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Ending Poverty is Urgent: Determining the Factors that Affect Prosocial Crowdfunding Success

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Master in Management

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BUSINESS
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This study is dedicated to my family, especially my parents and my grandparents, who always supported me during my academic journey and to all victims of poverty in the world that inspired me to develop a study about poverty and the urgency of eradicating it.

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Resumo

A pobreza extrema é um problema que atinge cerca de 9% da população mundial e o crédito é quase inacessível às populações mais desfavorecidas. Com vista a combater a pobreza e reduzir a exclusão financeira, várias abordagens têm sido utilizadas, sendo o microcrédito uma delas. Com o avançar da tecnologia, o *crowdfunding* social tem vindo a desempenhar uma alternativa ao microcrédito tradicional. Este estudo teve como objetivo identificar alguns fatores que podem contribuir para reduzir a duração das campanhas de *crowdfunding* social, a fim de ajudar pessoas desfavorecidas a ter acesso ao crédito de forma mais rápida, contribuindo para a redução da pobreza e como se comportam esses fatores em um ano de recessão. Aplicámos duas regressões lineares múltiplas: a regressão 1 cobriu campanhas publicadas nos anos 2017-2020 (N=791534) e a regressão 2 cobriu campanhas publicadas exclusivamente em 2020 (N=171498). Com base na regressão 1, concluímos que campanhas com prazos de empréstimo mais elevados, com maior número de *hashtags*, com prazos de reembolso mensais, individuais e do setor de agricultura estão associadas a campanhas mais lentas e que campanhas com descrições maiores, com beneficiários de empréstimos de países com IDHs mais elevados, com inglês como língua original e cujos beneficiários são mulheres, estão associadas a campanhas mais rápidas. Por outro lado, com base na regressão 2, concluímos que os únicos dois fatores associados a campanhas mais rápidas são descrições mais longas e mutuários do sexo feminino. No entanto, o prazo do empréstimo deixou de ser estatisticamente significativo na regressão 2.

Palavras Chave: Pobreza; Microcrédito; *Crowdfunding* Social; Duração de Campanhas

Códigos de Classificação JEL: L26; D64

Abstract

Extreme poverty is a problem that affects around 9% of the world's population and credit is almost inaccessible to the most disadvantaged populations. To fight poverty and reduce financial exclusion, several approaches have been used, with microcredit being one of them. As technology advances, prosocial crowdfunding has come to play as an alternative to traditional microcredit. This study aimed to identify some factors that might contribute to reducing prosocial crowdfunding campaigns' duration, to help disadvantaged people to access credit in a faster way, contributing to poverty reduction, and how do those factors behave in a recession year. We applied two multiple linear regressions: regression 1 covered campaigns published in the years 2017-2020 (N=791534) and regression 2 covered campaigns published exclusively in the year 2020 (N=171498). Based on regression 1, we concluded that campaigns with longer loan terms, with a higher number of hashtags, with monthly repayment terms, individual, and related to the agriculture sector, are associated with slower campaigns and that campaigns with longer descriptions, with borrowers from higher HDIs countries, with English as the original language and whose borrowers are women, are associated with faster campaigns. On the other hand, based on regression 2, we concluded that the only two factors associated with faster campaigns are longer descriptions and female borrowers. However, the loan term is no longer statistically significant in regression 2.

Keywords: Poverty; Microcredit; Prosocial Crowdfunding; Campaigns' Duration

JEL Classification Codes: L26; D64

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List of Abbreviations

BRAC - Bangladesh Rural Advancement Committee

GNI - Gross National Income

HDI - Human Development Index

LDC - Least Developed Countries

MIX - Microfinance Information Exchange

MFI - Microfinance Institution

NGO - Non-Governmental Organization

OECD - Organisation for Economic Co-operation and Development

OLS - Ordinary Least Square

RQ – Research Question

UN - United Nations

UNCTAD - United Nations Conference on Trade and Development

UNDP - United Nations Development Programme

1. Introduction

Access to credit represents a barrier to entrepreneurship and to the consequent economic growth, affecting the most disadvantaged populations, who tend to live in developing countries in poverty conditions.

Poverty has been a widely studied and discussed topic and its eradication was proposed by the United Nations (UN) in 2015. UN defined 17 sustainable development goals (see Appendix A, Figure A.1), which must be achieved by 2030. From this list, it should be noted that the primary goal is the eradication of all poverty in the world. Poverty is characterized by a lack of income and productive resources that guarantee a sustainable life, but it also includes other problems such as hunger and malnutrition, access to other basic services, lack of participation in decision-making, social discrimination, and exclusion (United Nations, 2021a). Thus, there have been some studies in this area, and some of them were recognized with Nobel Prizes in Economics. In 2015 Angus Deaton was awarded the Nobel Prize for economic sciences with his analysis of consumption, poverty, and welfare. In 2019, the same award was given to Abhijit Banerjee, Esther Duflo, and Michael Kremer for their experimental approach to alleviating global poverty. The fact that over 4 years, there have been 2 Nobel Prizes focusing on poverty, highlights the worldwide concern regarding this topic (The Nobel Prize, n.d.).

Since the 17 sustainable development goals proposed by the UN were released, the indicator “poverty headcount ratio at $1.90 a day", between 2015 and 2019, has decreased from 10.1% to 9.2% of the world population (World Bank, n.d.), an evidence of progress towards the goal of eradicating poverty. However, according to World Bank (2021), more than 40% of the total poor people live in economies affected by violence, fragility, and conflict. In addition, it is expected that, in the next decade, that number will rise to 67%. In terms of geographic location, as reported by the same source, 85% of the world’s poor live in Sub-Saharan Africa and South Asia, and “half of the world’s 736 million extremely poor people lived in just 5 countries in 2015: India, Nigeria, Democratic Republic of Congo, Ethiopia, and Bangladesh”. According to the UNDP (n.d.), the development of a country is measured by HDI and it includes three criteria: being knowledgeable, having a long and healthy life and having a decent standard of living. Thus, there are different groups according to the level of development, namely developed countries and developing countries, being the latter divided into Least Developed Countries (LDCs) and other (non-LDCs) developing countries, and the level of poverty varies accordingly. According to UNCTAD (2020)**,** LDCs host more than 50% of the people living on less than $1.9 per day. Furthermore, 14% of the world’s population lives in LDCs. LDCs and the remaining developing countries have been diverging. In fact, in 2020 the gross national income (GNI) per capita of LDCs was approximately six times lower than the GNI in other developing countries, whereas, in 1990, that indicator was only three times lower in LDCs in comparison with the GNI in the other developing countries. The same source also reported that the LDCs, in 2020, were 27% more vulnerable than the other developing countries, making the LDCs the most vulnerable group of countries in the world.

Some researchers have focused on possible solutions to extreme poverty and one of the options that have been presented as a possible solution to poverty is entrepreneurship (Naudé, 2010; Ali & Ali, 2013; Sutter et al., 2019; Moradi et al., 2020; Si et al., 2020; Lee & Rodríguez-Pose, 2021; Bruton et al., 2021; Morris & Tucker, 2021).

