown in Table 4.1, show that the relative funding goal had a negative and significant impact on the success of the project. Furthermore, Figure 4-1, below, shows how the probability of success changes with the relative level of confidence in the creator within their specialism. An increase from 0 to 1000 dollars relative to the average in the specialism leads to a decrease from 31.76 to 31.71. Thus, the scale of the impact on success is relatively small compared to the absolute level of confidence.

Figure 4-1 Marginal impact of Confidence



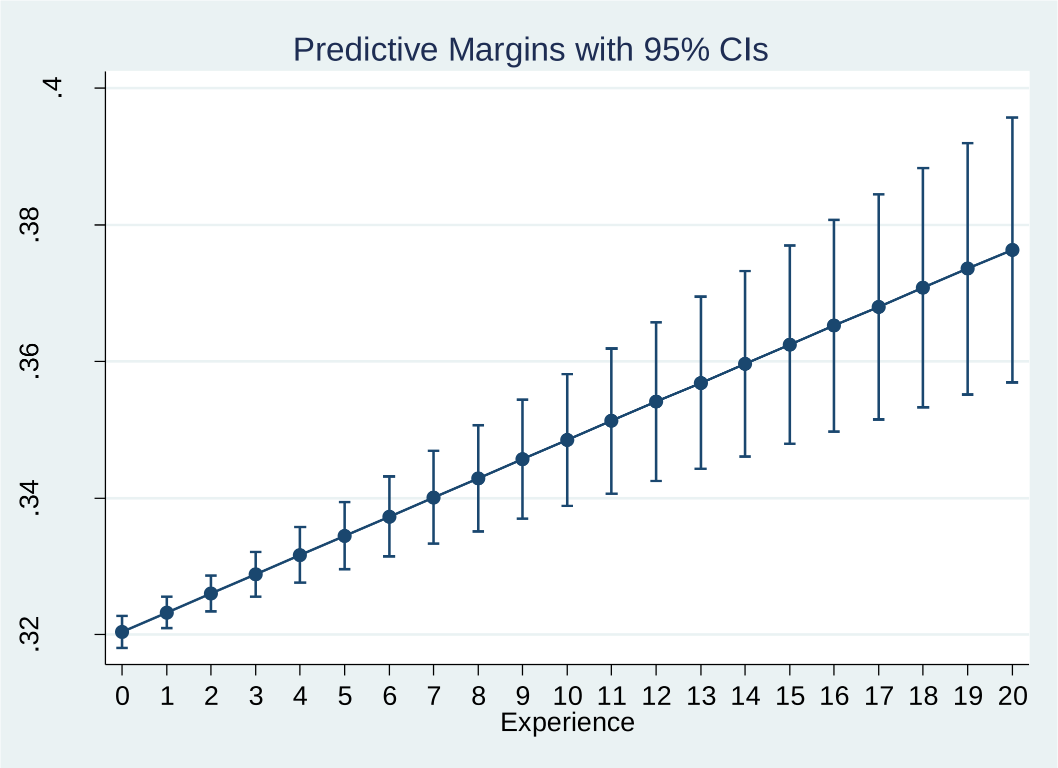
The results support the argument that higher levels of confidence relative to other creators, have a negative impact on the probability of a project succeeding within Kickstarter, showing strong support for the hypothesis H1a, both in terms of its significance and with regard to the scale of the impact. This evidence provides additional support to the statement that creators can be overconfident in their project. Thus, creators set a higher relative funding goal, leading to a decrease in the probability of observing a successful project. This evidence also shows how the enforced signals that Kickstarter demands to be sent out by the creators can have negative impacts on the success of the crowdfunding campaigns, a point discussed further in section 5.1.1.

4.2.1.2 Experience

Hypothesis 1b addresses the role that signalling increased levels of experience by the creator has a positive impact on project success: H1b: Signalling increased experience has a positive impact *on the probability of the project's success*.

This hypothesis stemmed from the concept that increased levels of experience can be seen as key indicators for successfully raising funds within start-ups, and this principle can be applied to crowdfunding, as discussed in section 3.3.2.2. The level of experience of the creator is captured via the number of projects the creator has previously launched on Kickstarter. The results shown in Table 4.1, show that experience has a positive and significant impact on the probability of a project succeeding, showing clear support for H1c.

Figure 4-2 Marginal impact of experience variable



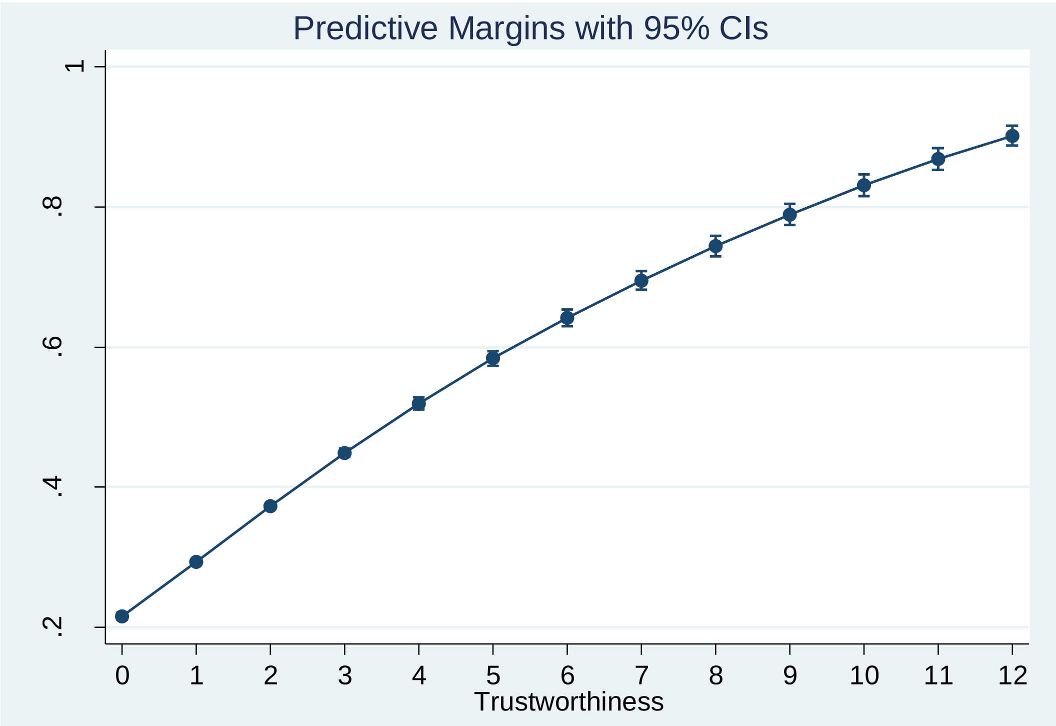
What is notable from Figure 4-2 is that while the scale of the impact is consistent with the marginal impact of one additional previously created project increasing the probability of observing a project succeeding by around 0.27 at all experience values. The confidence interval surrounding this value increases with the level of experience, demonstrating that the precision of the model in capturing the effect of experience decreases as the amount of experience increases. The mean number of previously created project that creators had was 0.571, as shown in Table 3.4, this was impacted by a large number of creators producing projects for the first time with 43162 creating projects for the first time out of the 54193 projects examined by the main model. Applying this mean value to underlying data of Figure 4-2, as shown in Table 3.6, displays that, on average, the model attributes a probability of a project succeeding of 32.2 percent. However, there was a large range of results with the most experienced creators having previously created 74 projects. At this maximum level, utilising the data from Figure 4-2, the expected probability of observing success increases to 51.9 percent, indicating that high levels of experience exert a significant impact on the probability of a project reaching its funding goal.

4.2.1.3 Trustworthiness

Hypothesis 1d addresses the role that signalling increased level of trustworthiness by the creator has a positive impact on project success: H1c: *Increased levels of trustworthiness has a positive impact on the probability of the project's success*.

This hypothesis stemmed from an examination of how trustworthiness is a key characteristic of entrepreneurs, demonstrated through the survival and growth of their ventures and how trustworthiness could be signalled by creators on Kickstarter through utilising the updates feature inbuilt into every Kickstarter campaign, concepts discussed in 4.2.1.3 . The results shown Table 4.1, demonstrate that trustworthiness has both a positive and significant impact on the probability of a project succeeding, showing clear support for H1c.

Figure 4-3 Marginal impact of Trustworthiness



The impact of the level of trustworthiness is shown in Figure 4-3 above. Natural Logarithms were utilised in this variable, thus the mean value of 0.99, as shown in Table 3.4, represents that, on average, each campaign had $e^{0.99}$ (2.69 3.sf) updates. Thus, utilising the underlying data for Figure 4-3 (also viewable in Table 3.6), shows that, at the mean level, 29.2 percent of campaigns are predicted to succeed. Furthermore, an increase from the mean of 2.69 to that of 5 updates would have shifted this probability of observing a success from 29.2 to 34.2 percent demonstrating that a relatively small extra number of updates can dramatically increase the probability of observing a success. The slight downward curve of the trend line within Figure 4-3 indicates that the marginal impact of extra updates decreases with increased number of updates. Furthermore, this is a relevant effect as log values were utilised and thus even a straight trend line would demonstrate a marginal decrease in the impact of extra updates.

4.2.1.4 Impatience

Hypothesis 1d addresses the role that signalling impatience will play on the project due to the inability of backers to distinguish between high-quality and low-quality campaigns, as discussed in section 3.3.2.4. The level of patience of the creator, as discussed earlier, is captured via the proxy of the duration of the campaigns. Stating H1d: Increased level of patience have a positive impact on the probability of a project's success.

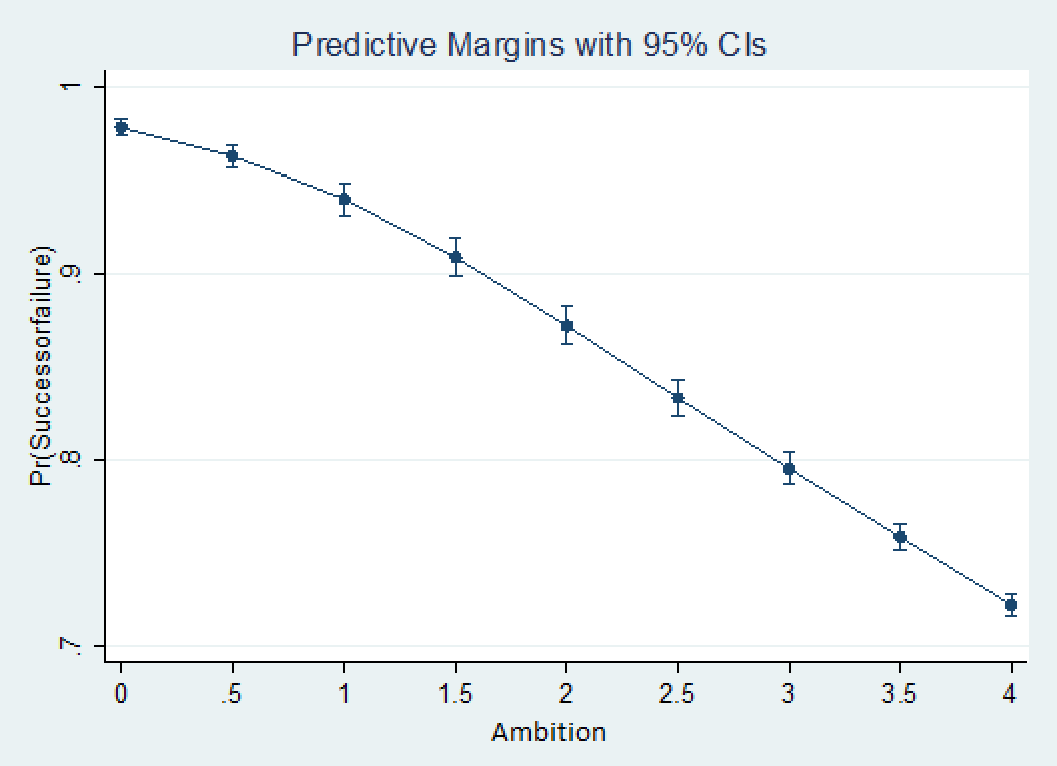
The results in Table 4.1, shows that impatience does not have a significant impact on the probability of a project succeeding and thus does not support the hypothesis. This insignificance of the result was discussed as a possibility within the generation of the hypothesis due to how the signal did not enable backers to distinguish between low quality and high-quality campaigns, due to the duration being limited to sixty days, the author argued that this timeframe was too limited to enable distinction between high- and low-quality projects. Thus, although signal patience becomes ineffective, providing a possible explanation as to why the hypotheses was not supported.

Suggesting that the human capital can be used to interpret the effect of signals but only when the signals are effective in overcoming asymmetric information. This point is discussed further in section 5.1.1.2.

4.2.1.5 Ambition

Hypothesis 14 addressed the role that Ambition played in crowdfunding project success on Kickstarter, stating H1E: *Creators' Ambition has a negative impact on the probability of the project's success.*

Figure 4-4 Marginal impact of Ambition



The scale of the impact of ambition is carried out considering the marginal impact of higher measures of confidence, as shown in Figure 4-4, displaying the probability of success for a project as a function of the observed ambition of the creator. The values on the x-axis are log values, thus the graph shows that an increase of the funding goal from e^2 (2.72 reported to 3.s.f) to e^4 (54.6 reported to 3.s.f) will lead to a decrease in the estimated probability of projects succeeding from 87.2 percent to 72.2 percent. The mean of the confidence level of all projects is 8.75, as reported in Table 3.4, expressed in funding goal terms this is 6321 US dollars and utilising the Figure 4-4, at this level the model predicts a 28.5 percent probability of the project reaching its funding goal, as shown in Table 3.6.

4.2.2 Backers signals

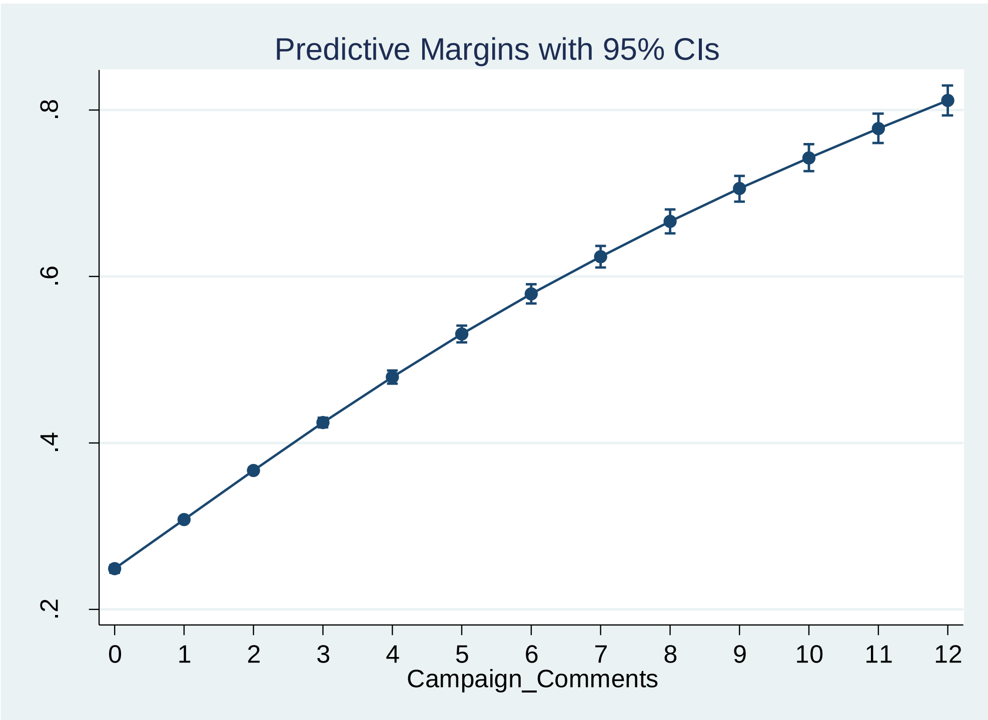
This section considers the impact of signals sent out by the backers of the crowdfunding campaigns as discussed in 3.3.3. The signals are all examined in relation to the H2, which stated: Increased numbers of signals sent by the backers have a positive impact on the probability of a project's success.

Four different signals were utilised in examining this hypothesis all demonstrating increased levels of signalling by the backers. The signals were as follows: the number of campaign comments, the amount of early funding provided, the amount of early backing provided, and the average pledge given by each backer in the early funding period. The early funding period consisted of the first 1/6th duration of the crowdfunding campaign. The results of these signals are displayed in Table 4.1.

Therefore, three out of four of the above proxies for backers' signals, support H2, as campaign comments, early backing and early average pledge all have both a positive and significant impact on the likelihood of a project succeeding. Early funding has a negative coefficient; however, this value is not significant at the relevant confidence levels. Hence, these results provide convincing support for H2. The scale of the impact of each of the significant signals is examined separately in Figure 4-5 to Figure 4-7 below.

4.2.2.1 Impact of campaign comments

Figure 4-5 Marginal impact of campaign comments



Campaign comments are rescaled in natural log values, and thus in interpreting Figure 4-5, the slight down turn in the slope of the curve demonstrates that the marginal impact of additional levels of comments decreased significantly at higher levels. On average, projects had $e^{0.912}$ (2.49) comments, as shown in Table 3.4, applying this mean level to the underlying data for Figure 4-5, displayed a probability of success at 30.26 percent, as shown in Table 3.6. Furthemore, Table 3.4 shows that there was a large range in the number of comments, with the project with the most comments having $e^{11.3}$ (78931.8) comments and the projects with the least having 1 comment. Thus, using the underlying data for Figure 4-5 shows that an increase from the mean to maximum level of comments increased the probability of success from 30.26 to 79.05 percent. Conversely, a decreasing number of comments from the mean level to the lowest level reduces the probability of observing success from 30.26 to 24.81 percent. Examination of the 95 percent confidence interval at the mean level was between 29.97 and 30.56 percent suggesting that the model is efficient at predicting the impact of campaign comments. However, the confidence intervals increase as campaign comments increases, suggesting the model is better at predicting the impact of comments on success and failure of projects at lower number of comments.

4.2.2.2 Impact of Early backing

Figure 4-6 Marginal impact of early backing

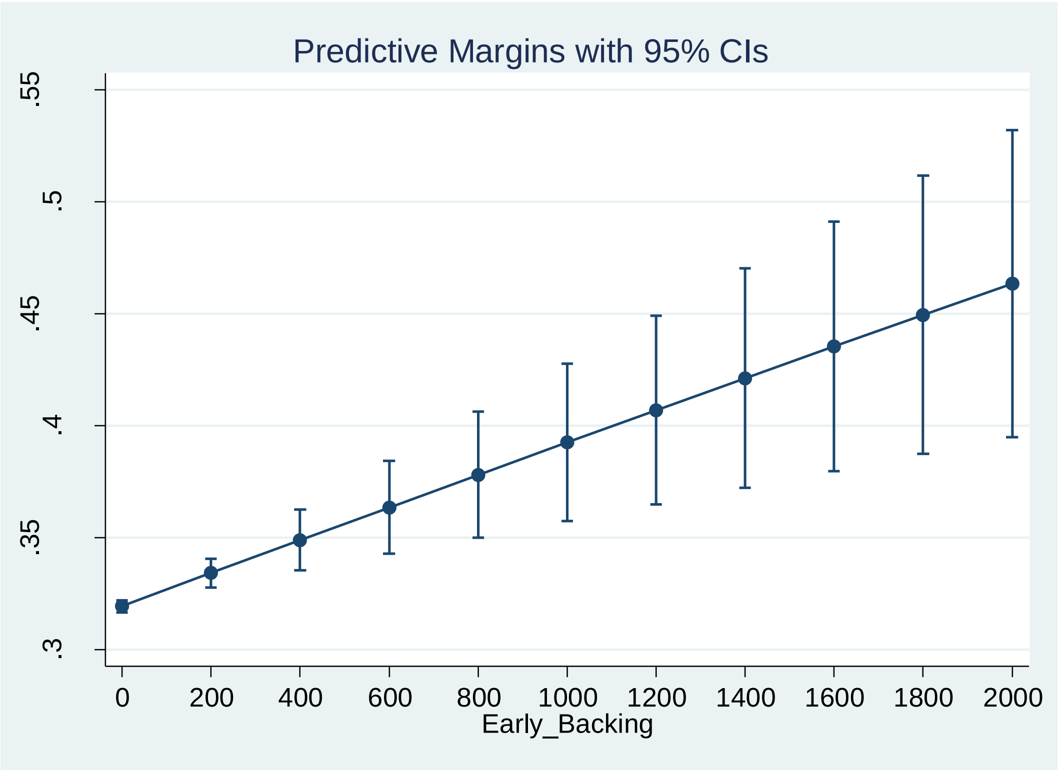
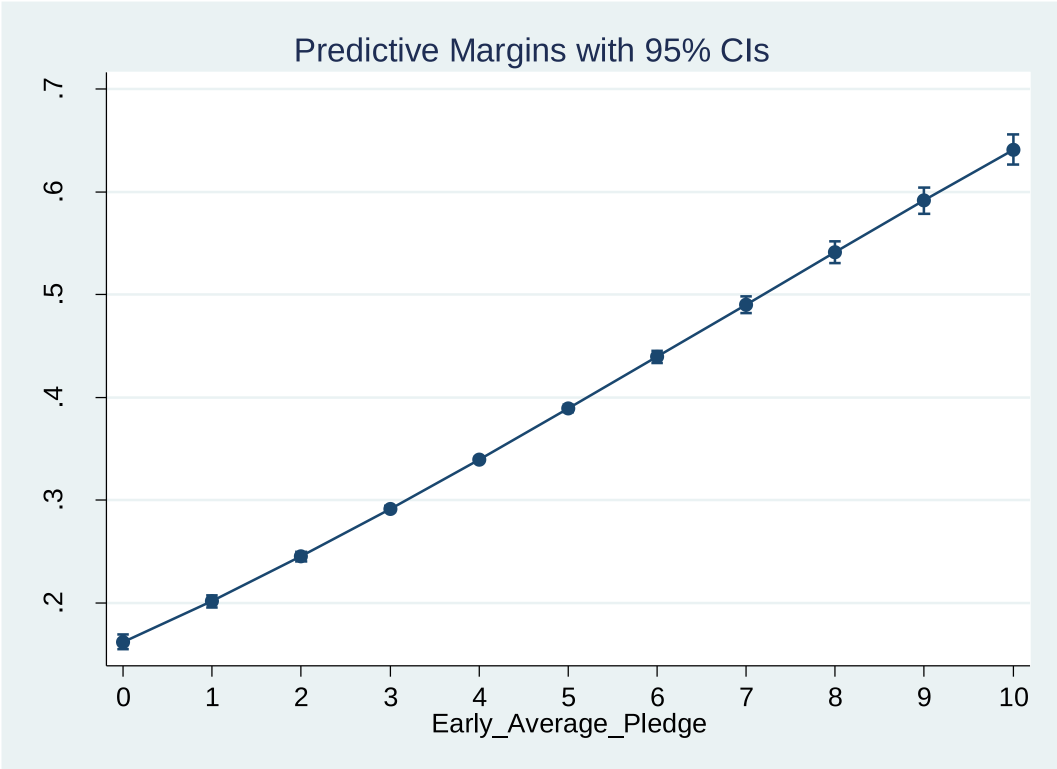


Figure 4-6 shows that increased early backing consistently increases success by around 1.48 percent per 200 additional early backers. This suggests that the marginal impact of each extra backers is a 0.0074 percent increase in the probability of observing a successful project, demonstrating a modest impact on the probability of observing a success. However, the 95 percent confidence boundary increases significantly as the number of early backers increases, suggesting that the model is better at precisely predicting the impact of early backing when lower levels of early backing are reported. Table 3.4 displayed that, on average, each campaign has 49.37 early backers, utilising the underlying data for Figure 4-6, this would predict the probability of observing a success at 32.30 percent.