Despite the evidence mentioned in the context of combating poverty, there are large barriers to entrepreneurship, such as lack of social network, aversion to risk, lack of economic stability, and weak business environment in developing countries (Bizri et Al., 2012).

Furthermore, Wonglimpiyarat (2015) concluded that the absence of entrepreneurship training programs, unfriendly investment business environments, unfavourable investment climate, lack of value chain in the entrepreneurship ecosystem, gender gap, and difficulties in access to finance also negatively affect entrepreneurship. Moreover, the lending institutions become more conservative, and, because of the previous barriers, they will be more reluctant to provide credit to entrepreneurs, which will accentuate the negative effects on entrepreneurship (Bizri et Al., 2012). In other words, the access to capital for initial investment might be hampered according to the situation. Depending on the type and size of the business, the amount needed for the initial investment varies. Following this reasoning, the question of the financing strategy for the initial investment arises.

A part of the population does not meet the requirements to receive credit from conventional bank or to beneficiate from other conventional financial products. Qamruzzaman & Wei (2019) defined financial inclusion as the ease of financial service access as well as the availability and the usage from formal financial institutions across the country.

According to Demirgüç-Kunt et al. (2018), 1.7 billion adults were unbanked in 2017 (which represented 31% of all adults in the world that year), with 56% of that unbanked population being women and 47% of unbanked adults were “out of labour force”, with only 32% of men in this condition, contrasting with 59% of unbanked women who were “out of labour force”. Furthermore, according to the same report, in 2017 approximately half of all unbanked adults (46% of the total population) came from just seven developing countries, namely: Bangladesh, China, India, Indonesia, Mexico, Nigeria, and Pakistan (Demirgüç-Kunt et al., 2018).

According to Ozili (2020) financial inclusion depends on the economic cycles, meaning that in good economic times, countries with larger financial inclusion have higher levels of local economic activity. By contrast, during economic recessions, people are less active in participating in the financial sector and, thus, credit will be scarce, the development level of local economic activities will decline, leading to higher unemployment.

To respond to the financing needs of aspiring entrepreneurs, but financially excluded, an alternative to conventional credit emerged: microcredit. This innovative alternative was proposed by the economist Muhammad Yunus, who was the 2006 Peace Nobel Prize Laureate and founder of Grameen Bank, considered the first modern microcredit institution. Grameen Bank makes small loans to the impoverished people without requiring collateral, representing a banking system based on mutual trust, accountability, participation, and creativity. Its mission is “empowering the poor to realize their potential and break out of the vicious cycle of poverty” by providing comprehensive financial services (Grameen Bank, 2021).

Since the award of the Nobel Prize to Muhammad Yunus (The Nobel Prize, n.d.), microcredit institutions have emerged all over the world and, at the same time, the concept of microcredit has been the object of study for many researchers, such as Campbell (2010), Knewtson & Qi (2020), Hwa Ang (2004), Gan et al. (2012), Woller & Woodworth (2001), Nawai & Shariff (2010), Golesorkhi et al. (2019). Microcredit providers are essentially focused on providing credit to financially excluded entrepreneurs. One of the strategic mechanisms of microcredit institutions that allow them to obtain the necessary amounts to finance financially excluded individuals is to ask for financial help (loans or donations) through the internet.

Access to the internet allows to bring the world population together and several advantages can come from it. One of the advantages of accessing the internet is the possibility to enjoy crowdfunding. Several researchers over time have been exploring this concept in their articles, such as Huili & Yaodong (2014), Bouncken et al. (2015) e Kim & Moor (2017). According to Oxford University Press (2019) “crowdfunding” means “the practice of funding a project or venture by raising money from a large number of people who each contribute a relatively small amount, typically via the internet”. Therefore, crowdfunding allows anyone with internet access to apply for funding as an alternative to conventional funding from banking institutions. In this scenario, it is important to mention that not all the world population have access to the internet and, therefore, part of the population remains financially excluded, because they do not meet the requirements to finance themselves in a conventional bank or they do not have access to internet and, therefore, to crowdfunding. In 2019, only 51.4% of the world population had access to the internet (Johnson, 2021). Furthermore, from the same source, it is possible to acknowledge that 86.7% of the population living in developed countries has access to the internet, in contrast to developing countries, where only 44.4% of the population has access to the internet (Johnson, 2021). Tapering even further, only 19.5% of the population of the world's least developed countries (LDCs) have access to the internet. Considering these data and considering that, as mentioned above, poverty is more prevalent in developing countries, without external help or intermediaries, the population in these conditions will hardly be able to take advantage of crowdfunding.

According to Statista (2021a) the transaction value of crowdfunding has been growing over years, being 965.6 million US dollars in 2017 and 969.9 million US dollars in 2020. Furthermore, in 2020 the market size of crowdfunding worldwide was 12,27 billion US dollars, and it is expected that, in 2027, it will value 25.8 billion US dollars, suggesting an expected growth in the crowdfunding market worldwide (Statista, 2021b)

There are four main crowdfunding categories: donation-based crowdfunding, reward-based crowdfunding, equity-based crowdfunding, and lending-based crowdfunding (Ryu & Kim, 2018; Berns et al., 2020). However, when focusing the attention on crowdfunding that aims to help the poor, a new typology arises: prosocial lending-based crowdfunding. Some authors have studied this type of innovative crowdfunding, such as Berns et al. (2020), Jancenelle & Javalgi (2018), and Jancenelle et al. (2019).

Crowdfunding platforms such as BRAC, Kiva.org, and Zidisha.org, are examples of platforms that use this new concept. Poverty values can fluctuate positively or negatively in certain periods such as economic growth or economic recession periods. As reported by Kallio & Vuola (2020), financial markets are characterized by “continuous fluctuation between economic cycles”. Therefore, financial markets tend to perceive expansions and retractions, leading to economic growth and recessions, respectively.

In historical terms, the world lived in a period of an economic recession between 2007 and 2009. This recession, according to United Nations (2011) generated an increase in global unemployment from 178 million people in 2007 to 205 million in 2009, which caused vulnerability intensification, particularly in developing countries. In consequence, some people who lost their formal jobs moved to the informal economy, which is characterized by lower productivity, lower earnings, more difficult working conditions, and a more prominent risk of poverty. The same report also mentions that that crisis caused an increase of the extremely poor, more precisely between 47 million people and 84 million people.

In 2020, another recession was triggered by the Covid-19 virus and, according to OECD (2020), that was the deepest economic recession in almost a century which, in turn, had negative effects on health, economic activity disruption, people's well-being, and jobs. Furthermore, it was also suggested that this economic crisis might affect the previously planned exit of some countries from the group of LDC, which might compromise the objective of eradicating poverty defined by the UN. Considering the economic recession that the world is currently going through due to the Covid-19 pandemic, the goal of eradicating poverty in its entirety by 2030 proposed by the UN may be compromised, considering that, as previously mentioned, poverty tends to increase during economic recession periods. In fact, according to United Nations Statistics Division (2021), between 119 and 124 million people were pushed back into extreme poverty in 2020 and it was projected that the global poverty rate will be 7% in 2030, which means that the target of eradicating poverty will be missed (see Appendix A, Figure A.2). Thus, it becomes important to bring together as much effort as possible to eradicate poverty. Noggle (2020) alerted to the fact that, because of the Covid-19 impact, it is critical that the financial inclusion community provide capital to the needed people as faster as possible and to contribute for them to save that capital. Governments and private institutions should keep lending and banks should maintain liquidity to allow families to cash out when they need it.