4.2.2.3 Impact of Early pledge per backer

Figure 4-7 Marginal impact of early average pledge



The early average pledge variables display the amount of money on average each backer gave in the early funding period. Natural logarithms were utilised in constructing this variable, and thus in interpreting Figure 4-7, the straight line shows that the positive marginal impact of average pledge on the probability of observing a successful outcome decreases as average pledge increases. On average, backers gave $e^{2.281858}$ (9.79) US dollars, extracted from Table 3.4, at this value utilising the underlying data for Figure 4-7, as shown partially in Table 3.6, would predict the probability of observing a success at 25.78 percent. Furthermore, increasing the average pledge by 5 dollars to 14.79 dollars would raise the probability of observing a success from 25.78 to 27.7 percent.

The combination of the three significant positive variables with their strong marginal impacts provides convincing support for the H2, showing the positive impact that increased backers signalling has on the probability of a project succeeding.

4.2.3 Reward hypotheses

The following section considers the results related to all hypotheses formulated to identify the impact of backers' incentives on the success in Kickstarter as they were developed in section 3.3.4 .

4.2.3.1 Reward levels

Increasing the number of reward levels offered to backers of the campaigns was considered to exert a positive impact on the probability of projects succeeding, as it would provide increased choice to the backers regarding how they wish to support the project, an argument discussed when developing H3a: *Increased number of reward levels within a campaign will have a positive impact on the probability of the project success*.

Figure 4-8 Marginal impact of reward levels

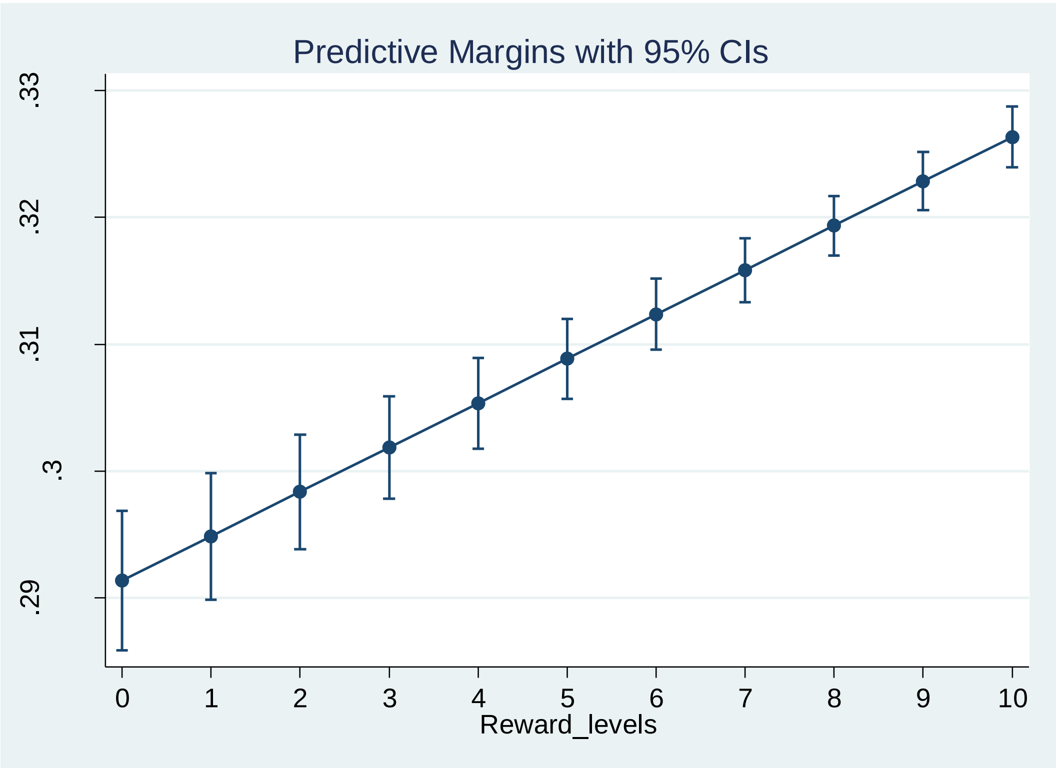


Table 4.1 shows that the number of reward levels has a positive and significant impact on the probability of a project succeeding, thus supporting H3a, as also displayed in Figure 4-8 below on the probability of observing a success for specific reward levels. The straight

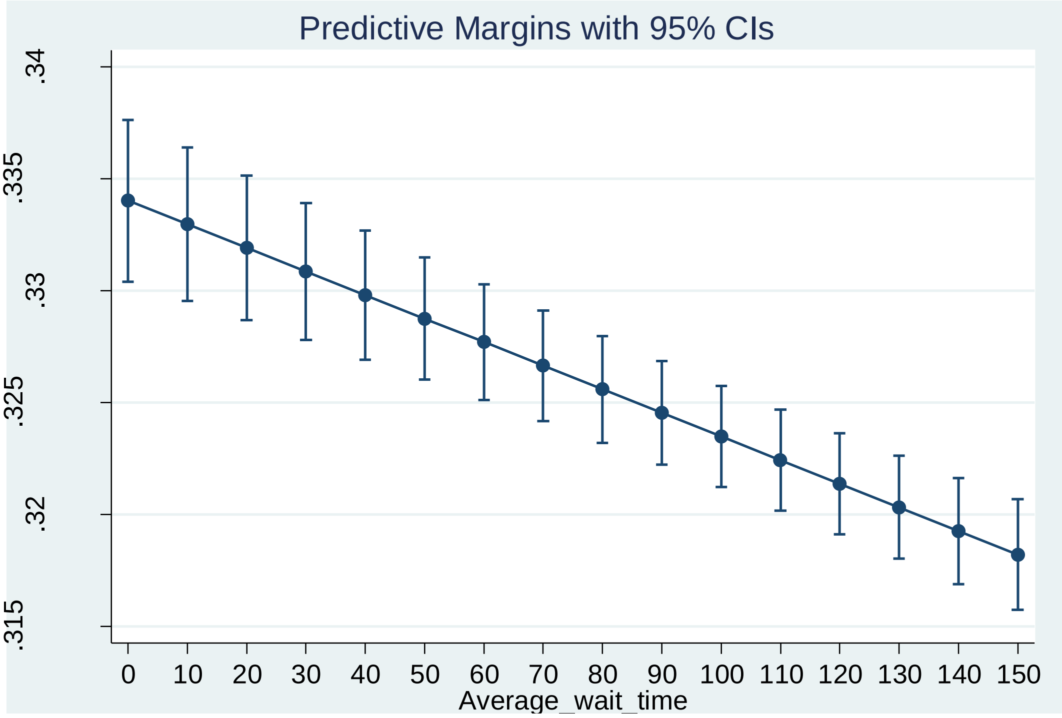
line within the graph shows that increasing the number of reward levels has a consistent effect for the first 10 increases, with each increase leading to an increase of around 0.34 percent in the probability of observing a success.

An examination of the mean number of reward levels, from Table 3.4, shows that on average each campaign had 7.39 reward levels. Utilising the underlying data for Figure 4-8 shows that at the mean level of 7.39, the probability of observing a successful project was 31.7 percent. Table 3.4 additionally shows the range of the reward levels of projects, with the minimum number of reward levels being 1 and the maximum being 179. Thus, using the underlying data for Figure 4-8 as partially shown in Table 3.6, at the minimum level a project was predicted to have a 29.6 percent probability of succeeding, conversely at the maximum level the project was predicted to have an 80.4 percent probability of succeeding providing support for hypothesis 3a.

4.2.3.2 Number of days for the rewards being delivered

The second hypothesis related to backers' incentives considered that backers would be less likely to support projects which delivered rewards at a later time period, or that they would discount future rewards, compared to closer ones, based on a typical positive discount rate assumption, as developed in section 3.3.4.1. Stating this hypothesis, H3b: *Increased expected delivery times of reward levels will have a negative impact on the probability of project success.*

Figure 4-9 Marginal impact of average wait time



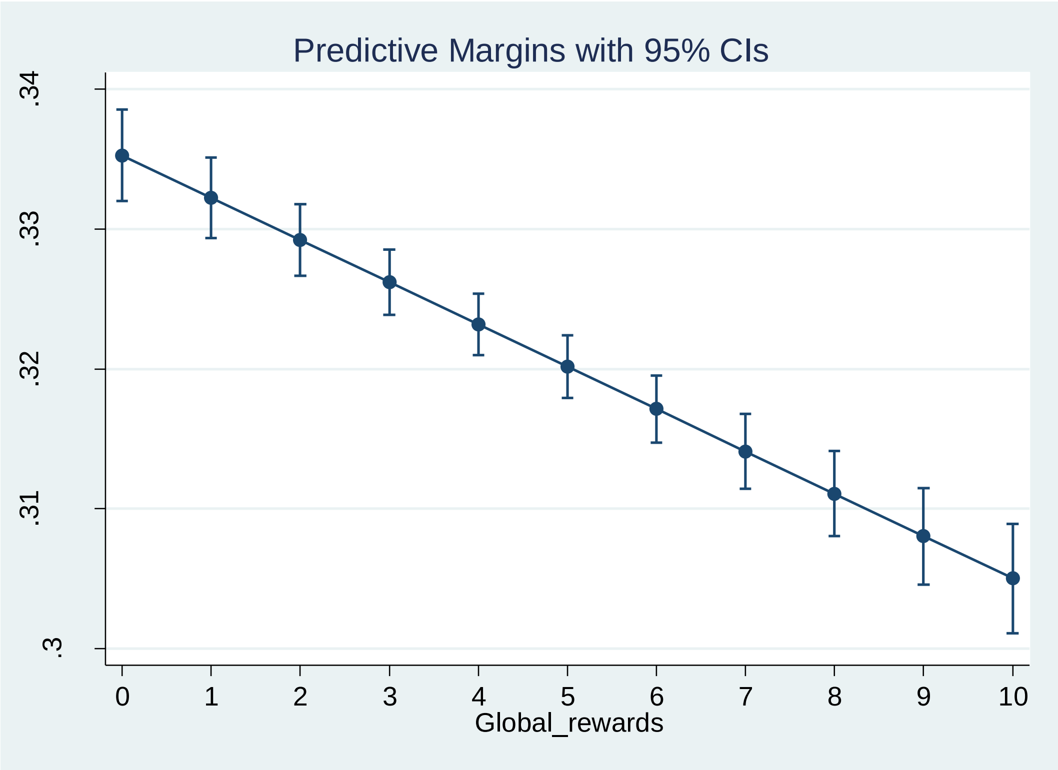
The results on the average waiting time, from Table 4.1 above, provide support for the hypothesis, stating that the average wait time of the backer had a negative and significant impact on the probability of a project succeeding. The scale of the impact is shown in Figure 4-9 below, the straight line in the Figure 4-9 shows a consistent decrease in the probability of success with increased waiting times, with an increase of 10 days consistently leading to a decrease of 0.11 percent chance of observing a successful outcome, to a 95 percent confidence level. This can be considered a relatively small decrease in the probability of observing success, suggesting a relatively small impact on the level of success by increased wait times.

Furthermore, on average, backers had to wait 130.1 days to receive their rewards, as shown in Table 3.4, utilising the underlying data for Figure 4-9 as shown partially in Table 3.6, at this level the probability of observing a success was 32.0 percent. Thus, a project delivering rewards instantaneously would only increase the probability of observing success from 32 percent to 33.4 percent. Providing evidence that people are mostly willing to wait for their reward, however, there is a still a negative impact on success by increased delivery times, thus supporting the proposed hypotheses.

4.2.3.3 Global reward levels

The final hypothesis considering the impact of backers' incentives examines the impact of global rewards on the probability of a project succeeding. With a global reward consisting of any reward which could be physically shipped to anywhere in the world. The hypothesis stemmed from the concept that backers would prefer local and digital rewards, compared to global rewards, as discussed in section 3.3.4.2,stating H3c: A larger number of global reward levels will have a negative impact on the probability of the project success.

Figure 4-10 Marginal impact of global reward levels



H3c is supported by the model as seen in the results from Table 4.1, which show that the number of global rewards has a negative and significant impact on the probability of a project succeeding. Furthermore, Figure 4-10 provides evidence that this impact is consistent as the number of global rewards increases. With a decrease of around 0.03 percent for each increase in the number of global rewards.

Table 3.4 shows that the average campaign had 3.69 global reward levels. Utilising the underlying data for Figure 4-10 at this level, the chance of observing a successful campaign was 32.4 percent. Having no global rewards would increase this chance to 33.5 percent, indicating the strength of the positive increase. This increase could be considered relatively small, showing a small impact on success by the number of global rewards, while still supporting the proposed hypothesis.

The support for these three hypotheses demonstrates that changes to the number of rewards does impact the probability of a project succeeding in Kickstarter. However, this impact may be relatively limited, suggesting that other factors outside of the actual rewards may also be relevant to capture success within Kickstarter.

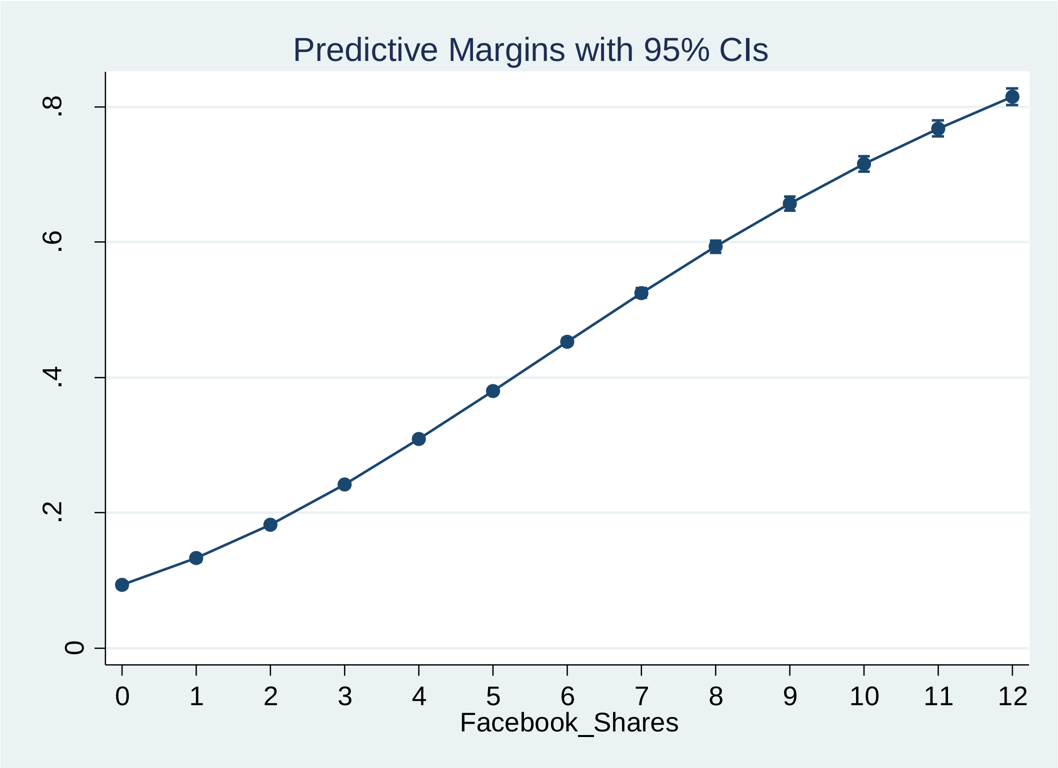
4.2.4 Social capital hypotheses

The following section considers the impact that *internal* and *external social capital* have on the probability of a project to succeed.

4.2.4.1 External social capital

The following hypothesis considers how the combination of the backers and creators' *external social capital* could positively increase the probability of a project succeeding, capturing the *external social capital* from the number of Facebook shares of the crowdfunding project, as discussed previously in section 3.3.5.1. Stating H4a: *Increased levels of combined creator and backer external social capital have a positive impact on the probability of the project's success.*

Figure 4-11 Marginal impact of Facebook shares



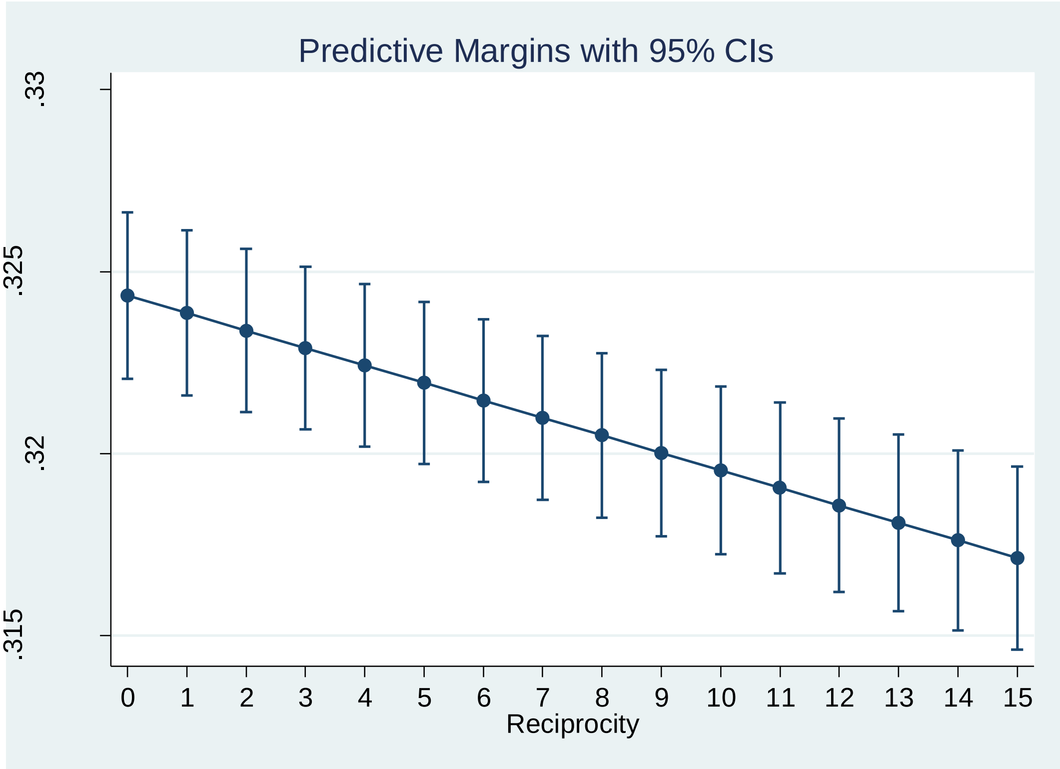
The results displayed in Table 4.1, show clear support for the hypothesis, with the number of Facebook shares being both positive and significant in their impact on the probability of a project succeeding. Natural logarithms were utilised as marginal impacts were expected to be smaller at larger number of Facebook shares due to the network distance between the original sender of the share and the recipient to be larger and thus less likely to impact their decision to support the project. Figure 4-11 demonstrates a relatively straight line, with a slightly gentler slope at early values and a slightly steeper slope at higher values, showing support for the decreasing marginal impact at higher levels of Facebook shares.

In examining the scale of the impact of Facebook shares on probability for the project to succeed, the log of the mean number of Facebook shares was 3.07, as shown in Table 3.4 below, thus on average each project had 21.7 shares, and utilising the underlying data for Figure 4-11 as partially shown in Table 3.6, the probability of observing a success at this level was 24.75 percent, compared to having zero Facebook shares, which gave the probability of observing a success at 9.42 percent. Furthermore, the highest observed number of Facebook shares at 331224 increased the probability of observing a success at 84.14 percent. These two points show that the number of Facebook shares had a positive impact on the likelihood of a project succeeding.

4.2.4.2 Creators Internal social capital

This hypothesis considers the impact of increased *internal social capital* captured via the number of previously backed projects by the creator. Arguing that the *internal social capital* of the creator can be captured by examining the amount of previously backed projects by the creator, which is used as a proxy for reciprocity, as discussed in section 3.3.5.2. Stating H4b: *Increased amount of creator internal social capital has a positive impact on the probability of the project's success.*

Figure 4-12 Marginal impact of Reciprocity



Contrary to our expectations, the results in Table 4.1, do not support H4b: with increased Reciprocity having a negative and significant effect on the probability of successfully funding a project. This is further seen when examining the impact of increasing levels of reciprocity demonstrated in Figure 4-12 above. The negative coefficient could suggest that utilising the number of backed projects by the creator is not a good indicator of the creator's *internal social capital*. Instead, creators backing other projects could be seen as wasteful to the potential backers of the creator's project. Why are they asking for money if they are already able to give money to other creators? Thus, leading to the negative coefficient observed in the model.

However, it should also be noted that the negative coefficient of the impact is quite small, the average campaign creator had previously backed 3.76 projects, as shown in Table 3.4. Utilising the underlying data for Figure 4-12 as partially shown in Table 3.6, would have the probability of observing a success at 32.2 percent. In comparison projects with zero previously backed projects had a probability of observing success of 32.4 percent, only 0.2 percent less than the average project. Therefore, the scale of the negative impact on the average project was very small.

Hence, the results regarding the different hypothesis on the impact of social capital on the probability of a project's success are mixed, showing strong support for the impact of *external social capital*, but a negative, if relatively small, impact for the *internal social capital*, these results are discussed in more details in the discussion of the results section.

The following section considers results for hypotheses which consider the impact of increased levels of competition internally and externally to the crowdfunding platform. The results utilise both models as some of the competition results can only be examined through the restricted model.

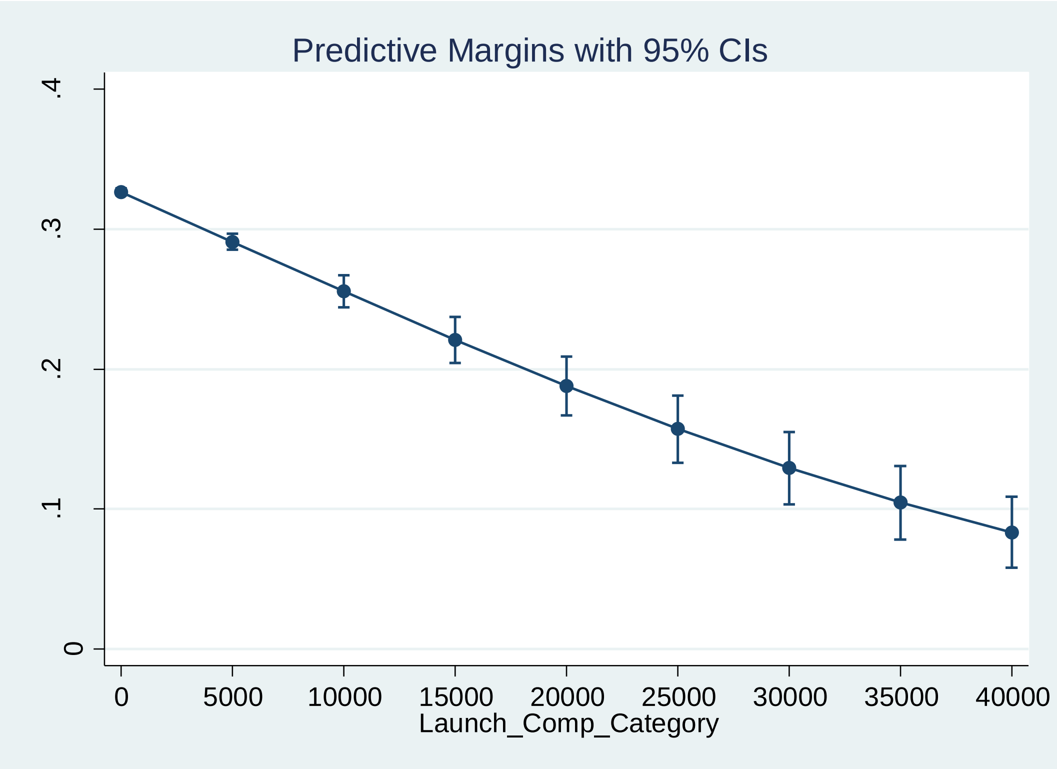
4.2.5 Competition within categories on Kickstarter

This hypothesis considered the impact of competition within categories on Kickstarter; the hypothesis stemmed from the concept that projects within the same category were likely to be potential substitutes of each other, making the demand for crowdfunding very competitive, and thus increasing the amount of projects running within a category at the same time would decrease the probability of projects reaching their funding goal, as discussed in section 3.3.6.1. Stating H5a: *Increased competition within the category has a negative impact on the probability of the project's success.*

This hypothesis was tested through the examination of two key variables, the amount of competition on launch day and a specific category index of competition. The competition on launch day was obtained through the main model and considered the number of backers which were attracted by other projects on the launch day of the creator's project. While the category index utilised the restricted model and calculated a competition index for a project across its entire duration. The results on launch competition, in Table 4.1, support the hypothesis reporting a negative and significant impact on the probability of a project succeeding. Conversely, the results on the competition index, in Table 4.6 do not support this hypothesis. They report a negative and significant impact, as higher values of the index indicate lower levels of competition, this result suggests that lower levels of competition within the category increase the probability of a project succeeding. This suggests that increased competition within the launch period of campaigns on the category does impact negatively on the project, however, increased competition outside of the launch period has a positive effect on competition. This is further examined by considering the impact of different levels of the variables on the probability of observing success.

4.2.5.1 Impact of Launch Competition within the category

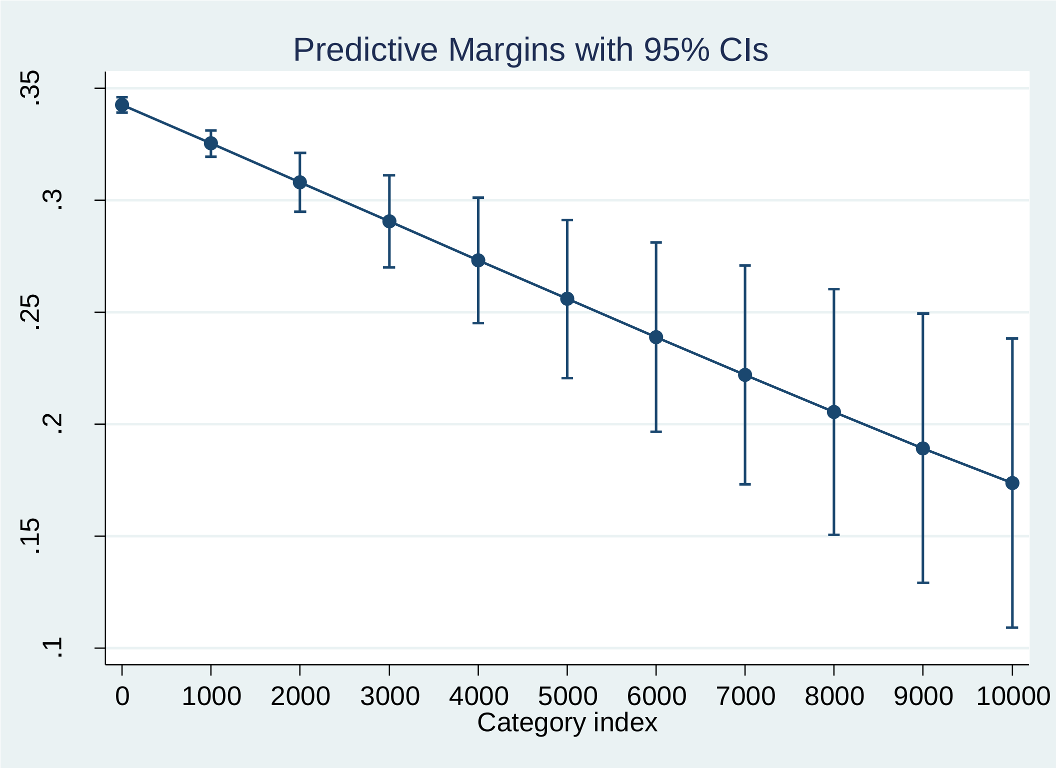
Figure 4-13 Marginal impact of the number of projects launching with the same category



In examining the precision of the predictive ability of increased launch competition, Figure 4-13 shows that the confidence interval is far smaller at lower level of competing firms, or that the model is more efficient at predicting the effect of increased launch competition within the category at low number of projects, as the number of projects increases the precision decreases. Furthermore, the mean number of backers obtained by other projects within the category on launch day was 647.48 as shown in Table 3.4. Utilising this mean value in combination with the underlying data from Figure 4-13 as shown partially in Table 3.6, at the mean value of launch competition projects have a 32.2 percent chance of observing a successful project. In comparison, projects with no competition had a 32.6 percent chance of observing a successful project. In contrast, the project with the highest amount of launch competition, as shown in Table 3.4, that of 42605 backers supporting other projects, had a 7.38 percent probability of succeeding, providing additional support for the proposed hypothesis.

4.2.5.2 Impact of increased category competition across a campaign's duration expressed as an index

Figure 4-14 Marginal impact of the amount of competition within the category



The mean value of the category index was 326.89, as shown in Table 3.5, showing that, on average, there were high levels of competition within each category. Moving to the Herfindahl-Hirschman Index (Hirshman, 1945), by construction, its minimum was 10,000 and the lower the value is the more competition, within the category, there is. Therefore, a value of 326.89 suggests that there was, on average, high levels of competition occurring within Kickstarter categories. Furthermore, the maximum value of 6644.80, as reported in Table 3.5, shows that every single project competed with at least one other project within its category. Furthermore, utilising the underlying data of Figure 4-14 as shown partially in Table 3.6, at the mean index value of 326.89, the likelihood of observing a success is 33.69 percent. In comparison, a project with the minimum observed level of competition, at an index value of 6644.80, only had a 20 percent chance of succeeding. In examining the precision of the predictive ability of the model, Figure 4-14 demonstrates that the predictive ability becomes less precise on the higher levels of the category index. Thus, the model is better at predicting the impact of highly competitive projects, over projects with low levels of competition.

This result suggests that competition within a Kickstarter category does not have a consistent effect across the entirety of the campaigns lifecycle and that competition early on in the lifecycle may have the opposite effect than competition throughout its lifecycle. This concept is further elaborated in section 5.3.1.

4.2.6 Competition outside of the category within Kickstarter.

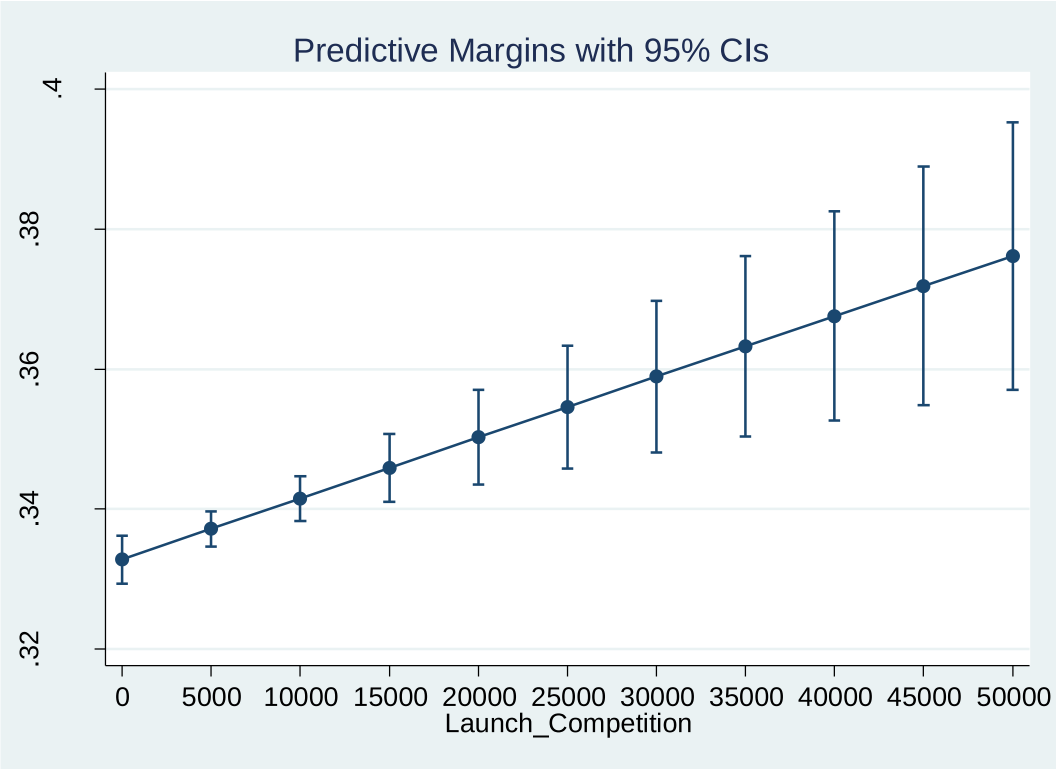
This hypothesis stems from suggesting that increased levels of competition outside of the Kickstarter category will increase the likelihood of a project to succeed. As projects not in the same category are less likely to be substitutes of each other, and thus the ability of extra projects to draw in more backers will have a positive impact on the likelihood of a project to succeed, as discussed in section 3.3.6.1. Stating H5b: *Increased competition on the rest of the platform has a positive impact on the probability of the project's success*.

This hypothesis was tested through the examination of two variables, the launch day competition generated by projects outside of the examined projects category and the amount of competition on the entire platform throughout the duration of the examined project, expressed in index form. The impact of competition on launch day from the rest of Kickstarter was obtained through the main model. Conversely the impact of increased competition through the rest of Kickstarter was captured on the restricted model.

The launch competition results support the hypothesis reporting a positive and significant impact on the probability of a project succeeding as shown Table 4.1. Conversely results regarding the competition index do not support this hypothesis, as shown in Table 4.6, although they also report a positive and significant impact, as higher values for the competition index indicate lower levels of competition, a positive coefficient thus suggests decreased levels of competition will increase the likelihood of a project succeeding. Suggesting that although H5b is supported at the launch of the project, the effect of increased competition within the rest of Kickstarter changes over a project's full duration. This is further examined by considering the impact of different levels of the variables on the probability of observing success.

4.2.6.1 Impact of launch competition from the rest of Kickstarter

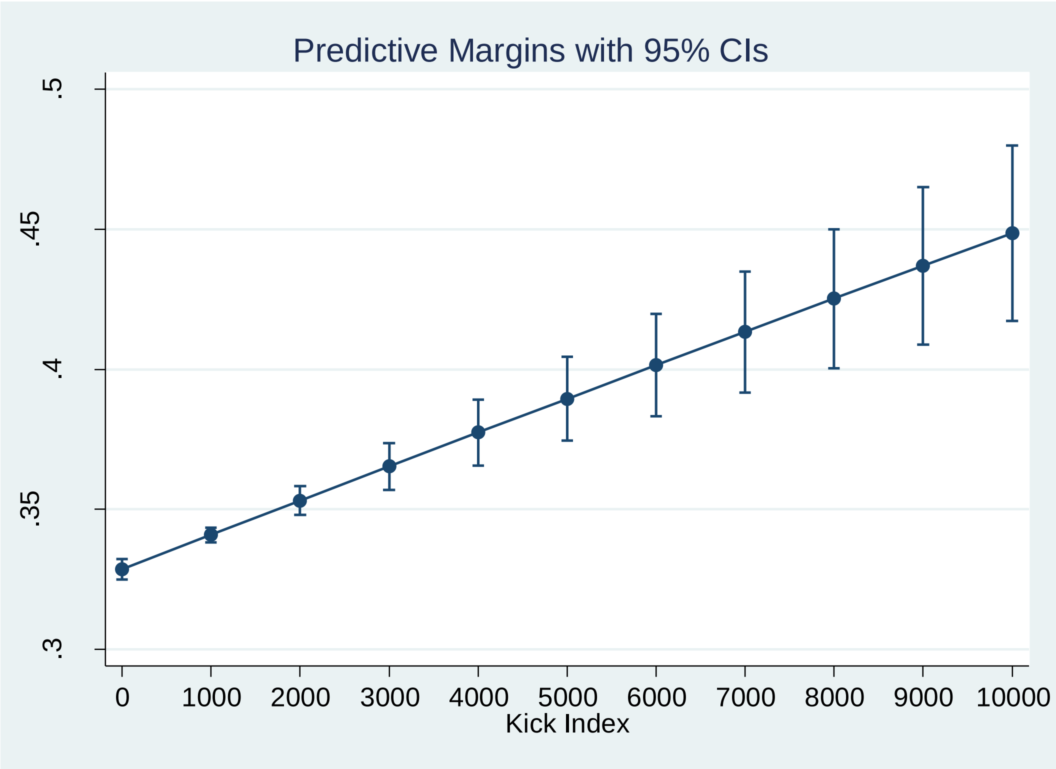
Figure 4-15 Marginal impact of launch competition



This straight line in Figure 4-15 demonstrated that there is a consistent positive effect of the increased amount of competition on launch day outside of the category of the creator. However, the precision of the model decreases as the amount of launch competition increases, as easily seen through the increase in the confidence intervals at higher levels of competition. On average, launch competition was equal to 4904.63, as displayed in Table 3.4. This states that on each project launch day, on average, other projects outside of the category of the examined project attracted 4904.63 backers to their projects. Utilising the underlying data from Figure 4-15, partially shown in Table 3.6, suggests that, at this average level of competition, there was a 33.70 percent chance of a project succeeding. In comparison, projects with the minimum level of competition of 27, as displayed in Table 3.4, lead to a 33.28 percent chance of observing a successful project. Conversely, the maximum level of competition observed of 50761, lead to a 37.68 percent chance of observing a successful project. Demonstrating a small impact on the probability of success based upon the level of competition at launch outside of the category of the project.

4.2.6.2 Impact of competition index from rest of Kickstarter

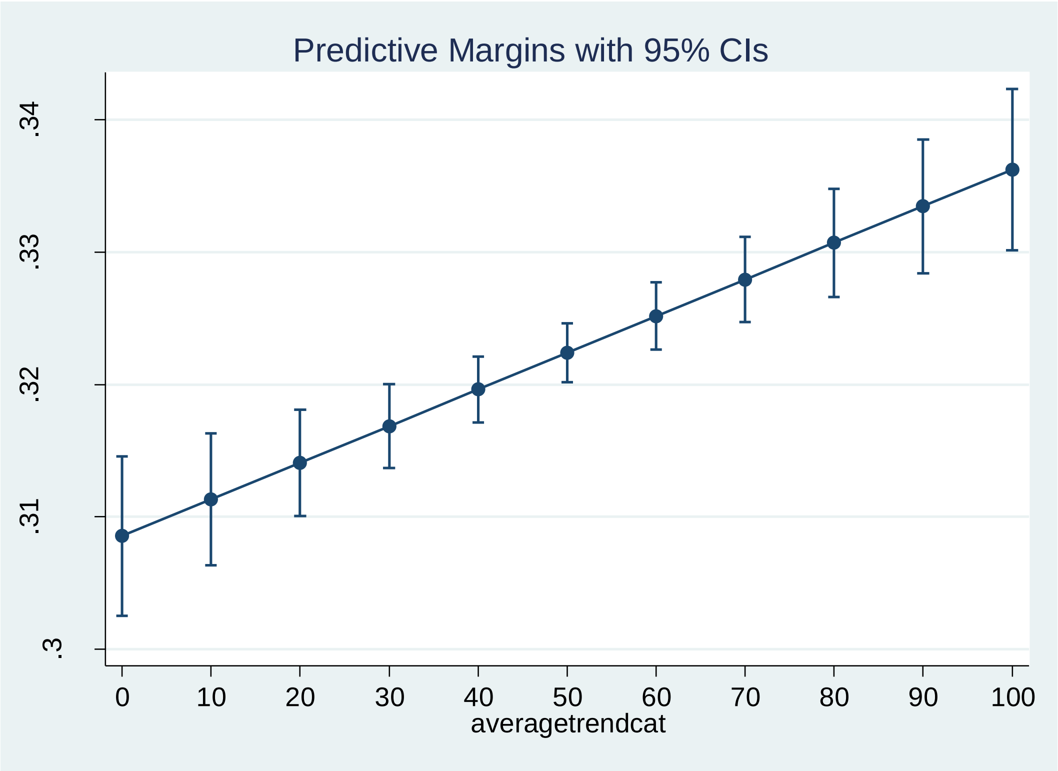
Figure 4-16 Marginal impact of Kickstarter Index



The straight line in Figure 4-16, displayed above, suggests that: as the level of competition decreases within the rest of Kickstarter, its impact on success is consistent. However, the precision of this impact declines as the index increases, as indicated by the widening of the 95 percent confidence intervals at higher levels of the Kick index. Kick index is an indexed value measuring competition between projects on Kickstarter within the same category. Index values are between 0 and 10000, with higher index values showing lower levels of competition. The mean level of the Kick index observed in the model was 671.83, as shown in Table 3.5. Utilising the underlying data presented in Figure 4-16 partially shown in Table 3.6, at the mean level of 671.83, there was a 33.69 percent chance of observing a successful campaign. In comparison, projects with the highest levels of competition, at an index value of 40, as shown in Table 3.5, had a 33.01 percent chance of observing a success. Conversely, projects with the least level of competition at an index value of 6320.38 had a 39.63 percent chance of observing a success. Thus, the largest possible decrease in the level of competition within Kickstarter outside of the category would only increase the likelihood of observing a success by 6.62 percent.

Therefore, in alignment with the hypotheses considering the impact of competition within the category, competition outside the category alters its effect depending on the duration of the campaign, with the initial increased competition having a positive effect on success and conversely increased competition across the entirety of its duration having a decreased impact on success. These points are further elaborated on and critically considered within section 5.3.1.

Figure 4-17 Marginal impact of average google trend



The straight line in Figure 4-17 above shows that the impact of how well the platform is competing, has a consistent and positive effect on the likelihood of a project succeeding. However, the model is most precise in the 40 to 60 range, as, at these values, the 95 percent confidence intervals are narrower than at more extreme values. The average campaign had a trend value of 48.78, as demonstrated in Table 3.4 above. Utilising the underlying data of Figure 4-17, as partially shown in Table 3.6, at this average value there is 32.20 percent chances of observing a successful project. At the lowest value recorded of 0, this chance decreased to 30.85 percent, and at the highest level of 100, it increased to 33.62 percent, showing that the impact was small with only a 2.77% difference between the highest and lowest values.

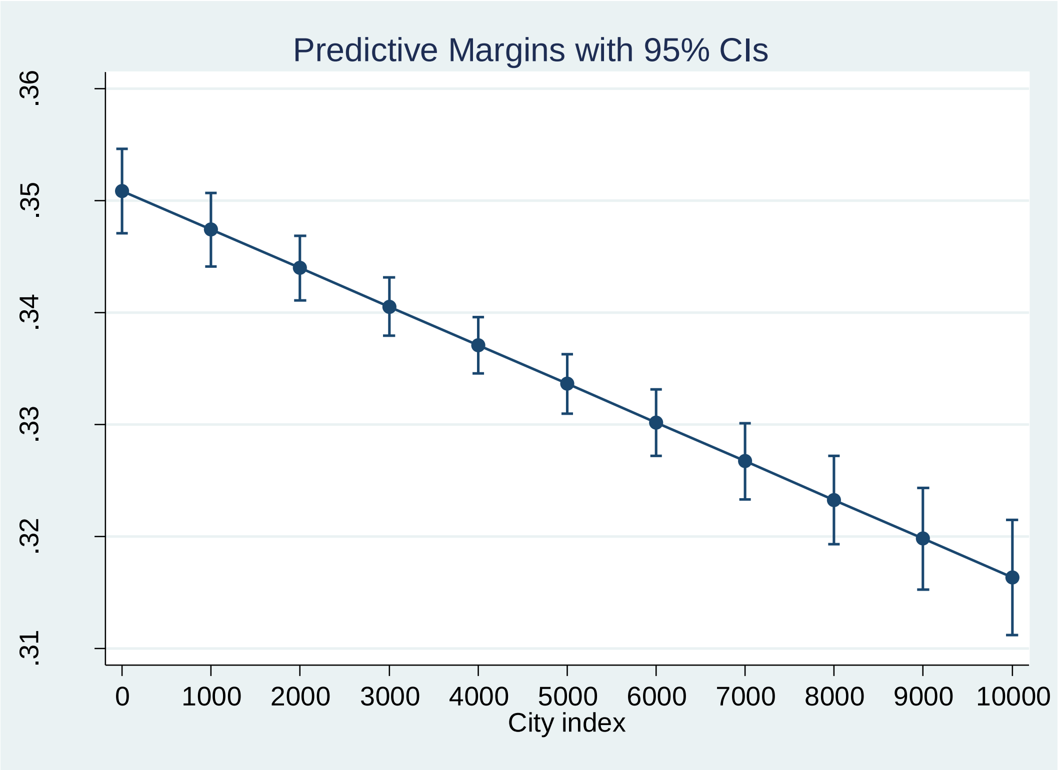
4.2.7 Geographic competition

4.2.7.1 Competition at a city level

The hypotheses focussing on the impact of geography on success in crowdfunding, were divided between city and national level. At city level, the key hypothesis considered how an increased amount of geographical competition at a city level is expected to decrease the probability of a campaign succeeding, arguing that projects within the same city are more likely to be substitutes of each other, thus increasing the level of competition, decreases the probability of a project reaching their funding goal. Stating H5d: *Increased geographical competition at a city level will decrease the probability of a project succeeding.*

However, the results displayed in Table 4.6, do not support this hypothesis, as they show a negative and significant impact on the probability to succeed based on an increase in the city competition index. An increase in this index shows a decreased level of competition within Kickstarter for that specific city, therefore leading to the opposite outcome compared to the one stated in hypothesis H5d.