As the increase in entrepreneurship was, as mentioned above, associated with the reduction of poverty, encouraging entrepreneurship could be one of the ways forward. Taking this into account and knowing that not everyone has access to credit that allows them to be entrepreneurs, microcredit combined with crowdfunding seems a favourable option to contribute to eliminate this problem.

Several studies have focused on exploring the factors that affect crowdfunding success, but there seems to be room for studies regarding campaigns duration, including in recession years such as 2020.

This study focuses on crowdfunding for financially excluded populations, mainly from developing countries, intending to investigate some of the factors that may be associated with the inefficiency of campaigns in terms of the speed of raising target value by the borrowers.

Thus, this study addresses the research problem: Which factors might contribute to reducing prosocial crowdfunding campaigns' durations, to help disadvantaged people to access credit in a faster way, contributing to poverty reduction, and how do those factors behave in a recession year? The current study focuses on the campaigns' duration as a measure of success and Figure 1.1 represents this idea.

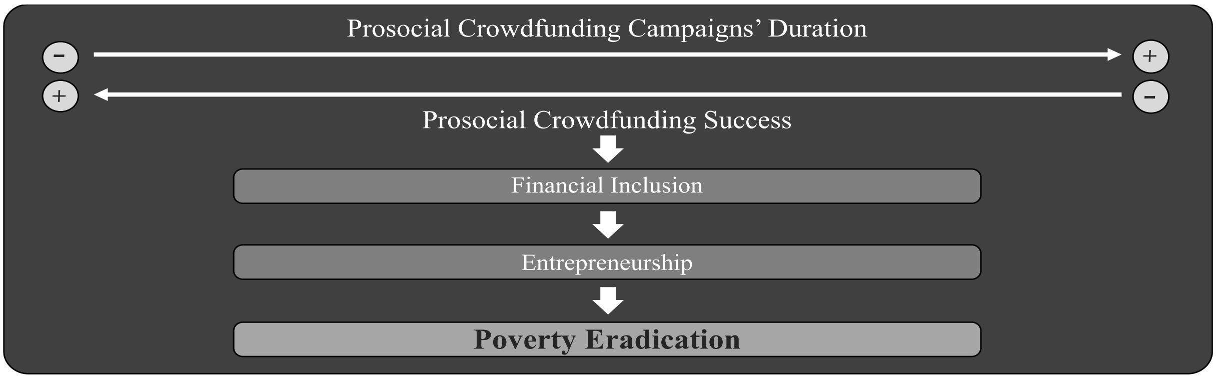

Figure 1.1 - Relation between Prosocial Crowdfunding Success and Poverty Eradication (Source: Own Research)

This problem allowed the following research questions (RQs) to be formulated:

RQ1 – How does the target amount affect prosocial crowdfunding campaigns' duration?

RQ2 – How does the loan term affect prosocial crowdfunding campaigns' duration?

RQ3 – How does the description size affect prosocial crowdfunding campaigns' duration?

RQ4 – How does the hashtags number affect prosocial crowdfunding campaigns' duration?

RQ5 – How does the HDI affect prosocial crowdfunding campaigns' duration?

RQ6 – How does the borrowers' language affect prosocial crowdfunding campaigns' duration?

RQ7 – How does the repayment frequency affect prosocial crowdfunding campaigns' duration?

RQ8 – How does the borrowers' number affect prosocial crowdfunding campaigns' duration?

RQ9 – How does the borrowers' gender affect prosocial crowdfunding campaigns' duration?

RQ10 – How does the sector affect prosocial crowdfunding campaigns' duration?

To respond to the identified problem and the mentioned research questions, this study is divided into five chapters: literature review, methodology, results and discussion, and conclusions, limitations and paths for future research.

In the literature review, we begin by explaining the concepts of microcredit and crowdfunding in more detail. After that, an overview of published studies related to this theme is presented as well as a comparative analysis of several crowdfunding platforms that focus on microcredit, to identify the most favourable platform for the development of this study. At the end of the literature review, the study hypotheses are also presented. In the methodology, we start by identifying the crowdfunding platform that was used in the study and describing its characteristics, so that we understand how it works. Afterward, information regarding the research design, data collection, and how the data was analysed is presented. In the results and discussion chapter, the results of the applied statistical tests and the analysis and interpretation of them are presented and compared with previous studies. In the last chapter, we present the key conclusions of the study, as well as its limitations and recommendations for future studies.

2. Literature Review

In this chapter, the concepts of microcredit and crowdfunding will be explained to frame the scientific knowledge regarding prosocial crowdfunding. Some studies will be presented to formulate the theoretical framework, including the hypotheses formulation.

2.1. Microcredit

"The most important step to ending poverty is to create employment and income opportunities for the poor (…) Self-employment is the quickest and easiest way to create employment for the poor (…) Credit can create self-employment instantaneously" (Yunus, 2005).

According to Campbell (2010), credit is responsible for fuelling the entrepreneurial innovation in developed countries and, with a new purchasing power, families from developing countries will be likely to enter the marketplace, increasing competition and consumerism, which, in its turn, will help lift those families out of poverty. In fact, people from all over the world are starting their own small businesses as they are aware of the potential for economic mobility and the flexibility provided by those businesses. Once the banking and finance industry understood the importance of small and micro businesses, either in developed and developing countries, providing lending opportunities to support those businesses became a priority. Some governments have been trying to develop political initiatives to extend the credit to the less developed markets but, despite that, traditional lending channels remain often inaccessible for some small and micro-entrepreneurs. Moreover, motivated by altruistic purposes, private individuals lend to small and micro businesses as well. Microfinance focus on micro-entrepreneurs' needs and plays a relevant role in credit formation (Knewtson and Qi, 2020).

Microcredit has been the object of study by several researchers, namely in the context of combating poverty. According to Hwa Ang (2004) microcredit is an effective tool against sub-standard living conditions and exploitation, and it has proven to be an effective tool against poverty. It allows to stimulate enterprises and, by increasing wealth and consumption, it benefits the individual borrower, their families, and the overall community. According to Woller & Woodworth (2001), microcredit is a popular development strategy, representing an alternative to the top-down macroeconomic approaches that have been implemented in the Third World, that relies upon small loans to help borrowers living in poverty to generate income through self-employment projects. In addition, these authors state that one advantage of microcredit besides contributing to poverty alleviation is to allow poor people to be able to become self-reliant, representing an improvement of their lives in the future. Gan et al. (2012) reinforce this idea by asserting that, microcredit loans facilitate the access to income-generating activities to gather capital and improve the lives of poor people in need.

Nawai & Shariff (2010) agree with the previous definitions and describe the microcredit loans as being short-term loans, very small amounts, without the need of collateral, that typically require weekly repayment and that usually come with high-interest rates. This strategy is an alternative to the traditional credit in which people that lack collateral, verifiable credit history, and steady employment have no access to the loans, being these people typically women.

Microcredit organizations are typically NGOs (Qudrat-I & Rahman, 2006). Nawai & Shariff (2010) believe that the access deprivation of social resources, such as credit, creates poverty. In fact, some institutions treat credit as a kind of human right (Qudrat-I and Rahman, 2006). However, Nawai & Shariff (2010) alert to the fact that NGOs are not profit-oriented, and, for that reason, those institutions rely on donations and in the repayments of the loans provided to the poor. Therefore, problems with the loan's repayment will affect the services of the microcredit institutions.

According to Knewtson & Qi (2020), the lack of understanding of the default risk of small and micro businesses is the biggest obstacle facing microfinance and generates numerous challenges for the lending industry. Thus, Microfinance Institutions (MFIs) may refuse to provide microfinance to small and micro businesses if there is not an accurate understanding of their default risk. Therefore, the competition among lenders becomes low and those who remain in the lending market can take advantage, charging exorbitant interest rates. As such, some NGOs try to obtain capital from other capital sources, such as through crowdfunding platforms, to be able to help the borrowers without compromising the institution.

2.2. Crowdfunding

According to the European Commission (2017), "Crowdfunding is an emerging source of financing involving open calls to the public, generally via the internet, to finance projects through monetary contributions in exchange for a reward, product preordering, lending, or investment."

Huili & Yaodong (2014) refer that crowdfunding derives from crowdsourcing and micro-finance and it means the idea of financing directly through the internet to a wide number of investors. Furthermore, Kim & Moor (2017) define crowdfunding as the "activity of collecting funds from a large number of people with small individual contributions to support certain individual or organizational activities or businesses via the Internet". According to Kim & Moor

(2017), crowdfunding can help the firms and the financially unserved people in the process of increasing funds in a quick way and at an affordable cost.

Bouncken et al. (2015) refer to the crowdfunding concept as an alternative way of funding compared to traditional borrowing, since it is open to everyone. In accordance, Venturelli et al. (2020) concluded that, by expanding the availability of funds to excluded and underserved groups of individuals, such as ethnic minorities and female entrepreneurs, crowdfunding is helping to drive financial inclusion.

Crowdfunding might be a possibility in terms of social entrepreneurship since investors make their investment decisions based on the social and environmental impact of the projects they fund (Rey-Martí et al., 2019). According to Kim & Moor (2017), all types of crowdfunding are valuable resources to promote financial inclusion.

2.2.1. Types of Crowdfunding

There are four types of crowdfunding: donation-based crowdfunding, reward-based crowdfunding, equity-based crowdfunding e lending-based crowdfunding (Ryu and Kim, 2018; Berns et al., 2020).

- *Donation-based crowdfunding*: The donation-based crowdfunding refers to a classic donation with the difference that the donations are made via the internet and, in most cases, a specific intermediary (Bouncken et al. 2015). By soliciting donations directly from the public through the web and social media, according to Lee et al. (2016), donation-based crowdfunding has the potential to democratize capital raising.
- *Reward-based crowdfunding*: Frydrych et al. (2014) mentioned that reward-based crowdfunding allows investors to invest small amounts in businesses and gain rewards in return and that this type of crowdfunding is the predominant online model. Entrepreneurs, in this case, are project founders and project supporters represent early customers or co-creators instead of being called investors.
- *Equity-based crowdfunding*: according to Mochkabadi & Volkmann (2020), equity crowdfunding is an emerging area of research within the broader sphere of entrepreneurship, and it involves investment decisions with a vision of a potential return on investment.
- *Lending-based crowdfunding*: according to Berns et al. (2020), funding that is provided expecting to have interest besides the return of capital. In accordance, Kim & Moor (2017) mention that lending-based crowdfunding, which is the same as debt-based crowdfunding, is "like a loan to individuals or the company".

However, there is an emerging sub-typology of lending-based crowdfunding, in the research academy and the managerial world, that aims to help the poor known as "prosocial lending-based crowdfunding" (Berns et al., 2020).

2.3. Prosocial Lending-Based Crowdfunding

Berns et al. (2020) define prosocial lending-based crowdfunding as funding that is provided as debt without interest and thus, allowing to emphasize a prosocial agenda.

Jancenelle et al. (2019) refer that prosocial crowdfunding is a recent international business phenomenon that allows entrepreneurs from emerging nations to post microloan requests online for fundraising. Prosocial Lending-Based Crowdfunding is a new business phenomenon that, according to Jancenelle & Javalgi (2018), is changing the microfinance sector, mainly because there are more and more microloans being posted online for fundraising. Dorfleitner et al. (2020) state that microfinance institutions (MFIs) started to use crowdfunding as a source of debt capital, because of their rising funding demand from the poor. This caused a widespread growth in the crowd-based approach.

Typically, the stakeholders involved in prosocial crowdfunding are the borrowers, the lenders, the microfinance institutions, and the crowdfunding platforms. The process can be easily explained as follows: financially excluded individuals need credit to start a new business that might help them to overcome their financial situation. Therefore, they request microcredit from a local microfinance institution. However, lending money to poor people has a high risk of default associated and, therefore, the interest rates tend to be high. To decrease the level of risk and do not charge interest rates, MFIs started to use crowdfunding platforms to advertise the borrower's project and split the risk of default among the lenders that want to lend money to that campaign. According to Berns et al. (2020), crowdfunding platforms connect crowdfunding lenders and businesses and protects that relationship by monitoring the relationship through MFIs. Thus, the lenders provide the amount to the crowdfunding platform and wait until the repayment of the loan.

According to Young (2010), MFI's possibilities of obtaining access to subsidized debt capital without interest obligation were effectively expanded by crowdlending as MFIs started to transfer the credit default risk to multiple lenders that lend only a parcel of the total loan. There are several prosocial lending-based crowdfunding platforms that allow lenders to do that.

2.3.1. Prosocial Lending-Based Crowdfunding Platforms

There are several crowdfunding platforms, some of which specialize in Prosocial Lending-Based Crowdfunding. According to Campbell (2010), to connect microlenders with micro-borrowers, online lending sites started to open the credit market to crowds of people across developing countries.

If the focus is on these specialized platforms for prosocial crowdfunding, it is possible to distinguish between three formats (see Table 2.1): the format in which funders choose the campaigns they want to support and receive the borrowed money back (which in this study we labelled "Format 1"), the model in which lenders do not choose the campaign they want to support and do not receive the borrowed money back (which in this study we labelled "Format 2") and the model in which funders can choose the first campaign they want to support but do not receive the borrowed money back (which in this study we labelled "Format 3"). In these three models, beneficiaries must return the borrowed money to the crowdfunding platform. The big difference is that, in Format 1, the crowdfunding platforms, after receiving the refund from the beneficiaries, send the money to the funders, while in Formats 2 and 3, the crowdfunding platforms, after receiving the refund from the beneficiaries, apply the money in other campaigns instead of refunding the funders.