Figure 4-18 Marginal impact of city index



An examination of the scale of the impact, shown in Figure 4-18 above, indicates that the impact of decreased competition constantly decreases as city index increases, with the model becoming slightly less precise as the city index value gets closer to 10000. The average index value for each project is 3986.17, as shown in Table 3.5. By applying this value to the underlying data for Figure 4-18, as partially displayed in Table 3.6, one sees that 33.71 percent of projects are predicted to be successful. The minimum value observed at 0 would lead to a 35.09 percent chances to succeed to, while the maximum value of 10000 reported at 31.6 percent chance to succeed, showing that the largest possible shift of 10000 would only decrease the probability of observing a success by 3.39 percent, indicating a relatively small impact of decreased competition on the probability of success.

This result suggests that the benefits of being close to other projects geographically outweighs the negatives of competing over similar resources. This point is further considered within discussion in section 5.3.

4.2.7.2 Competition at a country level

The final hypothesis developed within for Kickstarter conceptual framework, considers the geographical impact at a country level, stating that increased competition within a country would lead to an increased likelihood of a project success: stating H5e: *Increased geographical competition at a country level will increase the probability of a project succeeding.*

However, the empirical evidence did not support this hypothesis, as the estimates for the relevant logit coefficient was not statically significant at the usual levels, as shown in Table 4.6. This suggests that an examination of the geographical impact should not be considered at a country by country level, while still probably relevant when done at a finer state or city levels.

4.3 Kiva model Results

This section considers the models introduced to study the key features and role of the crowdfunding platform Kiva. The different models are ordered based upon the number of variables considered, with later models having additional variables, but also reduced observations based upon the restrictions concerning specific variables discussed in section 3.3.13. These models do not include dummy variables for specific categories or region. Models with dummy variables were originally attempted; however, these variables were found to be mostly insignificant or displaying high levels of multicollinearity. Instead a different category was modelled via the inclusion of competition indexes, based on such categories. Thus, enabling category effects to be captured. The effects of the specific country were instead captured through the variables: country funds and number of active loans.

4.3.1 Kiva 1: Signals model

The first model, below, only considers signals sent by the creators and by the platform Kiva itself, it was introduced, in section 3.4.8.1 as the following:

Y_i= Amount of money raised for project i

$$Log\ Yi = \alpha + \beta_1 logGenerosity + \beta_2 logTemporal\ Experienc + \beta_3 Capacity\ Experience + \beta_4 LogRating + \varepsilon_i$$

This results of the estimation for this model are reported here below:

Table 4.10 Kiva signals only model

Amount raised	Coef.	St.Err.	t-value	p-value	[95% Confidence	Interval]	Sig
Generosity	0.017	0.076	0.22	0.826	-0.132	0.165	
Temporal Experience	0.424	0.067	6.33	0.000	0.292	0.555	***
Capacity Experience	-0.248	0.018	-13.61	0.000	-0.284	-0.213	***
Rating	0.219	0.082	2.66	0.008	0.057	0.380	***
Constant	6.484	0.317	20.48	0.000	5.863	7.105	***

Mean dependent var	6.000	SD dependent var	0.755
R-squared	0.118	Number of obs	953.000
F-test	53.379	Prob > F	0.000
Akaike crit. (AIC)	2056.969	Bayesian crit. (BIC)	2081.267

**** p<0.01, ** p<0.05, * p<0.1*

Table 4.10 shows that all the variables, excluding generosity, are individually significant to a 99 percent confidence level. Furthermore, the variables are jointly significant to above 99.99

percent confidence level as reported by the F test having a p value of 0. However, an examination of the omitted variable test, as reported in Table 4.11 below, shows that omitted variable bias poses a problem within this model specification.

Table 4.11 Reset test for Model 1

```
Ramsey RESET test using powers of the fitted values of Amount_raised
       Ho:  model has no omitted variables
                 F(3, 945) =      7.33
                  Prob > F =      0.0001
```

4.3.2 Kiva 2: Signals and social capital

The second model used to study the determinants of amount raised by the Kiva platform, expands upon the first by including the measures of social capital and was defined as follows:

Y_i= Amount of money raised for project i

$$Log\ Yi = \alpha + \beta_1 logGenerosity + \beta_2 logTemporal\ Experience + \beta_3 logCapacity\ Experience + \beta_4 logRating + \beta_5 logEigen\ Centrality + \beta_6 logBetweeness\ Centrality + \beta_7 Closeness\ Centrality + \varepsilon_i$$

The estimates for this second model specification, are reported in Table 4.12, here below:

Table 4.12 Kiva signal and social capital regression model

Amount raised	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Generosity	0.036	0.063	0.57	0.570	-0.088	0.159	
Temporal Experience	0.313	0.055	5.72	0.000	0.206	0.420	***
Capacity Experience	-0.194	0.020	-9.52	0.000	-0.234	-0.154	***
Country Funds	-0.028	0.025	-1.14	0.257	-0.077	0.021	
Rating	0.119	0.071	1.68	0.093	-0.020	0.257	*
Eigen Centrality	0.098	0.013	7.23	0.000	0.071	0.124	***
Betweenness centrality	0.020	0.005	4.43	0.000	0.011	0.029	***
Closeness centrality	0.546	0.084	6.48	0.000	0.381	0.712	***
Constant	7.834	0.406	19.30	0.000	7.037	8.631	***

Mean dependent var	6.059	SD dependent var	0.722
R-squared	0.352	Number of obs	897.000
F-test	68.210	Prob > F	0.000
Akaike crit. (AIC)	1588.593	Bayesian crit. (BIC)	1631.785

**** p<0.01, ** p<0.05, * p<0.1*

This second model, as shown in Table 4.12, is jointly significant to above a 99.99 percent significance level however, three of the variables are now not statistically significant at a 95 percent confidence level and the model still suffers from omitted variable bias as demonstrated in Table 4.13 below.

Table 4.13 Reset test for Kiva signal and social capital regression model

```
Ramsey RESET test using powers of the fitted values of Amount_raised
       Ho:  model has no omitted variables
                 F(3, 885) =      4.15
                  Prob > F =      0.0062
```

4.3.3 Kiva 3: Complete OLS model

The third model derived from the Kiva conceptual framework, also considers measures of the level of competition measures thus defined as:

$$Y_i = \text{Amount of money raised for project i}$$

$$\begin{aligned} Log\ Yi = {} & \alpha + \beta_1 logGenerosity + \beta_2 logTemporal\ Experience \\ & + \beta_3 logCapacity\ Experience + \beta_4 logRating + \beta_5 logEigen\ Centrality \\ & + \beta_6 logBetweeness\ Centrality + \beta_7 Closeness\ Centrality \\ & + \beta_8 logActive\ Loans + \beta_9 logLaunch\ Competition \\ & + \beta_{10} logSector\ index + \beta_{11} logPartner\ index + \varepsilon_i \end{aligned}$$

The estimates for this third model specification, are reported in Table 4.14, here below

Table 4.14 Kiva complete OLS model

Amount raised	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Generosity	-0.072	0.064	-1.13	0.259	-0.197	0.053	
Temporal Experience	0.240	0.050	4.78	0.000	0.142	0.339	***
Capacity Experience	-0.104	0.032	-3.29	0.001	-0.166	-0.042	***
Country Funds	0.055	0.027	2.06	0.039	0.003	0.107	**
Active Loans	-0.152	0.017	-9.03	0.000	-0.185	-0.119	***
Rating	0.160	0.066	2.43	0.015	0.031	0.290	**
Eigen Centrality	0.095	0.013	7.48	0.000	0.070	0.119	***
Betweenness centrality	0.020	0.004	4.56	0.000	0.011	0.028	***
Closeness centrality	0.477	0.078	6.11	0.000	0.324	0.630	***
Launch competition	-0.046	0.020	-2.34	0.020	-0.085	-0.007	**
Sector index	0.056	0.024	2.32	0.021	0.009	0.103	**
Partner index	0.072	0.036	1.97	0.049	0.000	0.143	**
Constant	5.804	0.590	9.83	0.000	4.646	6.963	***

Mean dependent var	6.059	SD dependent var	0.722
R-squared	0.440	Number of obs	897.000
F-test	76.843	Prob > F	0.000
Akaike crit. (AIC)	1465.840	Bayesian crit. (BIC)	1528.228

*** *p<0.01, ** p<0.05, * p<0.1*

Table 4.15 omitted variable test for complete OLS model

```
Ramsey RESET test using powers of the fitted values of Amount_raised
       Ho:  model has no omitted variables
                 F(3, 881) =      1.95
                  Prob > F =      0.1200
```

The results from Table 4.14 show that the majority of variables are significant with only the generosity one not having a significant impact on the amount of money raised. The variables are also jointly significant to above a 99.99 percent confidence level with the F-test reporting a p-value of 0. Utilisation of the BIC and AIC values in comparison with the second model is possible due to them having exactly the same number of observations, a necessity when comparing models using these tests. In both measures the complete model has lower values than the second model, suggesting the complete model is a better fit for the data (Liddle 2007). Furthermore, examination of the Omitted variable bias, reported in Table 4.15, showing that the RESET test output, indicates that the null hypothesis of no omitted variables, cannot be rejected. Additionally, the VIF test shows that multicollinearity was below the boundary level of 5 utilised to indicate problematic level of multicollinearity (James et al, 2013).

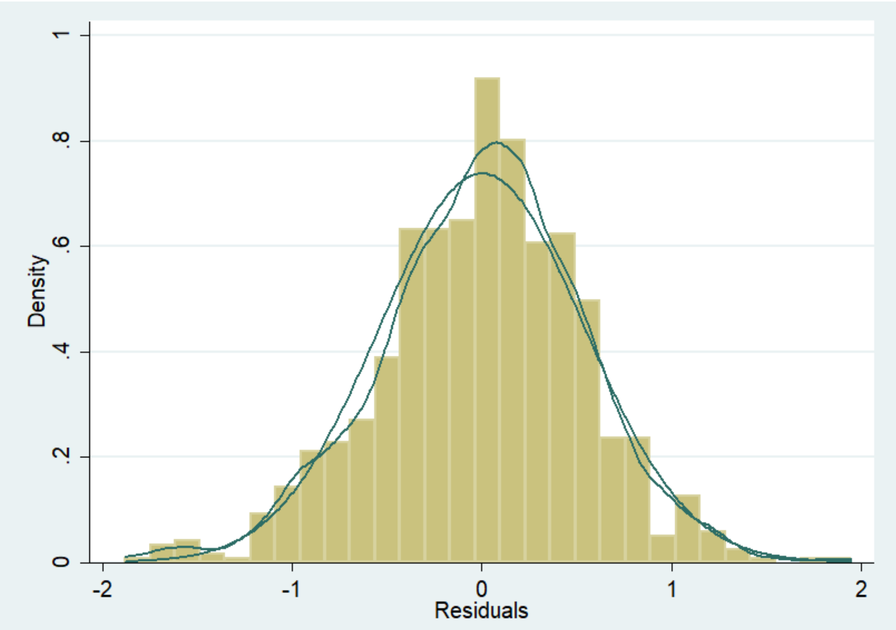
Table 4.16 VIF test for Kiva OLS model

	VIF	1/VIF
Capacity Experience	4.992	.2
Partner index	3.305	.303
Country Funds	2.939	.34
Temporal Experience	2.013	.497
Rating	1.915	.522
Eigen Centrality	1.837	.544
Active Loans	1.791	.558
Betweenness centrality	1.72	.581
Generosity	1.246	.803
Closeness centrality	1.151	.869
Launch competition	1.14	.878
Sector index	1.058	.945

Mean VIF	2.092	.

Finally, the regression residuals appear to be normally distributed based upon the spread of the residuals as displayed in Figure 4-19 below:

Figure 4-19 Residuals of complete OLS model



4.3.4 Kiva Truncated Regression

The fourth model developed in the Kiva conceptual framework, considered the necessity of restricting the dependant values to being positive and truncated at zero. Thus, the model was defined as:

Y_i= Amount of money raised for project i

$$With\ the\ restriction\ Log\ Yi > 1 \text{ and } Log\ \bar{Y}i > 1$$

$$\begin{aligned} Log\ Yi = {} & \alpha + \beta_1 logGenerosity + \beta_2 logTemporal\ Experience \\ & + \beta_3 logCapacity\ Experience + \beta_4 logRating + \beta_5 logEigen\ Centrality \\ & + \beta_6 logBetweeness\ Centrality + \beta_7 Closeness\ Centrality \\ & + \beta_8 logActive\ Loans + \beta_9 logLaunch\ Competition \\ & + \beta_{10} logSector\ index + \beta_{11} logPartner\ index + \varepsilon_i \end{aligned}$$

The estimates ‘results of this truncated model, are reported here below, in Table 4.17:

Table 4.17 Kiva Truncated regression results at boundary 0

Amount raised	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Generosity	-0.072	0.063	-1.14	0.255	-0.196	0.052	
Temporal Experience	0.240	0.050	4.81	0.000	0.143	0.338	***
Capacity Experience	-0.104	0.031	-3.31	0.001	-0.165	-0.042	***
Country Funds	0.055	0.026	2.08	0.038	0.003	0.106	**
Active Loans	-0.152	0.017	-9.10	0.000	-0.185	-0.119	***
Rating	0.160	0.065	2.45	0.014	0.032	0.288	**
Eigen Centrality	0.095	0.013	7.54	0.000	0.070	0.119	***
Betweenness centrality	0.020	0.004	4.59	0.000	0.011	0.028	***
Closeness centrality	0.477	0.078	6.15	0.000	0.325	0.629	***
Launch comp	-0.046	0.020	-2.35	0.019	-0.085	-0.008	**
sector index	0.056	0.024	2.34	0.019	0.009	0.102	**
partner index	0.072	0.036	1.98	0.047	0.001	0.142	**
Constant	5.804	0.586	9.90	0.000	4.655	6.953	***
Sigma	0.540	0.014	37.91	0.000	0.512	0.568	***
Mean dependent var		6.059	SD dependent var			0.722	
Number of obs		897.000	Chi-square			934.628	
Prob > chi2		0.000	Akaike crit. (AIC)			1467.840	

**** p<0.01, ** p<0.05, * p<0.1*

This model’ estimates, in Table 4.17, yet again indicate that the majority of variables are statistically significant, with only the level of Generosity failing to have a significant effect on the amount of money raised. The Chi squared test also shows that the variables are jointly significant. However, it is worth noting that the AIC value for this model is slightly higher than the complete OLS model. The multicollinearity is identical to the complete OLS model as shown in Table 4.18 below:

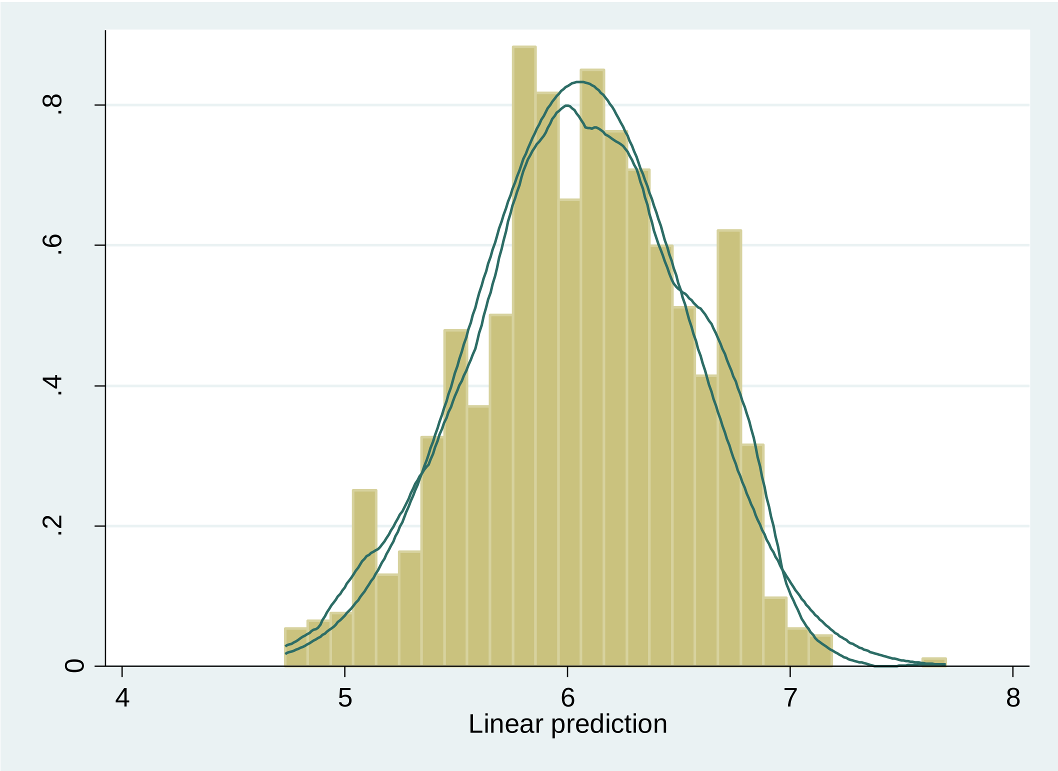
Table 4.18 Vif results for Truncated model

	VIF	1/VIF
Capacity Experience	4.992	.2
Partner index	3.305	.303
Country Funds	2.939	.34
Temporal Experience	2.013	.497

Rating	1.915	.522
Eigen Centrality	1.837	.544
Active Loans	1.791	.558
Betweenness centrality	1.72	.581
Generosity	1.246	.803
Closeness centrality	1.151	.869
Launch competition	1.14	.878
Sector index	1.058	.945
Mean VIF	2.092	.

While the model still appears to be normally distributed as shown in the Figure 4-20 below.

Figure 4-20 Residuals of truncated model



Thus, even though the model has a slightly higher AIC value, as this model overcomes a possible misspecification error and still passes the Gauss Markov assumptions, this will be utilised in the examination of the Kiva hypotheses.

4.3.5 Kiva model summaries

Table 4.19 Kiva results by model summary

	Signals only	**Social capital and signals**	**Kiva main**	**Tobit Model**
Generosity	0.0167	0.0356	-0.0718	-0.0718
	(0.22)	(0.57)	(-1.13)	(-1.14)
Temporal Experience	0.424***	0.313***	0.240***	0.240***
	(6.33)	(5.72)	(4.78)	(4.81)
Capacity Experience	-0.248***	-0.194***	-0.104**	-0.104***
	(-13.61)	(-9.52)	(-3.29)	(-3.31)
Rating	0.219**	0.119	0.160*	0.160*
	(2.66)	(1.68)	(2.43)	(2.45)
Country Funds		-0.0283	0.0548*	0.0548*
		(-1.14)	(2.06)	(2.08)
Eigen Centrality		0.0975***	0.0946***	0.0946***
		(7.23)	(7.48)	(7.54)
Betweenness centrality		0.0201***	0.0196***	0.0196***
		(4.43)	(4.56)	(4.59)
Closeness centrality		0.546***	0.477***	0.477***
		(6.48)	(6.11)	(6.15)
Active loans			-0.152***	-0.152***
			(-9.03)	(-9.09)
Launch competition			-0.0465*	-0.0465*
			(2.34)	(-2.35)
Sector index			0.0557*	0.0557*
			(2.32)	(2.34)
Partner index			0.0715*	0.0715*
			(1.97)	(1.98)
Constant	6.484***	7.834***	5.804***	5.804***
	(-20.48)	(-19.3)	(9.83)	(9.90)
Observations	953	897	897	897
R-squared	0.1180	0.3523	0.4401	0.2654

F Statistic	53.38	68.21	76.84	77.90
Prob > F	0.0000	0.0000	0.0000	0.0000

t statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001

4.4 Kiva results by hypothesis

The following section considers whether the collected empirical evidence supports the hypotheses developed in Chapter 3 within the Kiva conceptual models, aimed at better understanding the functioning of the Kiva platform. These results were grouped into separate subsections based upon the different components outlined within the Kiva conceptual framework (Figure 3-10)

4.4.1 Signalling hypotheses

The first set of hypotheses considered the impact that signalling increased levels of experience by the partnership organisation had on the amount of funds raised by the individual projects. Arguing that signalling higher levels of experience would increase the amount of funds raised by the projects the hypothesis states: A1: *Creators signalling increased experience has a positive impact on the amount of money raised in Kiva.*

This hypothesis was tested by using two diferent variables: *capacity experience,* capturing the number of backers that had previously supported the partnership organisation, and *temporal experience,* calculated as the amount of time which the partnership organisation has been present on the Kiva platform. However, the results do not consistently support this hypothesis as shown in Table 4.17.

The *temporal experience* variable shows a positive and statistically significant impact on the amount of money raised, supporting the key signalling hypothesis, A1. On the other hand, the *capacity experience* of the intermediary organization displays a negative and significant impact on the amount raised by a project on Kiva.

Due to the dependent and independent variables both containing log values, a 1 percent increase in the independent variable has a β_i% impact on the dependent one. Thus, a 1 percent shift in temporal experience increases the amount of money raised by 0.24 percent while a 1 percent raise in capacity experience decreases the amount of money raised by 0.1 percent, indicating that we should further explore the reasons for the different effects of these two variables. These results are discussed relative to the findings in section 5.1.2.2.

4.4.1.1 Generosity

The second signal examined was the one for *generosity*. This was measured by considering the interest rate charged by the partnership organisation to the project participant, arguing that a lower interest rate might capture some elements of a higher level of generosity, leading to hypothesis A2*: Signalling increased level of generosity has a positive impact on the amount of funds raised.*

The empirical results, however, did not support this hypothesis, as shown in Table 4.17, indicating that the level of generosity, has no statistically significant impact on the amount of money raised by a project advertised on the Kiva platform. This suggests that: either the interest rate is not a good proxy for generosity, or that signalling generosity is not really effective at overcoming the presence of credit rationing due to the pervasiveness of asymmetric information, a possibility further discussed within findings section 5.1.2.3.