Table 2.1 - Prosocial Crowdfunding Formats (Source: Own Research)

	Format 1	Format 2	Format 3
Funder's Perspective	Loan	Donation	Donation
Crowdfunding Platform's Perspective	Loan	Loan	Loan
Choice of the crowdfunding campaign	Lender	Crowdfunding Platform	Lender

Concerning the target, it is still possible to distinguish two types of platforms: platforms that focus on just one country and platforms that focus on more than one country. Furthermore, within the group of platforms that focus on more than one country, some platforms are more diversified than others in terms of the number and location of countries.

Following this order of ideas, in this work, it is important to know the most diversified platforms. Therefore, the following platforms stand out:

- Building Resources Across Communities (BRAC): is a non-governmental development organization founded in 1972 in Bangladesh. Its vision is "a world free from all forms of exploitation and discrimination where everyone has the opportunity to realize their potential". In accordance, its mission is "to empower people and communities in situations of poverty, illiteracy, disease and social injustice" (BRAC, 2021). It focuses on borrowers from 10 countries, and it follows Format 2 (see Table 2.1).

- Kiva: is an international non-profit, founded in 2005 in San Francisco, United States of America, with a mission "to expand financial access to help underserved communities thrive" and the vision of "a financially inclusive world where all people hold the power to improve their lives" (Kiva, 2021). It focuses on borrowers from 77 countries, and it follows Format 1 (see Table 2.1).
- Babyloan: is a social business founded in 2008 in France, which combines crowdfunding, solidarity finance, and microcredit. On Babyloan lenders choose a micro-entrepreneur in Europe, Asia, Arab World, Latin America, or Sub-Saharan Africa. The microentrepreneurs pay back the loan on a monthly basis. Babyloan defines its mission as "finding sustainable and responsible ways to answer to the need for funding and guidance of the microentrepreneurs who do not have access to the traditional banking system" (Babyloan, 2021). It focuses on borrowers from 17 countries, and it follows Format 3 (see Table 2.1).
- Zidisha: is the first online crowdfunding community that connects lenders and entrepreneurs without local banks and intermediaries, allowing instantaneous and open communication among members. It was founded in 2009 in the United States of America and its mission is "to help disadvantaged entrepreneurs in developing countries access affordable investment capital" (Zidisha, 2021). It focuses on borrowers from 5 countries, and it follows Format 3 (see Table 2.1).
- Women's Microfinance Initiative: is a non-profit organization founded in 2010 in the United States of America and its mission is "to establish village-level loan hubs, administered by local women, to provide capital, training and support services to rural women in the lowest income brackets in East Africa so that they can engage in income-producing activities" (Women's Microfinance Initiative, 2021). It focuses on borrowers from 3 countries, and it follows Format 2 (see Table 2.1).
- Microworld: is a social business that aims is "to promote the growth of microcredit in developing countries". Its mission is to "reduce world poverty, support microentrepreneurs in the development of their businesses through microcredit and create a worldwide community of lenders" (Microworld, 2021). It focuses on borrowers from 17 countries, and it follows Format 1 (see Table 2.1).

Although all the crowdfunding platforms mentioned above are related to fighting poverty through microcredit, in the context of this study, Kiva's platform stands out as it covers the largest number of countries, mostly developing countries and it follows the Format 1, which is in line with the present study that relies on the factors that might influence the lenders' choice regarding the prosocial crowdfunding campaigns they want to support. to understand the lenders' choices, it is important to know their motivations.

2.3.2. Crowdfunding Lenders' Motivation

According to Gerber & Hui (2013), the desire to collect external rewards is one of the supporters' motivations in crowdfunding communities. Examples of those rewards might be a tangible artifact, an acknowledgment, or an experience. The authors describe two different types of supporters: the ones that are motivated to "give" (philanthropic behaviour) and the ones motivated to "collect". In addition, helping creators to whom the supporters have a personal or extended connection as well as supporting causes similar to their personal beliefs represent a supporters' strong desire.

The findings of Formanowicz et al. (2017) suggest that some people, more than just focus on their own personal gain, want to invest their financial and social resources in projects that have a positive impact on the community. Formanowicz et al. (2017) add that people who donate through crowdfunding platforms, in addition to helping entrepreneurs build their successful businesses, are also contributing to community and sustainability building, which represent high prosocial goals.

2.3.3. Crowdfunding Campaigns' Duration

Over time, several studies have focused on studying the factors associated with crowdfunding success, which is perceived in different ways. For example, Berns et al. (2020) and Jancenelle et al. (2019) considered that campaigns are successful when reach the total amount requested. On the other hand, Gama et al. (2021), Proelss et al. (2021), and Jancenelle et al. (2019) measured success by how quickly the campaigns reached the total requested value. Table B.1 from Appendix B summarizes some of the studies carried out in this area, measuring success according to the campaigns' speed.

It is important to highlight that external factors such as economic crises might affect crowdfunding speed. For example, according to Di Bella, G. (2011) the global financial crisis that took place in 2008, had a negative impact on borrowing opportunities and asset quality and profitability, which in turn affected microfinance institutions (MFIs) negatively. As a consequence, the MFIs increased the interest rates that they charge to the borrowers, typically low-income people. In accordance, Visconti (2011) affirms that, during recessions, the high interest rates, the default probability, and the high repayment difficulties intensify the probability of increasing the credit risk. The same authors stated that recessions impact diverse microfinance stakeholders, including the international equity holders and bondholders which might end up without Microfinance Investment Vehicles financing. Additionally, the borrowers might find some constraints in repaying the loans, which in turn, will increase the probability to increase the delinquency rate, causing an effect of lenders' overcaution. Furthermore, Fatima et al., (2018) stated that the resistance to the financial crunch effects was more evident in MFIs located in countries politically stable and with robust political regulations. In addition to being influenced by economic factors such as economic recessions, lenders might choose the campaigns they want to support considering specific factors of the campaigns and borrowers.

2.3.3.1. Campaign Target Amount

Several studies present conclusions regarding the impact that the target value of crowdfunding campaigns has on the speed of the campaigns.

Gama et al. (2021) explored the relationship between the campaign target value and the campaign speed. According to its results, the requested amount harms the funding speed, meaning that microentrepreneurs who ask for larger loans receive funding slower than for smaller loans. According to the results of the study developed by Ly & Mason (2012a), an increase in funding time by 76% occurs if there is an increase in the requested loan amount by one standard deviation. According to Badding & Heller (2012) campaigns with larger loan amounts are slower than the campaigns with smaller amounts.

Therefore, the following hypothesis was formulated:

H1: Campaigns with a higher target amount are *slower* campaigns.

2.3.3.2. Loan Term

Ly & Mason (2012b) used Kiva.org data and concluded that longer loan terms are associated with slower campaigns by 26%. The authors suggested that those results indicate that the lenders may be impatient to receive the loan repayment. Social crowdfunding does not assume monetary returns for funders, which means funders know from the outset that they are not going to make a profit. Contrary to the cases in which the prosocial crowdfunding platform follows Format 2 or 3 (see Table 2.1), in Format 1 funders lend money in order to help, but beyond that, they also expect to receive the loan amount repayment at the end of the stipulated time.