4.4.1.2 Rating of the creator by the platform

Next, we focus, as discussed in the Kiva conceptual framework, on the impact of the signals sent by Kiva. From a platform point of view, the reason for signalling are clearly different from those driving the signalling of users of the platform. The specific signal specifically analysed, as discussed in section 3.4.2.3, is the *rating* Kiva provides about each partnership organisation, reflecting the level of trust/confidence Kiva has in the partnership organisation. This role is related to stated hypotheses: A3: *The platform signalling an increased rating for the partnership organization, exerts a positive impact on the amount of funds raised, by the final project.*

The results from Table 4.17 support hypothesis A3, showing that the rating given by Kiva to a project had a positive coefficient and was significant at 5%. Thus, a Kiva's rating increase of 1 percent would increase the amount of money raised for a project by 0.16 percent, indicating that a two-sided crowdfunding platform, itself, can act as a relevant signalling agent within the crowdfunding process.

The results from these sections regarding signalling in crowdfunding are discussed alongside and in comparison, to the signalling results from Kickstarter in section 5.1.1.

4.4.2 Social capital

4.4.2.1 Creators Internal social capital

The hypothesis focusing on the role of *internal social capital* in affecting the amount of funds raised by final projects, is grounded on the idea that an increased amount of creators' *internal social capital* should be positively associated with an higher levels of funding raised by projects advertised on Kiva. This idea was captured by constructing a latent network based upon the shared backer connections among different projects and focussing on *eigenvector centrality* as a proxy for capturing social capital of the project. This hypothesis is discussed in detail in section 3.4.3.1 and states B1: *Higher levels of internal social capital within Kiva have a positive impact on the amount of funds raised.*

The results from Table 4.17 show that hypothesis B1 is supported by the emprirical evidence, analysed through the model as *eigenvector centrality* having a positive and significant impact on the amount of money raised by projects on Kiva: with a 1 percent increase in *eigenvector centrality* leading to a 0.0946 percent increase in the amount of money raised.

The other two centrality measure of *betweenness centrality* and *closeness centrality,* also showed a positive and significant impact on the amount of money raised by projects on Kiva. *Closeness centrality* has the stronger impact as, increasing *closeness centrality* by 1 percent increases amount of money raised by 0.477 percent, while *betweenness centrality* has the small impact since a 1 percent. Suggesting that a node's independence (captured by *closeness centrality*) and control of information (captured by *betweenness centrality)* within the latent network does positively impact the amount of money raised within Kiva.

4.4.2.2 Past internal social capital generated by other creators

This hypothesis stemmed from the concept that social capital generated by an organisation or group could be utilised by new members of this group, regardless of whether they were involved in the original generation of the social capital. And thus, in relation to Kiva, social capital generated for a specific region could bring benefits for future projects within that region. This possibility was assessed by estimating the impact of the amount of money previously lent within the country where the Kiva project is occurring on this project's raised amount. This mechanism, discussed in section 3.4.3.2, lead to stating hypothesis B2: *Higher levels of social capital generated by previous creators within a geographic region have a positive impact on the amount of funds raised for a creator in that area.*

The results outlined in Table 4.17. provide clear support for hypothesis B2, with the amount of previously lent funds in the same country of the Kiva project having a positive and statistically significant impact on the amount of money raised for the project. Specifically, an increase in the country funds of 1 percent has a 0.0548 percent increase on the amount of money raised. Thus, the hypothesis was supported by the empirically evidence, demonstrating that social capital generated for past projects within a specific geographic region supports future projects within the region. This has implications for the findings with regard to social capital generation and retention within specific subsection of crowdfunding platforms and later discussed in detail in section 5.2.3.

4.4.3 Competition hypothesis

This hypothesis was grounded in the idea that increased levels of competition within the platform would decrease the amount of funds received by individual projects. The amount of internal competition within the platform was measured through four separate proxies, as discussed in 3.4.4, that of the number of active loans in the country, the number of other projects launched on the same day, a HHI (Herfindahl–Hirschman Index) competition index based on the sector of the project and a secondary HHI competition index based on other projects launched by the same partnership organisation within the examined dataset. All four metrics were utilised in the testing of hypothesis C1, stating that: *Increased amount of internal competition within the platform has a negative impact on the amount of money raised*.

The result from the estimations obtained with the main Kiva model, displayed in Table 4.17, all support the proposed hypothesis C1. With the number of actives loans and launch competition having negative and significant impact on the amount of money raised. Conversely, both the HHI index values show a positive and significant impact on the amount of money raised. As the index values increase with decreased levels of competition, these positive coefficients indicate that lower levels of competition increase the amount of money raised. Thus, all four of these measures support the proposed hypothesis.

The number of actives loans has the largest impact with a 1 percent increase in the number of active loans decreasing the amount of money raised by 0.15 percent. The smallest impact was caused by the amount of launch competition whereby a 1 percent increase in the launch competition index led to a 1 percent decrease in the amount of money raised. The partner index had a larger affect than the sector index, with a 1 percent increase in partner index leading to a 0.0715 percent increase in the amount of money raised, while an increase of 1 percent in the sector increase only lead to a percentage increase of 0.0557. This result and the rest of the results are discussed in detail across the section 5.3.1 of the findings.

5 Findings: Discussion of results, recommendations and limitations

This section is composed of six subsections, the first four consider the key findings and recommendations which emerged from the empirical work of the thesis. These four sections are divided based upon the underlying theories the findings are associated with. The final two sections contain recommendations derived from the empirical findings, the first focuses on recommendations relevant for the crowdfunding ecosystems, composed by *creators*, backers and *crowdfunding platforms*. The second and last section, instead, outlines recommendations for future research based upon the limitations of the study. These sections are outlined in more detail below:

1) Signalling: Finding and Recommendations: displays the key findings and recommendations relating to signals sent out by the three participant groups within crowdfunding: creators, backers and the platform itself. Providing support for the argument that each party involved can act as a signalling agent within the framework of crowdfunding and that effectively sending signals is a key driver of success within crowdfunding.

2) Social Capital: Findings and Recommendations: displays the key findings and recommendations derived from addressing the role of social capital across both the Kickstarter and Kiva models. It divides the findings into an examination of internal and *external social capital* and considers how both aspects of social capital impact success within crowdfunding.

3) Competition: Finding and Recommendations: considers how the empirical evidence gathered and analysed in the thesis and supported by the existing literature, supports the argument that increased competition does not necessarily always have a negative impact on success, while, instead, increased competition can have either a negative or positive impact depending upon the strength of the positive and negative network externality effects due to additional projects being added to the platform.

4) Backer Incentives: Finding and Recommendations: the findings and recommendations within this section all relate to how altering the backer's incentives affects the likelihood of success within a crowdfunding platform. This section is derived from the results of the Kickstarter model.

5) Recommendations to the participants of crowdfunding: outlines the key recommendations derived from the rest of the findings section for the three key parties involved in Kickstarter: the *creators* the *backers* and the *platform* itself.

6) Recommendations for future research: Outlines a set of possible extensions for the research based upon the limitations outlined in the rest of the findings section.

5.1 Signalling: Finding and Recommendations

5.1.1 Creator signals.

This section considers the findings and recommendations emerged from the evidence obtained on the hypotheses which were developed according to the key insights derived from the review of signalling theory.

5.1.1.1 Enforced and voluntary signals

The results provide support for the act of distinguishing between enforced and voluntary signals while examining success in crowdfunding platforms. Every single voluntary signal, across both models, sent by either the creators, backers or platform itself, was found to have a positive and significant impact on the success of projects. Conversely, enforced signals, which were chosen by the platform, were shown to have mixed results: with both positive, negative and insignificant impacts on success within crowdfunding.

The evidence provided suggest that while enforced signals may exert a negative impact on project success, the crowdfunding platform might still have the incentives to send these signals. Indeed, the platform uses these signals to distinguish between the low-quality and high-quality projects for the backers to be able to overcome the pervasive asymmetric information characterising crowdfunding platforms (Agrawal et al, 2014; Courtney et al, 2017). Failure to do so could result in the collapse of multi-sided platforms as seen with the collapse of Atari in 1983, which according to Boudreau and Hagiu (2009) was driven by unlicensed creators releasing low-quality games onto the console, systematically eroding the trust generated for the platform. Furthermore, Boudreau and Hagiu (2009) examined how in multi-sided platforms, the platforms themselves act as self-regulators in order to stop the market failure which led to the collapse of Atari.

Additionally, the results suggest that enforced signals have different effects as, following the incentives of the platform to sustain the long-term survival of the platform rather than of the projects, they are designed to identify and signal the presence of low-quality campaigns, not to blindly ensure projects success. This can be considered an interesting finding from our empirical evidence: these authors observed the presence as a trade-off for the crowdfunding platform, the lower the amount of scrutiny provided via enforced signals, the higher the likelihood of a project succeeding in the short-term, however lower levels of scrutiny also risk the continued stability and existence of the platform in the long-term. As the platforms are reasonably assumed to behave like self intererested entities, they need to face the key question of what is the optimal level of *creators'* quality scrutiny which can be applied to maximise their own long-term viability. A unique factor for crowdfunding which can be incorporated within this calculation is the delivery rate of projects, as a direct way of quantifying the reliability of the platform (Mollick, 2015). However, the delivery rate of projects might underestimate the total number of low-quality projects in the platforms as, although projects may successfully deliver their rewards, this does not imply that they will be of sufficient quality. Nevertheless, the issue of the optimal level of scrutiny which should be provided by the crowdfunding platform is relevant and provides a key area for future research, especially considering the emergence of new types of co-operative platforms, which radically transform the incentives structure by transferring ownership from a private organisation to the users of the platform themselves (Scholz, 2016; Hautamäki and Oksanen, 2018), dramatically transforming the incentives structure and thus the optimum level of scrutiny of the platform. In further exploring this question of the optimum level of scrutiny, one can utilise the differences between Google Play and the Apple App store (Hein et al, 2016). Whereby Google Play offers high levels of accessibility with almost no limits to app creation, the Apple App store has much higher requirements imposed upon for the apps sold in the store. This difference in platform policies results in Google Play's rapid development of apps with comparatively limited usability, while Apple App store has comparatively slower development but increased app quality and overall customer satisfaction (Hein et al, 2016; Fautrero and Gueguen, 2013; Pon et al, 2014). For these reasons these authors suggest that the more enforced signals are sent by the crowdfunding platform, the more restrictions, the platform will be placing upon its project creators. Hence, platforms sending more enforced signals seem to be adopting strategies comparable to those of the Apple app store, restricting project numbers to ensure project quality. On the other hand, platforms with fewer enforced signals can be seen to be aligning their signalling strategies to the Google Play Store model of having limited restrictions to increase projects number, while accepting the price of reduced reliability. Yet this still does not answer what the optimal level of scrutiny for a crowdfunding platform is, leaving the question open for further research.

In contrast to enforced signals, the voluntary signals are controlled by the creators and backers of the crowdfunding campaigns. The creators' incentives are clear as they obviously wish the project to succeed. The backers' signals are also clear, since signals can only be sent by backers who have already provided support to a project. This restriction was active across both platforms which were examined in this thesis; and can be seen as a filter to ensure that only signals concerning the project are raised. The restriction can be seen as a method for the platform to overcome the endless flow of internet spam as the restriction is similar to the actions undertaken by social networks to address the same issues (Boykin and Roychowdhury, 2005). Therefore, backers who are signalling have already backed a project and thus they are incentivised to signal their support for the project, in order to receive their own rewards for supporting the project. This is especially true on an all-or-nothing platform, assuming the backer is not willing to support the entirety of the project, then additional users are necessary for the original backer to receive their rewards. Even without the all or nothing condition, backers are still likely to wish to encourage further backing, under the assumption that a project with more funds is more likely to successfully deliver. Thus, the positive effects of the voluntary signals on success can be attributed to how the backers and creators are effective at persuading other potential backers to support the project through utilising voluntary signals.

These findings on enforced and voluntary signals have clear implications for creators, backers and the platforms themselves. Firstly, the creators should consider the impact of the enforced signals when choosing their crowdfunding platform, especially creators with lower quality campaigns which may be unable to succeed in platforms with higher levels of scrutiny. Backers should utilise the enforced and voluntary signals when determining both what crowdfunding platforms they utilise and which projects they choose to support, as the greater the number of enforced signals the more information available to the backers, enabling them to make more informed decisions. Finally, the crowdfunding platform themselves have to carefully consider the number of signals utilised, too few could undermine the platforms reliability, too many and creators may be unwilling to use the platform.

5.1.1.2 Creators Signals and human capital

Throughout section 3.3.2, on methodology, the connection was drawn between crowdfunding creators and entrepreneurs, building upon how some creators are entrepreneurs (Bruton et al, 2015) and expanding upon this to consider how general principles of entrepreneurship can be applied to crowdfunding creators. Enabling the utilisation of the entrepreneurship literature in examining the specific role of human capital. For example, in the development of the hypotheses surrounding the Kickstarter model five different elements of human capital were considered, namely: overconfidence (Astebro et al, 2014) experience (Gompers et al ,2010), trustworthiness (Rauch and Frese, 2007; Abdullah, 2013), patience (Kirby, 2004; Doepke and Zilbotti, 2014) and ambition (Davies and Giovannetti, 2019). The key argument discussed in the methodology chapter, was that these different dimensions of human capital could be studied, within crowdfunding, through the examination of the signals sent out by the *creators*, with signals, as representations of the different types of human capital. This approach enabled the formulation of the hypotheses about the impact of enforced signals by considering if the specific element of human capital captured by the signal was expected to have a positive or negative impact on projects' success. A key aspect of the analysis of signals was on considering that, for a signal to be effective in overcoming asymmetric information, it needs to be observable, manipulatable and costlier for low-quality projects, in line with the original contributions from signalling theory outlined in Ross (1977) and Spence (1978). Thus, for the signals to have an impact on the success within the crowdfunding they must have fulfilled these three criteria.

These core arguments were supported by the results of the models, in which all of the enforced signalling hypotheses were supported, apart from the two hypotheses focussing on *experience* and *generosity*. These were, shown to have not fulfilled the three criteria for being effective signals. The result of *Experience* and *Generosity* are discussed in more detail in section 5.1.2.3.

If the enforced signals are being intepreted as aspects of human capital by the backers of crowdfunding projects, then this has clear implication for both the design of crowdfunding platforms and of projects themeselves. Platform should aim to design the possibilities for projects to send these signals, to clearly communicate aspects of human capital, while ensuring that the signals are effective. Creators must consider the set of enforced signals made possible by the crowdfunding platform design and whether these will enable them to effectively support their projects. The following section considers the key findings and recommendations derived from specific hypotheses, in comparison to the previously outlined general signalling findings and recommendations.

5.1.2 Key findings and recommendations from specific creators' signals.

5.1.2.1 Confidence and altering expectations

The evidence presented in section 4.2.1.1, shows that creators can be overconfident in assessing their ability to raise funds on Kickstarter. With the relative level of confidence having a negative impact on the likelihood of a project to reach its funding goal. This observations lead to the recommendation that creators should consider setting a lower relative funding goal.

However, this recommendation needs specific action to be taken by the crowdfunding platform. At the moment, within Kickstarter, it is very difficult to see the average amount of money raised by each project, if creators are not provided with this information, they will likely overestimate their abilities, in part due to the existence of blockbuster projects (Liu et al, 2015), which create an unrealistic expectation for the outcome of the crowdfunding projects. Secondly, the focus should be shifted to setting realistic funding goals by demonstrating how creators can use new funding rewards and objectives to enable them to expand past their original funding goal.

5.1.2.2 Experience and its relation to social capital

The results on the impact of *experience* were not consistent across both models; in fact, while experience within Kickstarter had a positive and significant impact on the probablity of a project success, in Kiva's case[2], increased levels of capacity experience showed a negative and significant impact on the amount of money raised, while increased levels of temporal experience had a positive and significant impact.

These, apparently contradictory results, can be attributed to the fact that although experience is a desired trait and thus a should be a positive signal, experience also indicates that creators have utilised their internal and *external social capital* in support of past projects. The utilisation of social capital can divide the focus of social capital. Coleman (1988) key work on social capital in the creation of human capital, considered how social capital can be divided. By suggesting a single child would be better off than siblings as the siblings would split the social capital. In the same way, serial creators could be seen as having to split their social capital across multiple crowdfunding projects. However, the weakness with this

[2] Where experience was expressed in two forms, temporal and capacity experience, with temporal experience being a record of how long a creator (partnership organisation) had participated in Kiva and capacity experience recorded how many loans they had previously created.

argument is that the crowdfunding projects do not need social capital at the same time as long as they are not active at the same time. Thus the division of capital does not seem to fit this case accurately.

Instead, it could be argued that there is some form of social capital destruction, as social capital can be reduced by one side deciding that they no longer wish to communicate with the other side (Semih, 2011). This could occur in reward-based crowdfunding when a project fails to deliver its rewards, people within the social network which supported the project may feel wronged and thus destroy that connection. In the same way that connections are destroyed upon the revelation of negative marketing activities which utilises social capital, such as Ponzi schemes (Almassi 2018). Thus past experience in the platform may have decreased the social capital of the creator and negatively impacted the project success.

Furthermore, even experience in projects which deliver their rewards on time may still deplete social capital. To be more specific, past projects may deplete the ability of that specific social capital to be used to raise funds at this specific point of time. Utilising the concept that marginal utility of income decreases as income increases (Layard et al, 2008), if asked for money twice, an individual will effectively have a lower income and thus have higher utility cost of giving money, hence this second request will yield fewer returns to a project.

To address this loss of social capital through depletion, the creator could take multiple steps. Butticè et al (2017) suggested a substitution tactic, arguing that you could replace one form of social capital with another, specifically arguing that social capital could be replaced through backing other projects within the platform. Conversely, the results from the Kickstarter model do not support backing other projects as a method of generating social capital within a platform as an increased number of previously backed projects had a negative impact on the likelihood of a project to succeed. Instead, the author proposes that creators should increase the time between their projects as a way of allowing social capital to replenish its ability to be utilised to obtain funds. However, this needs to be further examined as an expansion to the current work, as it is not considered within the models and thus will not be utilised as a recommendation.

5.1.2.3 Generosity and impatience as insignificant signals

Generosity and *impatience,* came out as not statistically significant signals. With regards to *impatience,* this was possibly caused by the fact that Kickstarter only allows a maximum of sixty days for campaigns, thus high-quality creators are not able to distinguish themselves from low quality creators utilising this signal, as there is only limited extra cost for low quality campaigns in running a sixty days compared to a ten days campaign. In regards to *Generosity,* this signal did not enable discriminating between high and low-quality projects, as within Kiva the signalling agents were the partnership organisations, and low-quality partnership organisations may not carry out due diligence in the selection of the loan recipients, lowering costs and thus enabling them to display higher levels of generosity to their recipients. A second point to consider with Generosity is that it may not have been observable to all potential backers, this is due to the information being hidden behind a drop box within the project page, that you need to click in order to see this information. Some backers may not click this box and thus the signal is unobservable to these backers. This raises an interesting question about observability, that observability may not be absolute and that it may differ between users, creating possibility of partial observability which may impact the effectiveness of signals.

These two points further support the argument that signals cease to be effective if they are not costlier, observable and manipulatable, aligning the results with the original theory proposed by Ross (1977) and Spence (1978). These results enable to derive a key recommendation to platforms, that in order for enforced signals to be effective they must be manipulatable, observable (fully) and costlier for low quality projects, as otherwise they will have no impact on the success of the project.

5.1.2.4 Platforms ability to send out signals

One of the key results from the Kiva model was the positive impact of the platform providing a higher *Rating* for projects. As a higher rating signal sent out by the platform, increases the amount of money raised by a project. Thus, the platform itself acts as a signalling agent, both to the creators and to the backers, and this two-sided signalling role of the platform will impact the success of projects.

This result provides further evidence in the support for the concept that platforms may also act as self- regulators, as the results suggest that backers consider information provided by the platform, about a project, as a reliable way of judging the quality of the project. This signalling activity can be seen as a form of soft self-regulation whereby the platforms instead of restricting access to the usage of the platform, on the projects side, prefer to signal their own knowledge to direct and focus support on specific better-quality projects. These soft self-regulation signalling activities can be observed across multiple crowdfunding platforms as for example, within Crowdcube a valuation of the company seeking to raise funds is provided (Crowdcube, 2019) and in Kickstarter, a set of projects are recommended each day (Kickstarter, 2019c). One the limitations of the collected Kickstarter dataset is that it does not record which projects where supported by the platform, as this information was not recorded on the project page of the Kickstarter platforms.

From this result a key recommendation to platforms can be derived, emphasizing the relevant role that a platform can play in signalling support to higher quality projects.

5.1.3 Backers signals: Key findings

The results from the Kickstarter model showed that backers' signals are vital in the success of the crowdfunding projects. These signals were captured in two ways, firstly by examining the number of comments sent by backers and, secondly, by utilising the concept of the early funding period, outlined initially in (Colombo et al, 2015) and further developed in (Skirnevskiy et al, 2017), to examine the early campaign behaviour of backers, with backing a project early being seen as a signal of support for the project.

The empirical evidence on the impact of *comments* clearly showed that backers who vocally supported the campaign rather than simply silently backing it, increase the likelihood of the project succeeding. One reason why this occurs is due to how, within Kickstarter, only backers who have already supported the campaign may leave comments. Thus, the comments are likely to support the project as backers are incentivised to encourage further backing to ensure they receive their rewards as if the funding goal is not reached, no rewards are delivered. This, therefore, provides a clear recommendation to both the platform and backers that the platform should enable comments on the project from backers who have supported the project and that backers should leave comments on projects which they have supported.

Three different measure of backers' signals were utilised to capture the effects of support in the early funding period of a project: the amount of funds backed, the number of people backing and the average pledge which each backer made. Both the number of early backers and average pledge amount had a positive and significant impact on the likelihood of a project succeeding. Conversely, the early funding had a negative impact, but the variable was not statistically significant. In interpreting this result, it could thus be considered that the number of backers could be an effective signal of the initial support for the project from the crowds, and that a higher intensity of this signal denotes an increased general interest by the crowd. On the other hand, the average amount pledged could be seen to signal how strong this support is by each backer. And it is this element of crowd interest and strength of support which is key to encouraging further support through these signals. In addressing the reasons underlying the results that the amount of early funds did not have a significant impact, it could be considered that this may not be an efficient signal, due to how low-quality campaigns may be able to artificially increase this value with ease. Indeed, it would be very easy for a low-quality campaign to artificially increase the amount of early funding, simply by backing the project themselves. They could then remove that backing later on if the project exceeds their funding goal and thus the amount of early funding would not be an efficient signal. This would impact early average pledges as well, however as logarithmic values were utilised in examining the impact of early average pledges, this would decrease the impact that these false signals would have. As in the case of these false signals, one person or a few people could add large amounts of backing, this would thus lead to a very high average pledge, which would be greatly reduced when logarithms were utilised. This finding has clear recommendations for creators of the crowdfunding campaigns that they should be aiming to either increase the number of early backers or increase the amount pledged, since simply adding to the early funds through artificial self-funding will not increase the likelihood of the project succeeding.

5.1.4 Signalling and existing crowdfunding literature

The findings discussed above provide fresh evidence in support of the existing literature on the positive impact of signalling sent by both creators and backers in overcoming asymmetric information within crowdfunding platforms, as outlined in (Ahlers et al, 2015; Kromidha and Robson ,2016; Kunz et al, 2017; Chakraborty and Swinney, 2017; Courtney et al, 2017; Vismara, 2018). Furthermore, this work expands upon these papers through the introduction of, and the distinction between, the concepts of *enforced* and *voluntary* signals. With enforced signals referring to when the crowdfunding platform demands specific signals to be sent by backers or creators. Conversely, voluntary signals occur when the backers and creators are free to decide whether to, or not to, send the signal. The findings indicate that voluntary signals always have a positive impact on success, while enforced signals' effects are less certain, as they may increase or decrease the likelihood of a project succeeding depending on the specific context. The work developed in this dissertation, also contributes in an additional second way to the crowdfunding signalling literature: by clarifying the relationship between enforced signals and human capital and demonstrating that specific signals sent by the creators can be seen as a representation of specific elements of human capital for said creators, as considered by Davies and Giovannetti (2018). Moreover, the impact of a signal on a project success can thus be determined through examination of that specific element of human capital the signal represents. Furthermore, the results derived from the empirical evidence confirmed that these signals, in crowdfunding platforms, would only be effective if they were observable, manipulatable and costlier for low-quality projects, in line with the signalling theory results, as originally outlined in Ross (1977) and Spence (1978).

The findings on signals sent by backers provided additional evidence on the relevance of the early funding period, as discussed by Colombo (2015) and on utilising the average pledge per backer as a measure of success, as introduced in Kromidha et al (2016). This was shown by the number of backers, and the average amount pledged in the early funding period having a positive impact upon the likelihood of Kickstarter projects succeeding.

5.2 Social capital: Findings and recommendations

This section considers the findings and recommendations derived from results associated with the social capital of either the backers or creators.

5.2.1 Utilising Facebook shares as a measure of external social capital

One of the key challenges in considering *external social capital* is in selecting the appropriate metrics. In chapter 3, on methodology, it was proposed to utilise the number of Facebook shares of the specific crowdfunding project as a measurement of the *external social capital* of the project, instead of using the number of Facebook friends which had produced inconsistent results in past crowdfunding research (Beier and Wagner, 2015; Colombo et al, 2015; Mollick 2014; Moisseyev, 2013). The results from the Kickstarter model supported the usage of the number of Facebook shares, having a positive and highly significant impact on the likelihood of a project successfully reaching its funding goal. This result supports earlier work by Kromidha and Robson (2016) who also utilised the number of Facebook shares as a measure of social capital, however their result was only weakly significant, in comparison to the highly significant result observed within this study. The difference in the significance of the measure could be attributed to the fact that Kromidha and Robson's (2016) study only examined successful projects, compared to this thesis's analysis that also includes failed ones.

However, one flaw with using Facebook shares as a metric for *external social capital* is that these were captured only at the end of the project lifecycle and thus could be problematic when used for predicting projects outcomes. Upon saying this, Facebook shares, can be adapted by focusing on the early funding period only, by examining the number of Facebook shares obtained within the first 1/6th of the duration of the crowdfunding project, therefore overcoming the predictive limitation of this metric.

Furthermore, the fact that the number of Facebook shares can be captured within the early funding period highlights how this measure may fluctuate across the duration of the campaign. This fluctuation enables the impact of *external social capital* to be examined across the entire duration of the campaign rather than just at one single point in time. In comparison, the number of Facebook friends would have far more limited variation across the project duration. Therefore, utilising the number of Facebook shares would enable further research to consider the direct impact of increased *external social capital* on different phases of the campaign.

As previously discussed, the early funding period is considered vital to the success of the campaigns (Solomon et al, 2015; Kuppuswamy et Bayus, 2018), and it could be considered whether this aligns with an increased focus of *external social capital* activation at the beginning of campaigns. Alternatively, perhaps *external social capital* activation only increases after a successful early funding period. These points show how the choice of adopting Facebook *shares* as a metric for *external social capital* leads to the identification of further research topics, specifically due to its data flexibility, allowing it to be examined across the entire temporal profile of a crowdfunding campaign.

5.2.2 Reciprocity and internal social capital generation

One of the mechanisms suggested for capturing a metrics of a creator's *internal social capital* generation was the use of *reciprocity*. However, the empirical evidence did not support this possibility showing, on the contrary, a negative and significant impact on success within Kickstarter being associated with an increased level of backing of other projects by creators on Kickstarter. In understanding this result, the author considered that backing other projects imposes a financial cost to the creators. This cost could thus be viewed negatively by the backers of the campaign as to why should creators be asking for funds while also providing funds to other projects. The author assumed in the development of the hypothesis that the negative impact would overcome the indirect reciprocity effects created by backing other projects.

Furthermore, the author considers how direct reciprocity may be difficult to facilitate in Kickstarter, due to the amount of information which is provided to backers of the crowdfunding campaigns. Backers on Kickstarter are not aware of the online identity of other backers on Kickstarter, only the creators can see a full list of backers' information (Kickstarter, 2019d). For a backer to identify that the creator has backed the same project, the backer must first visit the project page of the creator and then open up the previously backed projects tab, scroll through this tab and identify projects which they have jointly supported. Therefore, this information is not going to be accessed by most people; the average user visits 2.76 pages on Kickstarter (Alexa, 2018). Thus the complex process necessary to identify linkages to the creator of a campaign will not be undertaken. Therefore, backing other projects can only encourage direct reciprocity from the creators. However each creator is backed by on average 112.7 backers, rounding up to 113 for ease of usage, according to the collected Kickstarter dataset.

So, for a creator to support another project out of a desire to repay this original support, they must notice that one of their 113 backers have become a creator. There is no notification system that their backer has become a creator, so the creator must stumble upon the new project and identify that they have supported them in the past in order for them to facilitate direct reciprocity. For this reason, even if creators and backers wish to support projects based on reciprocity, the structure of Kickstarter does not provide this functionality. What is intriguing about this result, is that it is in complete contrast to the previous results surrounding reciprocity in crowdfunding as presented in Zvilchovsky et al (2015), whereby reciprocity both in direct and indirect forms was seen to have a positive impact on the amount of money raised within Kickstarter. This could suggest as the dataset of this thesis was captured in 2016-2017 and Zvilchovsky dataset was captured between 2009 and 2013, that there has been an underlying change in backers behaviour within Kickstarter over time in regard to reciprocity. This could have occurred due to the increase in the number of projects seeking funding on Kickstarter, within Zvilchovsky's dataset 78,061 projects were identified in a 4 four-year process, averaging 19515 projects per year, in comparison in the single year of data collected for this thesis, 58,143 projects were observed to have occurred. Thus, this increase could have affected the ability for reciprocity to take place within the platform, by increasing the complexity for backers to identify projects where reciprocity occur. However, as there are differences between the studies in the examined variables, this can only be seen as a suggestion, leading to the recommendation of future research into consider whether there has been a shift in the attitudes towards reciprocity behaviour among backers within the Kickstarter platform.

In comparison, the other platform analysed in this dissertation, Kiva, provides this, critically relevant, functionality of enabling backers to clearly indicate their support for current and past projects. In this case, backers are now able to view the support of other backers on the project page of the ongoing Kiva projects. Additionally, backers have their own dedicated page, within Kiva, which lists every project they have supported and any team they belong to. The team feature encourages backers to work together by creating a group focused around specific nationalities or causes, providing a common focal theme around which backers interconnect (Kiva, 2019d).

While the Kiva system provides backers with the possibility to remain anonymous, this possibility is optional and, importantly from a behavioural perspective, not the default one. Since Kiva's platform structure enables backers to observe the support of projects and shared causes from other backers, it enables the possibility of signalling reciprocity and, even more interestingly, coordination in backing decisions. This functional differences between the two analysed platforms: Kiva and Kickstarter, demonstrates how the organizational and governance structure of the platform can influence the ability of backers and creators to engage in signalling reciprocity and ultimately, the possibility and ability of creators in generating *internal social capital*, for the benefit of the projects.

5.2.3 Utilising social capital generated by past creators within the platform

The Kiva model considered whether the social capital generated by past creators within the same country would have a significant impact on the success of an ongoing crowdfunding project. This potential impact due to the hypothesis that social capital generated within the platform for the specific country would remain within the platform, even after that specific project had ended, and to be thereafter still useful in reducing asymmetric information and hence supporting the success of future projects within the same country. The empirical evidence discussed in the results supported this hypothesis, as the amount of previously raised funds within the country of the crowdfunding project had a positive and significant impact on the amount of money raised in Kiva projects. This shows that *internal social capital* generated by one specific creator can be utilised by other creators within the same subset of the platform, once the correct platform design is adopted.

This finding helps in explaining why blockbuster projects (highly successful projects) can be so impactful on the success of crowdfunding projects within the same category (Liu et al, 2015) since the social capital of the blockbuster project can be utilised by other projects within the same category, showing how positive externalities are being generated within an approrpiately designed platform.

Furthermore, through this study social capital has primarily been considered to be created and utilised by either the backers or creators, the results highlight how social capital can be captured and stored on the platform itself. Thus, indicating that the platform itself should be considered as a third party in the generation and storage of social capital. Moreover, the design of crowdfunding platforms plays a critical role in facilitating, or blocking, the possibility for social capital externalities to take place: for example, it is clear that a platform and its governance should be designed to facilitate the generation and storage of social capital given its potential positive impact as signalling device. However, one of the limitations of this study is that it does not address what process would enable optimal generation and storage of social capital. Leading to the suggestion that a future research topic should address a new question asking: does the inclusion of subcategories in Kickstarter enable greater social capital transfer compared to an unsorted system? This is but one of many possible extensions to this research which may enable greater understanding of the role played by social capital generation within the platform itself.

5.2.4 Identifying internal social capital via latent connections of crowdfunding participants

The *internal social capital* of creators within Kiva was captured through an examination of the network formed through a set of latent connections. A latent connection, between two projects, was assumed to be provided by backers who jointly supported these projects, therefore creating a *latent* link between these projects. With this information it was possible to generate and analyse an entire network of the projects, their latent links and the emerging topological network properties.

In order to capture the amount of *social capital* for every project/node of this network this work advocated to use, as a working metric, the project's *eigenvector centrality*. As discussed in section 3.4.3.1 this metric captures the relevance of the project's location within the network formed by the set of projects linked by common backers.

The empirical evidence, discussed in section 4.4.2, showed that increased *internal social capital*, as captured via eigenvector centrality, had a positive and significant impact on the amount of money raised by projects within Kiva. This result rests on how *internal social capital* can be captured within crowdfunding platforms and in other online platforms, expressed in the assumption that underlying relationships between participants can be utilised to define an otherwise undefined latent network which can be examined through network analysis tools to capture the *centrality of projects* within the network as a proxy for their *internal social capital*.

Within this work, the specific relationship examined was in the connections formed by joint backers. However, the same idea can be applied to different relationships within a network. For example, in examining reciprocity, a network could be created based upon which projects were previously backed by creators of the crowdfunding projects. Creating a directional network where nodes (projects) would be connected based upon whether the creator or other backers had backed their project. Alternatively, the geographic relationships between backers and creators could be converted into network form, by connecting geographic locations based upon backers supporting projects in the other location. These different configurations of networks demonstrate clear routes for future research topics. This also highlights one of the main contributions of this research in highlighting how to utilise existing connections within a network to define and create a latent network enabling the impact of *internal social capital* to be captured through the usage of network analysis tools.

5.3 Competition: Finding and recommendations

The following section considers the key findings and recommendations relevant for the external and internal competition dimensions of the projects within a crowdfunding platform.

5.3.1 Competition within the platform

The results from the Kickstarter model provide evidence that the effects of competition among projects within a given category exert opposite effects from the competition from project belonging to a different category. For example, in regard to the amount of competition at the launch of a project on Kickstarter, the evidence, presented in Table 4.1 suggests that increased launch competition within a projects category had a negative impact on success, on the other hand, the presence of increased launch competition outside of the category had a positive impact on a project's success. The implications of these findings are that within a given category, the positive cross-platform externality created by the increased number of backers brought in by additional projects is weaker than the same-side negative network externalities due to the presence of additional creators, competing for attention and for resources, at the launch of the project. However, when focussing on the entire duration of the project, the positive cross-platform externalities appear to be stronger than the negative same-side ones.

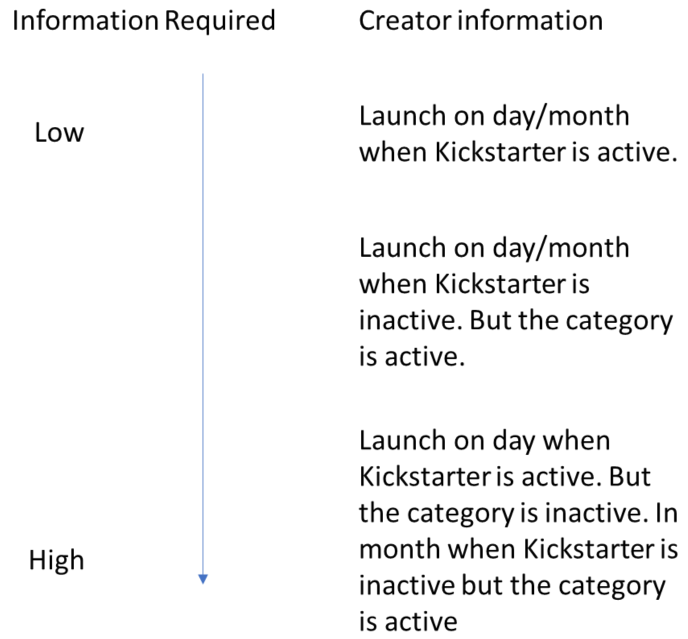
From this result, one could infer that the optimum degree of competition within a category for a project to succeed is reached when facing a low number of other projects launching on the same day as the project, while having as many projects competing within the category over the entire duration of the project. Therefore, this result would suggest that creators who wish to run an optimal campaign should launch on a very active month, but on the least popular day within that month.

However, the opposite effect is exerted by the presence of increased competition outside a specific project category, but within the same platform. With an increased number of Kickstarter projects on launch day having a positive impact on the success, while increased competition, again outside a project category but within the same platform, after the launch day exerting a negative impact on the probability of success of a project. Therefore, the positive cross-platform externalities created between the increased numbers of backers brought in by additional projects, outside of a project's category, are stronger than the negative externalities created by these additional projects at the launch of a project. However, across the entire duration of the project, the positive cross-platform externalities are weaker than the negative externalities created by additional competition between projects belonging to different categories.

From these results, the recommended behaviour for a project's creator would be to launch on a day when the category is not active, but the rest of Kickstarter is, and, in a month, where the category is active, but the rest of Kickstarter is not. By comparing the relative strength of the launch competition variables, it can be stated that the overall launch competition will have a greater impact than launch competition within the category. Launch competition outside the category has a higher coefficient and a higher mean value (as reported in Table 3.4). Showing that across all of Kickstarter increased levels of competition on the launch day will have a positive impact on the likelihood of a project succeeding.

Additionally, by comparing the coefficients of the competition index values and the Kickstarter index values (as shown in Table 4.6) within and outside of the category shows that the competition effects within the category are more impactful on the likelihood to succeed than the competition effects outside of the category. Therefore, for the entirety of Kickstarter increased competition both on the launch day and within the category has a positive impact on success. The following diagram can be suggested as the recommended choice system regarding the effects of competition based on the amount of information which is available to the creator:

Figure 5-1 Optimal launch day based upon creator information



The Implications of the analysis of these competition effects within platforms, show that internal divisions set up within a platform can create submarkets in which the effects of competition are fundamentally different compared to those affecting the rest of the platform. This has implications for the design of platforms and demonstrates that providing clear categories which act as sub-platforms can enable competition to have positive impacts where in general it would have a negative impact.

However, the empirical evidence and results obtained from the Kiva model demonstrates an opposite effect of increased competition, with increased competition having a negative impact across all of Kiva platform. In considering why there is such a qualitative difference in the results derived between the two platforms, the author suggests this is due to the relation between increased number of projects and *external social capital* on Kiva. In this platform, external social networks are not linked directly on the project page and projects are not created by new users but instead by the existing partnership organisation. Thus, additional projects don’t utilise *external social capital* and thus don’t draw in as many additional users, thus not leading to the otherwise negative impact of competition. There is low impact of *external social capital* due to how the majority of new projects are not created by new creators. And it is the new creators who are vital in drawing additional backers to the platform through the utilisation of *external social capital*.

5.3.2 Geographic competition

The effects of increased competition were also considered from a geographic perspective, considering if the amount of competition within a specific geographical region would improve the chances of success for projects within the crowdfunding platforms. This possibility was examined both in Kiva and Kickstarter, through three different variables. The degree of competition within category in Kickstarter was measured through the HHI (Herfindahl–Hirschman Index) based on the project's city or country. Concerning Kiva, the level of localised geographical competition on the platform, was measured through the amount of active loans occurring within the country, while the project was actively seeking funds.

The results from Kickstarter which considered the impact of increased competition in cities, rejected the proposed hypotheses that increased competition in cities would negatively impact the likelihood of projects succeeding, while providing support for the argument that higher level of competition within a city would instead increase the likelihood of projects succeeding. This evidence suggests the presence of some type of positive externalities arising from companies within the same category being based in close proximity, which overcome the negative externalities of increased competition within the region from those additional companies. These positive externalities could be tied to some form of urban agglomeration whereby the creators are benefitting from being physically near to each other, enabling them to share resources and learn from each other and thus gain competitive advantages (Duranton and Puga, 2004; Porter,1996). This result could be utilised in explaining why clustering has been observed within Kickstarter (Mollick, 2014). This argument is further supported by Gallemore et al (2019) who establish that within the crowdfunding platform Indiegogo, project based in cities were able to raise likely to succeed than projects based in rural locations.

In comparison, the results on the impact of increased competition within countries provided contrasting evidence across the two platforms, with no significant impact in Kickstarter while, for Kiva, increased levels of competition within the country resulted in a negative impact on the amount of funds raised by the projects. An understanding of these results requires a focus on the differences between the design and governance of Kiva and Kickstarter.

In Kiva, the search function enables division of projects based on the country of the projects, while Kickstarter does not allow projects to be searched by country, although the country of the project is displayed on the project page. One could argue that, as the potential backers in Kickstarter are not able to search projects by the country that they are based in, this will reduce the ability of backers to choose to support projects based on the country in which they are, thus leading to the insignificant impact of competition among projects in the same countries, as observed in the Kickstarter model. This highlights how the design of the crowdfunding platform may enable competition to occur based on what factors can be used to distinguish between the campaigns.

5.3.3 Competition between the creator's projects

The results on the impact of the Kiva partner index, indicate that creators' projects compete with each other if they are active at the same time. This provides a key distinction between Kickstarter and Kiva, whereby within Kickstarter, across the entire dataset collected, creators never had more than one project active at the same time. Creators may have previously created projects on Kickstarter, but they never ran two projects at the same time. Conversely, Kiva creators created multiple projects which were active at the same time and due to this, their success was negatively impacted by this synchronicity. This leads to the development of a clear recommendation to platforms: to encourage their creators to stagger their projects as otherwise they will compete with each other and negatively impact the success of the project.

5.3.4 How the competition findings relate to the existing literature

Within the relevant literature, the key papers which focus on competition amongst crowdfunding platforms are Janku and Kucerova (2018) and Wessel et al (2017). This thesis builds upon the original concept of separating competition into different measures, as outlined in Janku and Kucerova (2018), by further refining the measures to consider only projects that are active at the same time and introducing geographic market definitions. This was done by enabling both category and geography within the models rather than including them as dummy variables, which might lead to varying results of success due to the vast range of possible geographic or category variables, as discussed in Kromidha and Robson (2016). As a consequence, our findings showed that category competition had an opposite effect to general competition and that competition at a city level had a significant impact on success. Furthermore, our results support those by Wessel et al (2017) in showing how the HHI index can be utilised, for the number of backers, to generate competition metrics, within each platform, category and day.

5.4 Backers incentives: Findings and recommendations

This section considers the key findings and limitations surrounding the reward hypotheses examined through the Kickstarter model. The empirical evidence from the Kickstarter model provides clear indications about the relevance of backers' incentives in affecting the likelihood of a project succeeding, with all the relevant variables supporting the proposed hypotheses; H3a, H3b and, H3c.

5.4.1 Increasing the number of reward levels

H3a stated that; *an increased number of reward levels within a campaign would have a positive impact on the probability of the project succeeding*. This hypothesis is supported by the positive and significant impact that an increasing the number of reward levels had on the likelihood of a crowdfunding project succeeding. This result showed that the creator of crowdfunding campaigns should provide a wide selection of different reward levels to maximise the likelihood of the crowdfunding project succeeding, supporting previous results on the topic (An et al, 2014; Xu et al, 2014; Bretschneider and Leimeister, 2017). This result suggests that, by introducing additional reward levels, a project's creator can more accurately match the different utility levels of individual backers, enabling them to maximise their utility through the possibility of better modulating the different level of demand for rewards. Highlighting that in reward-based crowdfunding, a single product (the campaign objective itself) can be set to have multiple different support levels, with each different level being linked to a different combination of rewards in goods or services.

This result provides a direct and clear recommendation to project creators to increase the number of reward levels. However, this result also highlights one of the limitations of the model: that it does not address the issue of whether there is a specific point at which adding additional reward levels will have zero or negative impact on the likelihood of the project succeeding. This possibility seems likely as people are only going to physically be able to view so many reward levels. Xu et al (2014) addresses how additional reward levels being added throughout the campaign have a positive impact on the success of a campaign, however it does not address if there is a point at which new reward levels will have zero or negative impact on success. Furthermore, reward levels are examined across the entirety of Kickstarter. However, as demonstrated by other results, specific subcategories can have different finding on what leads to success within the platform, suggesting that the impact of rewards levels should also be examined category by category.

5.4.2 Decreasing wait times for rewards

H3b stated: *Increased expected delivery times of reward levels will have a negative impact on the probability of project success*. The empirical evidence supports this hypothesis as increased waiting time for rewards has a negative and significant impact on the likelihood of the project succeeding, hence, supporting the results of Joenssen et al (2014) into the examination of technology projects on Kickstarter and expanding this to all categories in Kickstarter.