Therefore, the following hypothesis was formulated:

H2: Campaigns with a larger loan term are *slower* campaigns.

2.3.3.3. Description Size

To increase the funding probability, borrowers tend to provide information in the description text and, therefore, it is possible that longer descriptions could be an indicator of creditworthiness and it could be expected to generate fewer defaults (Dorfleitner et al., 2016). To test that hypothesis, the results of Dorfleitner et al. (2016) indicated that, although "the funding probability increases by 5.2% if the description text is increased ceteris paribus by one standard deviation", very long description texts tend to decrease the funding probability. According to Dorfleitner et al. (2021) funding success and the reversed funding time are positively related to the borrower's willingness to share information and a possible justification is that information sharing might contribute to build trust and attract investors. According to the results of a study conducted by Formanowicz et al. (2017), the number of prosocial words used in a project's description contributes to campaign success, as it helps to achieve the project's financial goals by attracting a larger number of supporters.

According to a study developed by Proelss et al. (2021), donors consider the length of the campaigns' descriptions an important factor, but they prefer details over shorter descriptions. In the same study, Proelss et al. (2021) found that poorly understandable campaign descriptions are negatively correlated with funding speed and that campaign descriptions should not be either too technical or too short in length.

Therefore, the following hypothesis was formulated:

H3: Campaigns with longer descriptions (number of words) are *faster* campaigns.

2.3.3.4. Hashtags Number

Hashtags are becoming popular among social media users (Rauschnabel et al., 2019). Yu & Zhu (2015) in their study focused on hashtags, define a hashtag as a set of letters without whitespace in between that normally are concatenated words and prefixed by a #.Also, hashtags are prevalent on micro-blogging systems facilitate both the search by other relevant users of online publications such as tweets (on social media Twitter) and conversations among users.

The results of the study developed by Rauschnabel et al. (2019) reveal that one motivation to use hashtags is to engage in trendy topics and transmit a message or opinion to a wider audience, usually interested in a specific topic. Hashtags are also associated with the desire to create unique and creative postings. Social media users with this motivation want to give their postings more "character" and make them visually appealing to the other users.

Therefore, the following hypothesis was formulated:

H4: The higher the number of hashtags, the *faster* is the campaign.

2.3.3.5. Human Development Index

The world is unequal, and, for that reason, it is possible to group the countries according to their level of development. There are 46 countries labelled as Least Developed Countries in the World. Table C.1 from Appendix C contains the list of those countries UNCTAD (n.d.).

Bukhari et al. (2020) analysed 223 crowdfunding campaigns from LaunchGood, a crowdfunding platform that aims to help the Muslim community around the world, finding evidence that the creator credibility and supporter endorsement impact the levels of donation to crowdfunding campaigns in a focal Muslim community and the success factors of projects in developing and developed countries. They concluded that there is more crowdfunding projects endorsement from backers in developed countries than in developing countries. Also, there is a positive result for funding success in developed countries.

When it comes to prosocial crowdfunding, it is fair to assume that the main purpose is to help the most disadvantaged as there is no associated monetary gain. There are countries with more disadvantaged people than others, and the least developed countries in the world are the countries with more disadvantaged people. According to United Nations (2019), "Least developed countries (LDCs) are low-income countries confronting severe structural impediments to sustainable development. They are highly vulnerable to economic and environmental shocks and have low levels of human assets".

According to Linh (2019), the nationality of the borrower affects the crowdfunding campaign's success, and those results are in accordance with the idea that they presented that borrowers from developed countries are more trustworthy in lender's perspective than borrowers that come from poor or developing countries. However, in a study developed by Chen et al. (2019), lenders found that lending to poor developing world micro-entrepreneurs is appealing on its own. With that study, its authors could conclude that there is more likely that the lenders prefer to lend to borrowers they perceive to be needier. In addition, after analysing the results, the authors of that research suggested that the study participants appear to be willing to accept some additional risk if that means that they will help a needier borrower. In other words, the greater the level of need, the greater the risk the lenders will be willing to accept, which reinforces the idea of the impacts of philanthropic motivation.

Following these reasons, it may be plausible to say that lenders prefer to help people who live in poorer countries (developing countries), which have lower HDIs compared to other countries.

Therefore, the following hypothesis was formulated:

H5: Campaigns of borrowers from higher HDI countries are *slower* campaigns.

2.3.3.6. Borrower's Original Language

One of the main success funding predictors is the information contained in the texts descriptions as it fosters the investors' trust (Dorfleitner et al., 2021). Therefore, the idiom in which the descriptions are written might impact the way information is absorbed by the lender.

Some platforms contain descriptions in borrower's original language and in English, and it might occur because of an eventual idea of associating language to the campaign's success, as it may attract more lenders. According to the study developed by Chen et al. (2019) although lenders and borrowers are more likely to operate in different cultural and social environments, the supporters tend to make loans to people from the same ethnicity and the same gender as them. Guiso et al. (2009) concluded that shared language has significant positive effects on trust formation and bilateral trade. Furthermore, Burtch et al. (2014) stated that, despite campaigns are translated into English, lenders may prefer to lend money to borrowers who speak the same language. These authors suggested that one possible reason for that is the fact that translations may result in grammatical errors or miscommunications. It is reasonable to assume that most of the campaigns posted online on international crowdfunding platforms are written in English and, thus, the lenders might prefer to donate to campaigns from borrowers from English speaking countries.

Therefore, the following hypothesis was formulated:

H6: Campaigns with English as original language are *faster* campaigns.

2.3.3.7. Repayment Frequency

Repayment frequency is another factor that might have an impact on the decision to support a certain campaign from a certain borrower. Thus, the question about the ideal repayment frequency might arise. The results of the study conducted by Feigenberg & Pande (2013) shows that a development program that stimulates repeat interactions can contribute to increasing long-term relationships and enhance social capital among members of a community in a very short period of time, corroborating the idea of economic theory, where repeated interaction among individuals help building and maintaining social capital that might culminate in economic returns. More precisely, Feigenberg & Pande (2013) concluded that there is a loan default reduction when the meetings with the borrowers are more frequent, especially during the first loan cycle and, thus, concluded that social interactions among group members are the most important channel of influence.

According to Field & Pande (2008) usually, MFIs offer a repayment schedule of weekly repayments which start up to two weeks after the loan disbursement, as it is believed that that short repayment frequency will reduce the default risk in the absence of collateral. However, these authors did not find evidence that the repayment frequency reduction has a negative effect on repayment behaviour in their study.

As monthly repayments might be part of the social interactions mentioned above and that short repayment frequencies might be associated with default risk reduction, the lenders might prefer to lend their money to campaigns that have defined repayment dates and a shorter repayment frequency.

Therefore, the following hypothesis was formulated:

H7: Campaigns with monthly repayments are *faster* campaigns.