This provides a clear recommendation to creators to offer rewards which can be delivered quickly. Furthermore, as this variable utilises the average waiting time across all rewards weighted by the number of backers which chose this reward, this also suggests that the impact of longer delays can be balanced out by offering rewards which are delivered quickly as long as these quick rewards are popular with backers. However, this also highlights a further limitation of the study: that there is no consideration of whether the amount of money required for backing the reward impacts on how long the backer is willing to wait for the reward. For example, do lower monetary requirements increase, decrease or have no effect on the length of time a backer is willing to wait for the reward? Finally, are these effects consistent across subcategories and reward types or are there different effects based on categories or reward types?

5.4.3 Providing local or digital rewards

H3C stated: *Increased number of global reward levels will have a negative impact on the probability of the project success*. The analysed empirical evidence supports this hypothesis, with an increased number of global rewards having a negative and significant impact on the likelihood of a project succeeding. The rewards were self-classified by the project creator, rewards which were not marked as global, where either local or digital in nature. With local rewards referring to rewards which are delivered within the same country or region and digital goods referring to rewards which are digital in nature and thus are delivered through the internet. Therefore, providing a clear recommendation that creators should offer rewards which are digital or local in nature. This result also highlights one of the limitations of this model, namely that the discussion of the impact on success due to the type of rewards is limited to considering whether the reward is local or global.

The creators in Kickstarter do not separate the rewards into specific categories, requiring rewards to be classified by the researcher. Which would require either a restriction in the examined dataset as it would be implausible to manually classify over 500,000 rewards or the utilisation of machine learning in classifying the rewards. These problems prompt a recommendation for further expansion of research into considering the relation between types of rewards and project success within Kickstarter, either on a more restricted dataset or utilising machine learning in categorising the reward text (Sebastiani, 2002). Furthermore, such an extension could consider if separate categories are affected differently by the types of rewards offered.

5.5 Recommendations to the three parties involved within Crowdfunding.

The following sections outline a set of recommendations derived across the earlier sections of the thesis. The recommendations are split into specific recommendations for each party involved in crowdfunding, those of creators, backers and the crowdfunding platform itself. Each recommendation includes the rational for the recommendation and the empirical or theoretical evidence used as the basis of the recommendation.

5.5.1 Recommendations to creators (encouraging crowdfunding success)

Creator recommendation 1) When carrying out reward-based crowdfunding, set realistic funding goals, which take into account the surrounding funding goals of other projects within the category:

Rationale: The results from the Kickstarter model provide clear evidence that creators are overconfident in their projects and set funding goals which are too high that acting as signals to the backers, negatively impact the likelihood of a project succeeding. Thus, creators should set more realistic funding goals, to offset these effects.

Empirical evidence: Results in section 4.2.1.1 leading to support of H1a.

Linked theoretical areas: Signalling theory

Creator recommendation 2) Consider the set of signals which are requested by the crowdfunding platform:

Rationale: Each platform decides a set of enforced signals, as demonstrated throughout the empirical results, these signals can negatively affect success within the crowdfunding platforms, thus creators should consider what signals they are being forced to send and how these will affect their likelihoods to effectively raise money on the platform.

Empirical evidence: Results in sections 4.2.1 and 4.4.1

Linked theoretical area: Signalling theory

Creator recommendation 3) Actively engage in communication with backers via updates on the crowdfunding platform while the campaign is ongoing:

Rationale: Increased number of updates is shown to have a positive impact on the likelihood of a project succeeding within Kickstarter, signalling the trustworthiness of the creators. Thus, creators should update their projects continuously across their campaigns.

Empirical evidence: Results in section 4.2.1.3

Linked theoretical area: Signalling theory

Creator recommendation 4) Utilise external social capital in support of your crowdfunding project:

Rationale: Evidence from our study on Kickstarter supports the argument that *external social capital* can be utilised to positively impact success within crowdfunding platforms. Thus, creators should utilise their *external social capital* in support of their crowdfunding campaigns.

Linked empirical evidence: Results in section 4.2.4.1

Linked theoretical area: Social capital

Creator recommendation 5) Demonstrate your experience on a platform by linking past and current projects

Rationale**:** Evidence from the Kickstarter results shows that creators who signal increased levels of experience are more likely to succeed. While it is obviously difficult and unadvisable to artificially increase crowdfunding experience, it is relevant that current projects should be launched on the same account-page as past projects to reflect the real level of past experience.

Empirical evidence: Results in section 4.2.1.2

Linked theoretical area: Signalling theory

Creator recommendation 6) Provide a large number of reward levels in reward-based crowdfunding:

Rationale: Evidence from the Kickstarter model supports the argument that having an increased number of reward levels increases the likelihood of a project to succeed. Thus, creators should offer a wide range of rewards. This effect can be tied to how increased reward levels may enable a crowdfunding campaign to appeal to more people by tailoring specific rewards to specific groups of consumers.

Empirical evidence: Results in section 4.2.3.1

Linked theoretical area: Backers motivation within crowdfunding, see section 2.4.1.5

Creator recommendation 7) Minimise the expected delivery time of rewards, in reward-based crowdfunding:

Rationale: Evidence from the Kickstarter model supports the argument that a lower expected waiting time increases the likelihood of a project to succeed.

Empirical evidence: Results in section 4.2.3.2

Linked theoretical area: Backers motivation within crowdfunding, see section 2.4.1.5

Creator recommendation 8) When possible, set rewards which are local or digital in nature:

Rationale: Evidence from the Kickstarter model suggests that rewards which are local or digital in nature are more likely to succeed than rewards which are global. With global rewards referring to rewards which are physical in nature and can be shipped to anywhere in the globe.

Empirical evidence: Results in section 4.2.3.2

Linked theoretical area: Backers motivation within crowdfunding, see section 2.4.1.5

Creator recommendation 9) In reward-based crowdfunding, launch on a day where the category you launch on is not busy.

Rationale: Increased level of launch competition within the same category was shown to have a negative impact on the likelihood of a campaign succeeding in Kickstarter. Thus, creators should launch projects when there are few other projects being launched within their category.

Empirical evidence: Results in section 4.2.5.1

Linked theoretical area: Competition within platforms, see section 2.4.1.4

5.5.2 Recommendations for backers (in supporting and choosing between projects)

Recommendations for backers 1) Utilise the signals sent out by creators to compare crowdfunding projects:

Rationale: The empirical results across both Kiva and Kickstarter provide support for the argument that success in crowdfunding is affected by the signals which are sent by the creators. Thus, backers can utilise this information to distinguish between crowdfunding campaigns.

Empirical evidence: Results in section 4.2.1 and 4.4.1

Linked theoretical area: Signalling theory

Recommendations for backers 2) Supporting a project early on, greatly increases the likelihood of a project succeeding.

Rationale: The findings on the impact of early backing, show that projects which are supported earlier on are more likely to succeed. Therefore, if backers want a project to succeed, they should support the project as early as possible, as this acts as a signal of support to the project and can thus encourage other backers to support it.

Empirical evidence: Results in section 4.2.2.2 and 4.2.2.3

Linked theoretical area: Signalling theory

Recommendations for backers 3) Utilise backers' external social capital in support of projects they wish to succeed:

Rationale: Alongside backing projects, backers can also utilise their own *external social capital* to support projects.

Empirical evidence: Results in section 4.2.4.1

Linked theoretical areas: Social capital theory

Recommendations for backers 4) Actively comment on projects to encourage other backers to support said project:

Rationale: Backers can also increase the likelihood of a project succeeding by commenting on projects. Whereby the act of commenting can be viewed as a positive signal to potential backers.

Empirical evidence: Results in section 4.2.2.1

Related theory: Signalling theory

5.5.3 Recommendations for the crowdfunding platform

Recommendation for platforms 1) Enforce a key set of signals to be sent by the creators and backers:

Rationale: As a platform, one of the key factors which has to be considered is how much information is requested and presented on the project page, from both the backers and creators. Increasing the amount of information required may enable backers to better identify projects, but it also may reduce creators desire to use the platforms. This research does not identify a clear level of information which should be requested, but rather simply suggests that it should be considered as a trade-off between creator quality and creator quantity.

Empirical evidence: Results in sections 4.2.1 and 4.4.1

Linked theoretical area: Signalling theory

Recommendation for platforms 2) Design signals which are observable, manipulatable and costlier for low-quality projects

Rationale: For signals to be effective they must be observable, manipulatable and costlier for low-quality projects. Manipulatable refers to the ability of the sender to be able to adapt the intensity of the signal, observable refers to the ability for the public to view the signal. Finally, there must also be an increased cost to low quality projects compared to high quality projects as otherwise low-quality projects can simply send signals as if they were high quality projects. The results observed from both platforms support this argument, as signals which did not achieve these three criteria had no statistically significant impact on projects' success.

Empirical evidence: Results in sections 4.2.1 and 4.4.1

Linked theoretical area: Signalling theory

Recommendation for platforms 3) Provide clear information on the amount of money raised by projects at a category level.

Rationale: The results demonstrated that backers tend to be overconfident in their ability to raise funds. One way of combating this may be to provide information on the average amount raised within a category, as this would enable backers to more accurately predict their funding ability, rather than comparing themselves to blockbuster projects.

Empirical evidence: Results in section 4.2.1.1

Recommendation for platforms 4) Encourage projects within the same category to launch on different days

Rationale: The empirical results from Kickstarter and Kiva both showed that the amount of launch competition had a negative impact on the likelihood of projects to succeed. Thus, this suggests that projects should be encouraged to launch on separate days. Perhaps this could be achieved by creating a pre-launch indicator showing when other projects are launching and thus enabling creators to better plan their launch. Or creating a system where a set number of projects can launch on each day, thus reducing the launch competition

Empirical evidence: Results in sections 4.2.5.1,4.4.3

Linked theoretical area: Competition within platforms, see section 2.4.1.4

Recommendation for platforms 5) As a platform, you should signal support for specific projects that you consider high quality.

Rationale: Within the Kiva crowdfunding projects, the platform gave every partnership organisation a star rating from one to five stars. The result showed that this rating had a significant impact on the amount of money raised within Kiva. Supporting the argument that the platform itself can signal support for projects and thus increase the likelihood of the project succeeding.

Empirical evidence: Results from section 4.4.1.2

Linked theoretical area: Signalling theory

5) Enable creators to link their project pages on external social media

Rationale: The Kickstarter model results showed how the number of Facebook shares a crowdfunding page had, exerted a positive impact on the likelihood of a project to succeed.

One contributing factor for this result was the ability of the creator to link their Facebook profiles to the crowdfunding campaigns. Thus, this author proposes that other platforms should also enable creators to link to their Facebook pages.

Empirical evidence: Results from section 4.2.4.1

Linked theoretical area: Social capital theory

7) Encourage creators to stagger projects, in order to decrease competition between their own projects.

Evidence from Kiva demonstrated how projects which were produced by the same creator could be competing with each other. Negatively decreasing the level of success of the projects. Thus, suggesting that serial creators should be encouraged to stagger projects to stop them competing with each other.

Empirical evidence: Results from section 4.4.3

Linked theoretical area: Competition within platforms, see section 2.4.1.4

8) Enable backers to comment on projects, however, with the restriction that only those who have backed the project can comment.

Rationale: Kickstarter results support the argument that backers' comments have a positive impact on the likelihood of a project to succeed, as they can be seen to show support for the project. The comments should be restricted to those who have already backed the project to reduce internet spam. It is worth noting that many crowdfunding platforms have comments, however some platforms such as Kiva do not.

Empirical evidence: Results from section 4.2.2.1

Linked theoretical area: Signalling theory

5.6 Recommendations for future research topics

This section considers how the limitations within the research can be overcome by considering future expansion for the research.

Research recommendation 1) Further investigation into the relation between external social capital generation and crowdfunding success.

Rationale: Within this thesis, external *social capital* was shown to positively impact success in crowdfunding. However, one of the limitations of the study is that it does not consider the possible reverse causality, i.e. what is the effect of crowdfunding success on *external social capital*? This author proposes that a successful crowdfunding campaign may generate *external social capital*, if this proposition is true then it could help explain the increased success of serial crowdfunders (Butticè et al, 2017).

Related theoretical areas: Social capital, Serial crowdfunding.

Research recommendation 2) Expanding upon utilising latent network in the examination of crowdfunding and non-crowdfunding platforms.

Rationale: The latent network utilised with the Kiva model to capture *internal social capital* can be adapted to be utilised to examine other crowdfunding platforms. As fundamentally all that is necessary for the creation of such a network is to be able to identify some indicator which links the projects together. For example, in Kickstarter, a latent network could be built based upon the top ten cities which back crowdfunding projects.

Related theoretical areas: Network analysis, Internal social capital

Research recommendation 3) Considering the impact of rewards in different categories:

Rationale: One of the limitations of the study is that the effects of increased reward levels and the waiting time for rewards is only considered at a platform level. It is not considered whether the category of the rewards affects the impact these variables are having. Furthermore, machine learning could be utilised to further categorise the rewards, enabling mass categorisation of the different reward levels (Sebastiani, 2002), thus, enabling the consideration of what is the best type of reward to be offered for each subcategory within a crowdfunding platform.

Related theoretical areas: Machine learning, Backer motivations.

Research recommendation 4) Utilising conditional crowdfunding to overcome asymmetric information within crowdfunding:

Rationale: Conditional crowdfunding enables a new way of overcoming or limiting asymmetric information. Due to the creation of conditional requirements which have to be fulfilled before the creators receive their money (Elsden et al, 2019). However, to the authors knowledge there is very limited work within the literature onto the impact of utilising conditional crowdfunding and due to the theoretical framework within the thesis being applicable to conditional crowdfunding, serves as a natural expansion of the research.

Related theoretical areas: Asymmetric Information, Conditional Crowdfunding.

Research recommendation 5) Considering the effect of competition between crowdfunding platforms:

Rationale: One of the limitations with the competition effects studied within this thesis is that it did not capture the competition effects from other crowdfunding platforms; this was due to the limited availability of data on the success of other platforms. Thus, this serves as a key area of future expansion, utilising the expanded sub division methodology to select similar crowdfunding platforms and then consider if the success of one platform negatively or positively impacts the other crowdfunding platforms.

Related theoretical areas: Competition on crowdfunding platforms, Subdividing crowdfunding.

6 Conclusions

In this section, we aim to derive the key conclusions from the work done and to summarise the main achievements of this thesis. This work was developed throughout the different chapters, having discussed: the relevant literature, the theoretical and contextual frameworks to develop the key hypotheses, the complex data collection processes and the identification strategies to select appropriate models utilised to test the relevant hypotheses, and the key recommendations derived in the previous chapter, from the multiple interconnections amongst all the components of this thesis.

In summary, this thesis achieved the following:

A broad definition of crowdfunding was introduced, which was then utilised to create a point of distinction at which crowdfunding becomes traditional financing, this enabled crowdfunding platforms to be clearly identified (section 2.1) and it enhanced the system for sub-dividing crowdfunding platforms based on the participation rights of the backers and creator in the crowdfunding platforms (section 2.2).

A theoretical framework was developed for identifying the determinants of success and failure in crowdfunding based upon the concepts of social capital, competition, backer motivation and signalling theory (section 2.4).

A research philosophy of pragmatism was chosen and utilised to opt for a quantitative research design (section 3.1). The theoretical framework was successfully applied to both

Kickstarter and Kiva platforms, which enabled the creation of two separate conceptual frameworks and a set of hypotheses for each platform (section 3.3.1; section 3.4.1).

The thesis utilised highly customised web crawling software and techniques to successfully capture 54193 projects for Kickstarter (section 3.3.9) and 1,000 projects for Kiva (section 3.4.6). Appropriate econometrics models were chosen based upon the underlying characteristics of the key dependent variables within each platform: with a set of logistic regressions being used to model the probability of a project's success in the Kickstarter platform (section 3.3.10) and a set of OLS and Truncated regression models, being used to model the amounts raised on the Kiva platform (section 3.4.7). A set of model specifications were developed for each platform with the goodness of fit of the models compared, to identify the best fitting model for each platform (section 4.1; section 4.3). These models were then utilised to empirically test each one the developed platform's relevant hypotheses (section 4.2; section 4.4).

The econometric estimations lead to the development of a set of generalised findings for crowdfunding platforms, based on the empirical evidence and results which were then used to identify the contribution, recommendations and limitations of the study (section 5).

Furthermore, a set of key recommendations was created for each of the core participant groups in crowdfunding, the backers, the creators and the platform itself (section 5.5) and, finally, a set of recommendations was made about future research topics which have been identified through the findings and limitations of this research (section 5.6).

At this stage, it must be considered whether these outcomes and results have achieved the main research aim, as stated: "To create a broad system for identifying the key determinants of success within crowdfunding platforms, which is applicable regardless of the type of crowdfunding platforms examined".

The author would argue that this aim has been achieved, through the creation and testing of the theoretical framework. This framework was based on four key areas of research on social capital, competition, backers' motivation and signalling effects. This enabled the identification of the main determinants of success or failure within crowdfunding platforms. The empirical evidence, painstakingly collected by the authors, supported the utility of this framework as both the specific models for the two analysed platforms, Kickstarter and Kiva, that were built from this theoretical framework, captured statistically significant effects of the main identified determinants of success (section 4.1.1; section 4.3.3).This empirical success, supports this author's belief that the theoretical framework developed in this thesis, can be utilised to assist in identifying key determinants of success and failure within crowdfunding platforms and that the primary aim of this thesis has been achieved.

6.1 Additional key contribution

Alongside the main contribution of the development of the theoretical framework, additional key contributions are also identified:

Key Contribution 1) Construction of a broad definition of crowdfunding:

Through the section on literature review, the following definition was created: Crowdfunding is the interaction between three parties: creators, backers and a platform. Creators seek to obtain funds for a project, backers provide those funds, and the platform acts as an exchange between the backers and creators, without itself making funding decisions. This definition enables a clear point of separation between crowdfunding platforms and traditional funding platforms, that point being when the platform itself starts making funding decisions. This definition can be utilised to decide whether a platform is a traditional fundraising or a crowdfunding platform, as shown through the examples created by the author in section 2.1.5. Thus, enabling the whole crowdfunding market, itself to be clearly defined.

Key Contribution 2) Expanding subdivision of crowdfunding

The thesis set out a system for subdividing crowdfunding beyond the main four classifications utilised within the existing literature. This is not to say that this other literature had not utilised different measures of subdivision, as shown in the discussed literature on medical crowdfunding (Renwick and Mossialos, 2017; Burtch and Chan, 2014; Snyder et al 2017). Instead, this' thesis' contribution resides in the more formal method for subdividing crowdfunding, i.e. utilising the creator's participation rights to identify four additional subdivisions for crowdfunding platforms. These categorisations enabled the subdivision of existing crowdfunding platforms to be expanded, as shown in Figure 2-8. This expansion can be utilised in future work to identify similarities and differences between crowdfunding platforms.

Key Contribution 3) Distinguishing between enforced and voluntary signals on crowdfunding platforms

This thesis introduced the concepts of enforced and voluntary signals, linked to how the platform controls the access and information exchange modalities of, and between, creators and backers. This control enables the platform to force signalling information to be sent out by the creators and the backers. These enforced signals need to be understood as different, and possibly contrasting, from the voluntary signals which the creators can send out by their own choice. Due to enforced signals being chosen by the platform, they can have a positive or negative impact on the likelihood of a project to succeed and, in order to predict the effects of these signals, new proxy metrics for human capital were utilised. The collected empirical evidence, once analysed, showed that, as long as the signals had a significant impact, proxies for human capital would correctly predict the effect of the enforced signals. Moreover, non-significant signalling results occurred when signals were not efficient, i.e. they were not observable, manipulatable and/or costlier for low-quality projects. This finding helps in pointing to the relevance of distinguishing between the different types of signals sent within crowdfunding platforms in future work.

Key Contribution 4) Construction of a latent network with crowdfunding platforms

Within the Kiva model, it was shown that a latent network could be built from the inherent connections between participants within a crowdfunding platform. And that this latent network could be utilised to capture the impact of social capital within the platform. This process of creating a latent network to capture social capital can be applied to other crowdfunding and non-crowdfunding platforms. As all that is necessary for a latent network to be developed is defining a rule to connect projects based upon the actions of backers or creators.

Key Contribution 5) A clear set of recommendations to creators, backers and the platforms itself.

Utilising the empirical evidence collected for each model, a set of recommendations was developed for each category of participants in crowdfunding. For creators, the recommendations consider how they can increase the likelihood of their crowdfunding projects succeeding. For backers, the recommendations consider how to choose between crowdfunding projects and how to increase the likelihood to succeed for the projects they supported. For the crowdfunding platform themselves, the recommendations considered ways to ensure platform long-term sustainability.

6.2 Impact of this research

The contribution to the literature of this research can be demonstrated through the ongoing impact of the work, as this work has directly led to the successful publication of:

Davies, W.E. and Giovannetti, E., 2018. “Signalling experience & reciprocity to temper asymmetric information in crowdfunding evidence from 10,000 projects”. Technological Forecasting and Social Change, 3 CABS Impact Factor: 3.129 vol 133, pp.118-131. Whereby a subset of the Kickstarter dataset was utilised in the creation of this paper.

Furthermore, the work has been presented at multiple international conferences, via the following conference papers:

“Be impatient but not overambitious, a key for success of crowdfunding campaigns: Evidence from 10,000 Kickstarter innovation projects” which was presented in Milan at the 18th Institute of International Forecasters Conference (May 2016)

“Determinants of success in crowdfunding, identifying key factors crucial to success” Which was presented to International Telecommunications Society Conference in Cambridge (September 2016).

“The Role of Social Capital for Micro-funding: evidence from the KIVA database.” Which was presented at the International Telecommunications society Asia 2017, Kyoto Conference. Studying Crowdfunding for developing countries.

“Network Centrality in Cryptocurrency crowdfunding: how can cryptocurrency facilitate social capital in supporting innovations?” Presented at the first Cryptocurrency Research Conference, on 24 May 2018 at Anglia Ruskin University, Cambridge, UK.

“Transforming crowdfunding platforms into pseudo-social networks” which was presented at Anglia Ruskin Annual Research student conference in June 2018.

“Capturing the Impact of Social Capital for Microfinance through Crowdfunding: A neural network approach” which was presented at Predictive Analytics: Theory, Applications and Algorithms workshop, on July 2019 at Hughes Hall, Cambridge, UK.

Additionally, an article entitled “There are six main traits that successful crowdfunding campaigns had in common” was published by the World Economic Forum, demonstrating how this work can be used to create recommendations for participants in crowdfunding (World Economic Forum, 2016).

6.3 Final remarks

In conclusion, this thesis has achieved the aim of creating a system to identify the key determinants of success and or failure, within crowdfunding platforms, this has led to the creation of multiple conference papers and to the successful publication on the journal *Technological Forecasting and Social Change*. Work is ongoing into developing further papers and studies based upon the concepts and ideas created within this thesis. Specifically, papers are currently developed relative to the Kiva model and a paper focusing on a cryptocurrency based crowdfunding platform.

6.4 Acknowledgements

This work would have been impossible without the excellent support of my supervisory team, Professor Emanuele Giovannetti and Professor Nick Drydakis whose guidance and assistance have been crucial at all stages of the development of this thesis. Additionally, I would like to thank my family for their support over the years, especially listening to my endless rambles about crowdfunding. Finally, I would like to thank anyone who reads this thesis, I have thoroughly enjoyed, the creation of this work and hope you have enjoyed reading, yours sincerely, William Davies.

7 Appendix

7.1 Item 1: Excel data commands

VLOOKUP: This command can be used to lookup other value associated with a specific cell. After the cell is chosen, the command requires a specific range of columns to be selected, the first column must contain the value which you are searching for. The command then asks for a column number which returns the desired value to the right of the cell. For example, with an input of 1 the value 1 row to the right of the specified cell is returned, 2 returns the value 2 to the right and so forth. This was utilised in the data collection multiple times for the Kickstarter dataset, most notable in checking whether the url of a new campaign already existed. Acting to ensure that there was no duplication when collecting results. Additionally, it was utilised in the creation of the early backing and early funding variables, as by utilising the duration as the column number and dividing by a specific value, the early funding and early backing data could be extracted from the funding and backing tables.

COUNTIFS: This command enables the counting of cells with specific criteria, this was utilised in the counting of the number of competing concurrent projects within the Kickstarter platform. By setting the required criteria as being between the start and end date of a single campaign this command was used to identify all of the other campaigns which were active in that time period. Thus, showing the number of competing projects on Kickstarter at that time.

CONCATENATE: This command is used to merge two or more cells text values together. For example, if cell a1 contained the text hit and cell a2 had the text man, utilising the concatenate command enables the combination of the two text values into a singular cell that would contain hitman. This was utilised in creating the URLs for the web crawlers, as often page numbers would have to be altered in order to extract the full range of desired results.

Custom Macro: Excel also has the ability to create custom macro for the editing of mass data, this was primarily used in the process of arranging data into the correct format to for data analysis techniques. The macros were created through utilising the record macro features, which enable recording of specific features, then additional lines of code were added to fine tune the process Figure 7-1. the following code would use the X value cell B77 then copy the current selection to sheet 3 and delete that selection.

Figure 7-1 Example of excel macro

```
Let X = Range("B77")
Do While X > 0
   Selection.Copy
   Sheets("Sheet3").Select
   ActiveSheet.Paste
   ActiveCell.Offset(1, 0).Range("A1").Select
   Sheets("Sheet2").Select
X = X - 1
Loop
   Application.CutCopyMode = False
   Selection.delete Shift:=xlUp
      Range(Selection, Selection.End(xlDown)).Select
   Selection.Copy
   Sheets("Sheet3").Select
   ActiveCell.Offset(-1, 1).Range("A1").Select
   Selection.End(xlUp).Select
   ActiveCell.Offset(1, 0).Range("A1").Select
   ActiveSheet.Paste
   ActiveCell.Offset(1, 0).Range("A1").Select
   Selection.End(xlDown).Select
   ActiveCell.Offset(1, -1).Range("A1").Select
   Sheets("Sheet2").Select
   ActiveCell.Select
End Sub
```

7.2 Item 2: Logit model equations expanded

This section considers a more expanded version of the creation of the logit model.

The logit function is defined that as:

$$f(x) = logit(x) = \log\left(\frac{f(x)}{1-f(x)}\right) \qquad (2)$$

Thus, using this function, we can write y_i as

$$y_i = f(x) = Logit[f(x)] = \ln\left[\frac{f(x)}{1-f(x)}\right] \qquad (3)$$

Now if we also considered the inverse logit function that:

$$f(x) = inv.logit(x) = \frac{exp(x)}{1+exp(x)} \qquad (4)$$

Now if we consider this for this case then using equation (1)

$$f(x) = \frac{e^{(\beta_0+\beta_1 x_{1,i}+\quad {}_2 x_{2,\ i}+..+\varepsilon_i)}}{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}} \qquad (5)$$

If we then input this into equation (3)

$$\ln \frac{f(x)}{1-f(x)} = \ln \left[\frac{\frac{e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}}{1-\frac{e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}}\right] \qquad (6)$$

This can be simplified due to the following

$$1= \frac{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}$$

Therefore we can rewrite equation (6) as

$$ln\left[\frac{\frac{e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}}{\frac{1}{1+e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}}}\right]$$

Which simplifies to

$$ln[e^{(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,\ i}+..+\varepsilon_i)}]$$

Thus

Logit[f(x)]= $\beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,\ i}+..+\varepsilon_i$

Yi= $\beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,\ i}+..+\varepsilon_i$

7.3 Item 3: Models testing early funding period

This appendix section displays the classification and comparison between the 1/6th, 1/8th and 1/10th early funding period durations. With 1/6th referring to the duration of a project divided by six, 1/8th refereeing to the duration divided by eight, and 1/10th referring to the duration of a project divided by 10.

Figure 7-2 Successfully classified for 1/6 duration

Logistic model for successorfailure

Classified	True D	True ~D	Total
+	15111	2608	17719
-	2355	34119	36474
Total	17466	36727	54193

Classified + if predicted Pr(D) >= .5
True D defined as successorfailure != 0

Sensitivity	Pr(+| D)	86.52%
Specificity	Pr(-|~D)	92.90%
Positive predictive value	Pr(D| +)	85.28%
Negative predictive value	Pr(~D| -)	93.54%
False + rate for true ~D	Pr(+|~D)	7.10%
False - rate for true D	Pr(-| D)	13.48%
False + rate for classified +	Pr(~D| +)	14.72%
False - rate for classified -	Pr(D| -)	6.46%
Correctly classified		90.84%

Figure 7-3 Successfully classified for 1/8th the duration

Logistic model for successorfailure

Classified	True D	True ~D	Total
+	14657	2671	17328
-	2809	34056	36865
Total	17466	36727	54193

Classified + if predicted Pr(D) >= .5
True D defined as successorfailure != 0

Sensitivity	Pr(+| D)	83.92%
Specificity	Pr(-|~D)	92.73%
Positive predictive value	Pr(D| +)	84.59%
Negative predictive value	Pr(~D| -)	92.38%
False + rate for true ~D	Pr(+|~D)	7.27%
False - rate for true D	Pr(-| D)	16.08%
False + rate for classified +	Pr(~D| +)	15.41%
False - rate for classified -	Pr(D| -)	7.62%
Correctly classified		89.89%

Figure 7-4 Successfully classified for 1/8th the duration

Classified	True D	True ~D	Total
+	14660	2673	17333
-	2806	34054	36860
Total	17466	36727	54193

Classified + if predicted Pr(D) >= .5
True D defined as successorfailure != 0

Sensitivity	Pr(+| D)	83.93%
Specificity	Pr(-|~D)	92.72%
Positive predictive value	Pr(D| +)	84.58%
Negative predictive value	Pr(~D| -)	92.39%
False + rate for true ~D	Pr(+|~D)	7.28%
False - rate for true D	Pr(-| D)	16.07%
False + rate for classified +	Pr(~D| +)	15.42%
False - rate for classified -	Pr(D| -)	7.61%
Correctly classified		89.89%

Figure 7-5 Comparing 1/8th duration to 1/6th duration

	Current	Saved	Difference
Model:	logit	logit	
N:	54193	54193	0
Log-Lik Intercept Only:	-34064.931	-34064.931	0.000
Log-Lik Full Model:	-13378.028	-13354.393	-23.635
D:	26756.055(54176)	26708.786(54176)	47.269(0)
LR:	41373.808(16)	41421.077(16)	-47.269(0)
Prob > LR:	0.000	0.000	0.000
McFadden's R2:	0.607	0.608	-0.001
McFadden's Adj R2:	0.607	0.607	-0.001
Maximum Likelihood R2:	0.534	0.534	-0.000
Cragg & Uhler's R2:	0.746	0.747	-0.001
McKelvey and Zavoina's R2:	0.850	0.852	-0.002
Efron's R2:	0.660	0.662	-0.001
Variance of y*:	21.917	22.228	-0.311
Variance of error:	3.290	3.290	0.000
Count R2:	0.899	0.899	-0.001
Adj Count R2:	0.686	0.688	-0.002
AIC:	0.494	0.493	0.001
AIC*n:	26790.055	26742.786	47.269
BIC:	-563778.978	-563826.248	47.269
BIC':	-41199.403	-41246.672	47.269

Difference of 47.269 in BIC' provides very strong support for saved model.

Saved model is the 1/6th early funding period and current model is 1/8th duration early funding period. Providing strong support for using the 1/6th early funding.

Figure 7-6 Comparing 1/10th duration to 1/6th duration

	Current	Saved	Difference
Model:	logit	logit	
N:	54193	54193	0
Log-Lik Intercept Only:	-34064.931	-34064.931	0.000
Log-Lik Full Model:	-13386.917	-13354.393	-32.524
D:	26773.834(54176)	26708.786(54176)	65.048(0)
LR:	41356.029(16)	41421.077(16)	-65.048(0)
Prob > LR:	0.000	0.000	0.000
McFadden's R2:	0.607	0.608	-0.001
McFadden's Adj R2:	0.607	0.607	-0.001
Maximum Likelihood R2:	0.534	0.534	-0.001
Cragg & Uhler's R2:	0.746	0.747	-0.001
McKelvey and Zavoina's R2:	0.849	0.852	-0.003
Efron's R2:	0.660	0.662	-0.001
Variance of y*:	21.834	22.228	-0.394
Variance of error:	3.290	3.290	0.000
Count R2:	0.899	0.899	-0.001
Adj Count R2:	0.686	0.688	-0.002
AIC:	0.495	0.493	0.001
AIC*n:	26807.834	26742.786	65.048
BIC:	-563761.200	-563826.248	65.048
BIC':	-41181.625	-41246.672	65.048

Difference of 65.048 in BIC' provides very strong support for saved model.

Saved model is the 1/6th early funding period and current model is 1/10th duration early funding period. Providing strong support for using the 1/6th early funding.

7.4 Comparison between probit and logit models for restricted Kickstarter model

Figure 7-7 shows a comparison between probit and logit models for the restricted model of Kickstarter. The restricted model was utilised as the main model did not converge when utilising the probit model. It provides clear support for utilising the logit model.

Figure 7-7 Comparison between probit and logit models for restricted Kickstarter model

```
Model:                          probit           logit
N:                               42277           42277                0
Log-Lik Intercept Only:     -27030.708      -27030.708            0.000
Log-Lik Full Model:          -9700.010       -9447.594         -252.416
D:                           19400.021(42256)  18895.188(42256)   504.832(0)
LR:                          34661.395(20)    35166.227(20)     -504.832(0)
Prob > LR:                       0.000           0.000            0.000
McFadden's R2:                   0.641           0.650           -0.009
McFadden's Adj R2:               0.640           0.650           -0.009
Maximum Likelihood R2:           0.560           0.565           -0.005
Cragg & Uhler's R2:              0.775           0.783           -0.007
McKelvey and Zavoina's R2:       0.879           0.894           -0.015
Efron's R2:                      0.699           0.704           -0.006
Variance of y*:                  8.296          31.091          -22.795
Variance of error:               1.000           3.290           -2.290
Count R2:                        0.910           0.910           -0.001
Adj Count R2:                    0.732           0.734           -0.002
AIC:                             0.460           0.448            0.012
AIC*n:                       19442.021       18937.188          504.832
BIC:                       -430710.827     -431215.659          504.832
BIC':                       -34448.355      -34953.187          504.832
```

7.5 Item 5: Summarised Do file for Kickstarter model (please note Ambition was changed to Ambition and Relative Ambition to Ambition)

Importing selected file, tabulating categories and dropping funding goal
import delimited "C:\Users\wdtau\Google Drive\Will Davies PhD\April 2018 beginning of full write up\backups of dataset\KickstarterwithIndex.csv", clear drop if funding_goal>1000000
Model 1 creators signal
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience eststo creator_signal estat classification fitstat, saving(mod1) fitstat
Model 2, Creator and Backer Signals

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
eststo backers_signals
estat classification
fitstat, saving(mod2) using (mod1)
fitstat
```

***Model 3 Backers Incentives included

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time

eststo Incentives
estat classification
fitstat, saving(mod3) using (mod2)
fitstat
```

*** Model 4 External and Internal Social Capital added

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity

eststo Social_capital
estat classification
fitstat, saving(mod4)
```

***model 5 competition effects unrestricted

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category averagetrendcat

eststo Main_model
estat classification
fitstat, saving(mod5) using (mod4)
```

```
regress successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category averagetrendcat
```

```
***Model 6 Restricted competition
```

```
asdoc logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category averagetrendcat cityindex countryindex
categoryindex kickindex if startdate<(42726-60) & startdate>(42322+60)

estat classification
eststo restricted_model
regress successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category averagetrendcat cityindex countryindex
categoryindex kickindex if startdate<(42726-60) & startdate>(42322+60)
vif
esttab, mti star label nodepvars  gaps
```

```
*** probit vs logit
```

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category cityindex countryindex categoryindex
kickindex if startdate<(42726-60) & startdate>(42322+60)
fitstat, saving(mod4)

probit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category cityindex countryindex categoryindex
kickindex if startdate<(42726-60) & startdate>(42322+60)
```

fitstat, saving(mod5) using (mod4) force
*** main model margin effects at mean
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity Launch_Competition Launch_Comp_Category averagetrendcat margins, at (Ambition=(8.751633)) margins, at (Confidence=(-25.02325)) margins, at (Experience=(.5712915)) margins, at (Trustworthiness=(.9906329)) margins, at (Impatience=(.9906329)) margins, at (Campaign_Comments=(.9128139)) margins, at (Early_Funding=(4245.817)) margins, at (Early_Backing= (49.37754)) margins, at (Early_Average_Pledge=(2.281858)) margins, at (Reward_levels=(7.388242)) margins, at (Global_rewards=(3.687063)) margins, at (Average_wait_time=(130.1454)) margins, at (Reciprocity=(3.759563)) margins, at (Facebook_Shares=(3.078752)) margins, at (Launch_Comp_Category=(647.4876)) margins, at (Launch_Competition=(4904.628)) margins, at (Global_rewards=(3.687063)) margins, at (averagetrendcat=(48.77506))
*** Restricted model margin effects at mean
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity Launch_Competition Launch_Comp_Category cityindex countryindex categoryindex kickindex if startdate<(42726-60) & startdate>(42322+60) margins, at (kickindex=(671.8295))

margins, at (cityindex=(3986.172)) margins, at (countryindex=(447.8236)) margins, at (categoryindex=(326.8946))
*** main model margin effects at max
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity Launch_Competition Launch_Comp_Category averagetrendcat margins, at (Ambition=(13.81551)) margins, at (Confidence=(990672.3)) margins, at (Experience=(74)) margins, at (Trustworthiness=(11.37094)) margins, at (Impatience=(60)) margins, at (Campaign_Comments=(11.27634)) margins, at (Early_Funding=(9570510)) margins, at (Early_Backing= (50311)) margins, at (Early_Average_Pledge=(9.21035)) margins, at (Reward_levels=(179)) margins, at (Global_rewards=(179)) margins, at (Average_wait_time=(2129)) margins, at (Reciprocity=(890)) margins, at (Facebook_Shares=(12.71055)) margins, at (Launch_Comp_Category=(42605)) margins, at (Launch_Competition=(50761)) margins, at (Global_rewards=(3.687063)) margins, at (averagetrendcat=(100))
*** Restricted model margin effects at max
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity Launch_Competition Launch_Comp_Category cityindex countryindex categoryindex kickindex if startdate<(42726-60) & startdate>(42322+60) margins, at (kickindex=(6320.38))

```
margins, at (cityindex=(10000))
margins, at (countryindex=(10000))
margins, at (categoryindex=(6644.796))
```

```
*** main model margin effects at minimum
```

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category averagetrendcat
margins, at (Ambition=(0))
margins, at (Confidence=(-125811.4))
margins, at (Experience=(0))
margins, at (Trustworthiness=(0))
margins, at (Impatience=(1))
margins, at (Campaign_Comments=(0))
margins, at (Early_Funding=(0))
margins, at (Early_Backing= (0))
margins, at (Early_Average_Pledge=(-2.302585))
margins, at (Reward_levels=(1))
margins, at (Global_rewards=(0))
margins, at (Average_wait_time=(0))
margins, at (Reciprocity=(0))
margins, at (Facebook_Shares=(0))
margins, at (Launch_Comp_Category=(0))
margins, at (Launch_Competition=(0))
margins, at (Global_rewards=(0))
margins, at (averagetrendcat=(0))
```

```
*** Restricted model margin effects at minimum
```

```
logit successorfailure Ambition Confidence Experience Trustworthiness Impatience
Campaign_Comments Early_Funding Early_Backing Early_Average_Pledge
Reward_levels Global_rewards Average_wait_time Facebook_Shares Reciprocity
Launch_Competition Launch_Comp_Category cityindex countryindex categoryindex
kickindex if startdate<(42726-60) & startdate>(42322+60)
```

```
margins, at (kickindex=(39.99643))
margins, at (cityindex=(0))
margins, at (countryindex=(0))
margins, at (categoryindex=(19.77083))
```

7.6 Item 6:Do file for Kiva model

```
Open file and drop loans that raised less than 50
```

```
import excel "C:\Users\wdtau\Google Drive\Will Davies PhD\April 2018 beginning of full write up\backups of dataset\kiva dataset.xlsx", sheet("datasetforstata") firstrow clear
drop if loanamount<=50
```

```
***Moded 1 Signals
```

```
eststo clear
asdoc regress Amount_raised Generosity  Temporal_Experience Capacity_Experience Rating,robust
asdoc ovtest
eststo Kiva_signals
fitstat, saving(mod1)
```

```
**** Model 2 Signals and social capital
```

```
asdoc regress Amount_raised Generosity  Temporal_Experience Capacity_Experience Country_Funds  Rating Eigen_Centrality Betweeness_centrality Closeness_centrality, robust
eststo Social_capital
fitstat, saving(mod2) using (mod1) force
```

```
*** model 3 Signals, social capital and competition
```

```
regress Amount_raised Generosity  Temporal_Experience Capacity_Experience Country_Funds Active_Loans Rating Eigen_Centrality Betweeness_centrality Closeness_centrality launch_comp sector_index partner_index, robust
asdoc vif
eststo Kiva_main
ovtest
fitstat, saving(mod3) using (mod2)
```

```
vif
predict myResiduals, r
sktest myResiduals
histogram myResiduals, kdensity normal
```

```
***model 4, truncated regression
```

```
truncreg Amount_raised Generosity  Temporal_Experience Capacity_Experience
Country_Funds Active_Loans Rating Eigen_Centrality Betweeness_centrality
Closeness_centrality launch_comp sector_index partner_index, ll(0) robust
drop myResiduals
predict myResiduals
sktest myResiduals
histogram myResiduals, kdensity normal

eststo Tobit_model
```

7.7 Item 7: Winsorization main model results (99 percent level and 95 percent level)

Table 7.1 Winsorization of main model 99 percent level

Logistic regression				Number of observation	=	54193
				LR chi2(17)	=	43500.8
				Prob > chi2	=	0
Log likelihood = -12314.531				Pseudo R2	=	0.6385
successorfailure	Coef.	Std.	Z	P>|z|	Conf.	Interval]
Ambition	-1.38235	0.018406	-75.1	0	-1.41843	-1.34628
Confidence	-6.49E-06	8.10E-07	-8.01	0	-8.08E-06	-4.90E-06
Experience_w	0.039334	0.007231	5.44	0	0.025162	0.053505
Trustworthiness_w	0.892616	0.018037	49.49	0	0.857265	0.927967

Impatience_w	-0.00128	0.001602	-0.8	0.425	-0.00442	0.001863
Campaign_Comments_w	0.707408	0.016926	41.79	0	0.674234	0.740581
Early_Funding_w	-3.53E-07	2.12E-06	-0.17	0.867	-4.50E-06	3.80E-06
Early_Backing_w	0.001032	0.000264	3.91	0	0.000515	0.001549
Early_Average_Pledge_w	0.615308	0.01516	40.59	0	0.585595	0.645022
Reward_levels_w	0.046879	0.003926	11.94	0	0.039185	0.054574
Global_rewards_w	-0.04334	0.004199	-10.32	0	-0.05157	-0.03511
Average_wait_time_w	-0.00158	0.000186	-8.47	0	-0.00194	-0.00121
Facebook_Shares_w	0.784163	0.012797	61.28	0	0.75908	0.809245
Reciprocity_w	-0.00673	0.00082	-8.21	0	-0.00834	-0.00512
Launch_Competition_w	1.97E-05	2.87E-06	6.88	0	1.41E-05	2.54E-05
Launch_Comp_Category_w	-0.0001	8.69E-06	-11.59	0	-0.00012	-8.4E-05
averagetrendcat_w	0.003907	0.000811	4.82	0	0.002317	0.005497
_cons	3.448613	0.120682	28.58	0	3.21208	3.685145

Table 7.2 Winsorization of main model 95 percent level

Logistic regression				Number of obs	=	54193
				LR chi2(17)	=	43500.8
				Prob > chi2	=	0
Log likelihood =	-12314.5			Pseudo R2	=	0.6385
successorfailure	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Confidence_w	-1.38235	0.018406	-75.1	0	-1.41843	-1.34628

Relative_confidence_w	-6.49E-06	8.10E-07	-8.01	0	-8.08E-06	-4.90E-06
Experience_w	0.039334	0.007231	5.44	0	0.025162	0.053505
Trustworthiness_w	0.892616	0.018037	49.49	0	0.857265	0.927967
Impatience_w	-0.00128	0.001602	-0.8	0.425	-0.00442	0.001863
Campaign_Comments_w	0.707408	0.016926	41.79	0	0.674234	0.740581
Early_Funding_w	-3.53E-07	2.12E-06	-0.17	0.867	-4.50E-06	3.80E-06
Early_Backing_w	0.001032	0.000264	3.91	0	0.000515	0.001549
Early_Average_Pledge_w	0.615308	0.01516	40.59	0	0.585595	0.645022
Reward_levels_w	0.046879	0.003926	11.94	0	0.039185	0.054574
Global_rewards_w	-0.04334	0.004199	-10.32	0	-0.05157	-0.03511
Average_wait_time_w	-0.00158	0.000186	-8.47	0	-0.00194	-0.00121
Facebook_Shares_w	0.784163	0.012797	61.28	0	0.75908	0.809245
Reciprocity_w	-0.00673	0.00082	-8.21	0	-0.00834	-0.00512
Launch_Competition_w	1.97E-05	2.87E-06	6.88	0	1.41E-05	2.54E-05
Launch_Comp_Category_w	-0.0001	8.69E-06	-11.59	0	-0.00012	-8.4E-05
averagetrendcat_w	0.003907	0.000811	4.82	0	0.002317	0.005497
_cons	3.448613	0.120682	28.58	0	3.21208	3.685145

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