2.3.3.8. Borrowers Team Size

The study developed by Ly & Mason (2012b) shows evidence that the mean of borrower's team size is 1.7 borrowers. In fact, the campaigns from groups of borrowers were funded slower than individual loans by 84%. However, the funding speed for groups of seven borrowers or more is higher than individual campaigns. One possible explanation is that lenders might think that groups' solidarity can improve repayment rates. Another possible explanation is to consider that lenders may perceive that lending to group loans will allow them to help more beneficiaries at once. However, according to the results of the study developed by Desai & Kharas (2018), focused on 250 campaigns posted between January 1, 2006, and December 31, 2010, Kiva's lenders prefer to fund individual borrowers than group borrowers.

According to Gan et al. (2012), in group lending, each group member will pressure the other members to repay the loan and in the stipulated deadlines. Thus, if the loan repayments are not met, each member of the group has responsibility for the default (Van Tassel, 1999). In addition, according to Armendáriz De Aghion (1999) joint responsibility might potentially contribute to peer monitoring as well as reduce the rate of strategic defaults and enhance the lender's ability to recover the invested amount.

Given the urgency of eradicating poverty by 2030 and because of the group lending effect mentioned before, lenders may prefer to contribute to group campaigns rather than individual campaigns, as they will more people at once and the repayment might be more secure when dealing with groups of borrowers.

Therefore, the following hypothesis was formulated:

H8: Individual campaigns are *slower* campaigns.

2.3.3.9. Borrower’s Gender

As was already mentioned before, crowdfunding campaigns highly depend on the lender’s motivation to participate. Furthermore, in prosocial crowdfunding, they might be highly sensitive to the intrinsic characteristics of the borrower. In this sense, gender might have a high impact on the lender’s decision-making. According to Yunus & Jolis (1999), providing credit to women brought changes more quickly than when providing credit to men and women have more hunger and poverty issues than men.

Several studies suggested a possible relation between crowdfunding success and borrowers’ gender, such as Gama et al. (2021), Proelss et al. (2021), and Jancenelle et al. (2019). Additionally, most of the campaigns of prosocial crowdfunding belong to borrowers in the developing world, and, according to Denton (2002) communities from that portion of countries have prevalent gender-related inequalities. This is in line with the results of a study focused on developing and least developed countries in Asia and Africa conducted by Girón & Kazemikhasragh (2021)**,** who stated that a sustainable economy might be created in developing and LDC by implementing gender equality. This study shows that the gender inequality index is significantly and negatively related to economic growth. Another study, conducted by Giroud & Huaman (2019), demonstrates that, in developing countries, the major direct benefit received by women from largescale investment is to generate employment opportunities. Nevertheless, the same study shows that the participation rate in access to equal salaries, formal employment, higher-level positions, and employment areas are different according to gender. Therefore, microfinance institutions try to target women since they have fewer opportunities than men to obtain credit. According to Campbell (2010) women in the developing world were empowered by microfinancing. The same author refers that the majority of loans made by lending institutions such as Kiva.org, Grameen Bank, and Compartamos Bank, have been to women.

In addition to lending institutions focusing on campaigns to help women, lenders themselves seem to have a certain preference for women's campaigns over men's campaigns, as shown by Chen et al. (2019). In that study, the authors found that lending to females was a significant preference among the respondents in all specifications and it is suggested that a potential explanation for those preferences could be the belief that females and small-scale farmers are predominantly needy, and another explanation could be the fact that females might be more responsible than males about repaying. Furthermore, if lenders prefer lending to female microentrepreneurs, their campaigns will be faster in achieving the target amount compared to male campaigns (Gama et al., 2021; Proelss et al., 2021; Jancenelle et al. 2019; Ly & Mason 2012a; Anderson & Saxton, 2016; Badding & Heller, 2012; and Dorfleitner et al., 2021).

After examining the campaign speed in health crowdfunding, using 4677 donation campaigns from Watsi.org, Proelss et al. (2021) concluded that campaigns about treatments for female (infant) patients were faster than campaigns about treatments for male (infant) patients.

A study conducted by Gama et al. (2021) using data from the prosocial crowdfunding platform Kiva.org between 2011 and 2018, shows that whether individually or in a group, campaigns from female microentrepreneurs are faster than campaigns from male microentrepreneurs. Another study based on Kiva.org data conducted by Jancenelle et al. (2019) reveals that, on average, female campaigns are funded 38% faster than male campaigns. The authors of that study try to justify those results with the idea that lenders prefer to help the most vulnerable borrowers and with the idea that women have higher repayment rates than men. Another study, developed by Ly & Mason (2012a), used Kiva.org data to find what types of projects individuals perceive as more effective. It showed that 76% of the loans were made to individual women borrowers or groups of women, being the average speed of projects involving women (groups or individuals) 2751 minutes, while the average speed of the projects with male borrowers was 4871 minutes. Anderson & Saxton (2016) developed another study using Kiva.org data from 2009 to examine the persuasive effects of images in the context of online peer-to-peer microfinance in 323 campaigns from Azerbaijan, Cambodia, Mongolia, Philippines, Samoa, and Tajikistan. The descriptive statistics of that study revealed that female campaigns that include photos with women and males are 23.7% slower compared to the ones that do not include males in the campaign photo. In line, a study conducted by Badding & Heller (2012) using 289,501 campaigns from Kiva.org, between 2006 and 2010, shows that loans to female's campaigns are funded approximately 30% faster when compared to male's campaigns.

Finally, according to a study targeting 6121 campaigns from US inhabitants between 2011 and 2017, developed by Dorfleitner et al. (2021), in which the purpose was to explore the funding determinants in interest-free peer-to-peer lending, shows that investors prefer to lend to female borrowers. This reveals that Kiva.org lenders seem to be sensitive to gender even when the target is poor people living in a developed country, in this case, the United States.

Overall, the previous studies reveal that women's campaigns are faster than men's campaigns. Although there are some studies regarding the impact that gender has on crowdfunding campaigns' duration, we decided to include it in our study as well, to undertint if gender keeps having a significant impact on the most recent years and considering economic situations such as global recessions like the one caused by Covid-19.

Therefore, the following hypothesis was formulated:

H9: Female campaigns (both individual and group ones) are *faster* campaigns.

2.3.3.10. Campaign Sector

The sector of the campaign might also be considered when the lenders are choosing the campaign they want to support.

The agricultural sector, according to Giroud & Huaman (2019) is an essential source of and food security, economic growth, poverty reduction, and employment. Following the same idea, García et al. (2006) stated that, in many developing countries, taking into account that it affects domestic production and employment in a positive way, agriculture is an important component of the economy. As mentioned, agriculture helps in ensuring food security, being this problem more evident in developing countries, especially in LDCs. Also, agriculture contributes to increasing export earnings and reinforcing rural development in most developing countries. However, agriculture continues struggling in the generality of the developing countries, and that can be verified by the fact that, according to the same study, agricultural production per capita for domestics and export markets were declining in the 1990s, and in the late 1990s LDCs continue to be marginalized, representing only 1% of global agricultural in that period.

According to García et al. (2006), in LDCs, the reduced direct foreign investment in the farming sector to invest in technologies and improve the rural infrastructure are ongoing issues for smallholder farmers who must compete with foreign imports in the domestic market.

Lavopa & Szirmai (2018) divided the economy into modern and traditional components. According to the same authors, small-scale subsistence agriculture activities belong to the traditional sector whereas highly mechanized and technologically advanced agricultural activities, mostly oriented towards exports, are part of the modern sector.

Concerning the lenders' sector preference when supporting prosocial lending-based crowdfunding campaigns, Gama et al. (2021) showed that modern sector campaigns are faster than traditional sector campaigns, and the authors suggest that this is because lenders may prefer to support high-return projects.

In addition to what was previous mentioned, a study conducted by Chen et al. (2019) about the willingness to lend and the preference over borrowers in microfinance lending, showed that farmers are perceived to be significantly riskier and needier than retailers, from the study respondents' perspective.

Therefore, the following hypothesis was formulated:

H10: Agriculture-related campaigns are *slower* campaigns.

2.3.4. Hypothesized Conceptual Framework

In this section, we present the expected conceptual framework of this study. Figure 2.1 illustrates the mentioned framework, taking into account the hypotheses presented in section 2.3.3. of this study to answer the research questions, presented in chapter 1.

It is important to highlight that we used campaigns' duration as a proxy variable to measure the success of the campaigns in terms of duration, which means that we consider that success, in this case, is measured by campaign duration, which should be as short as possible.

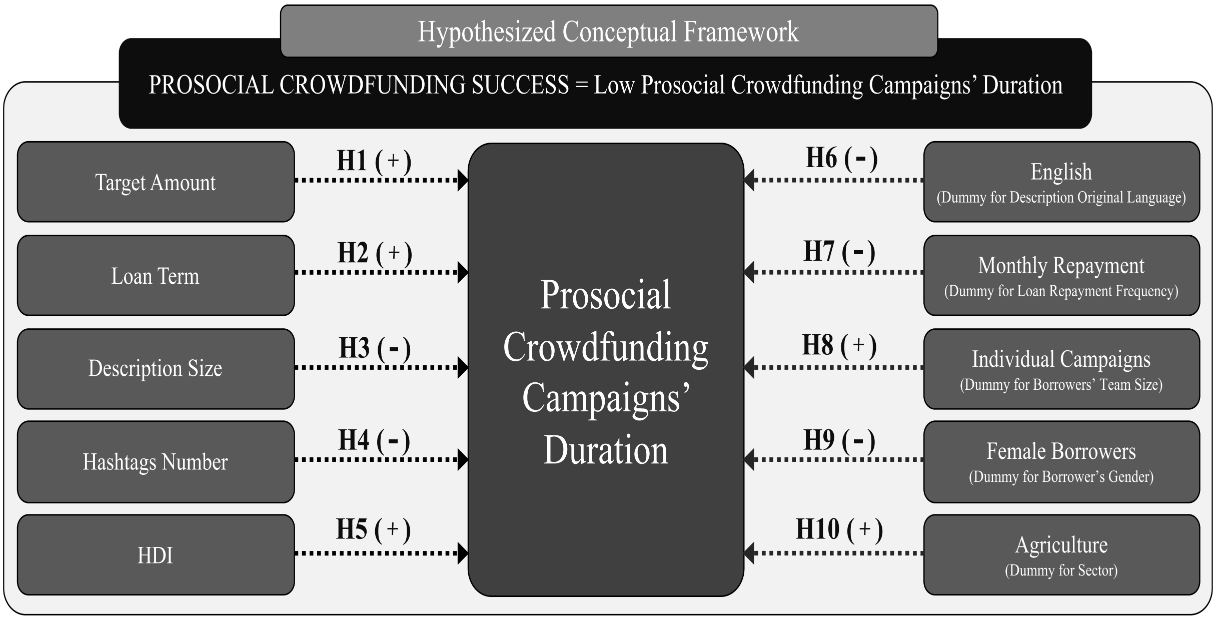

Figure 2.1 - Hypothesized Conceptual Framework (Source: Own Research)

The validation of this hypothesized conceptual framework is presented in section 4.1.1. of this study.

3. Methodology

This chapter is divided into four parts: research context, research design, data collection and data analysis.

3.1. Research Context

Many crowdfunding campaigns have failed since they have not been able to reach the total of the defined amounts in the established timeframe. Many studies were developed to determine the success drivers of crowdfunding campaigns. However, those studies seem to be developed in random years, without taking into account the world economic context, particularly the HDI.

Hence, this study will measure the effect of some campaign factors in the duration of prosocial debt-based crowdfunding campaigns. This study was developed based on data from Kiva, a large crowdfunding platform, and the following information of this section was gathered from its website, Kiva.org.

Kiva is a U.S. non-profit institution founded in 2005 and based in San Francisco. According to Kiva (2021), Kiva has offices in Bangkok, Nairobi, Portland, and staff around the globe. Kiva "envision a financially inclusive world where all people hold the power to improve their lives" (Kiva, 2021). In accordance, Kiva's mission is to expand financial access to help communities to prosper since more than 1.7 billion people around the world are unbanked and are not able to access the financial services they need. To achieve its goal, Kiva business model is based on crowdfunding loans, as they allow to improve the cost and the quality of financial services around the world (more than 80 countries) to the financially excluded communities that cannot access other sources of credit to all the borrowers who are creating social impact on their communities (Kiva, 2021).

Kiva has been recognized for its commitment: Global impact Awards (Google) and 2015 award winner for operational effectiveness (The Wall Street Journal). The minimum amount that a lender can borrow is $25 and, as a non-profit institution, Kiva does not keep any part of the borrowed money. To cover operating costs, Kiva uses the money donated by some lenders, foundations, and supporters. Moreover, grants and field partners service fees can also help to cover these costs. In terms of numbers, according to Kiva (2021), this prosocial crowdfunding platform already allowed $1.53B loans, 1.9M lenders, $2.5 million in loans each week, 3.5M borrowers, Amount lent through Kiva = 1.4 Billion, repayment rate is 97%, default rate is 3%, 77 countries, 15 years, 450 volunteers, 83% of Kiva borrowers are women, a Kiva loan is funded every 2 minutes, has 2967 Field Partners and Trustees and it has 110 Employees.

To be able to reach more borrowers (even in some of the most remote places in the world), Kiva works with a global network of field partners, which are local organizations aspiring to improve people's lives (especially poor, vulnerable, and/or excluded populations) through safe and fair access to credit. The field partners work in communities to provide services (such as literacy skills and entrepreneurial training), look over borrowers in more than 80 countries and administer loans to expand access to beneficial products and services (Kiva, 2021). These organizations are microfinance institutions (MFIs), non-profit organizations, schools, social enterprises, among others.

In terms of loan interest, borrowers do not pay interest to individual Kiva lenders, but some Kiva borrowers pay interest to Kiva's local Field Partners, as there are numerous expenses related to providing small loans in developing markets, particularly in rural areas. However, Kiva refuses to work with eventual field partners that charge unreasonable interest rates. Furthermore, Kiva charges small service fees to some field partners. A due diligence process is conducted by Kiva on all Field Partners before allowing them to begin posting loans on the Kiva website. All Field Partners are obligated to provide financial documentation, leadership information, and detailed plans for using Kiva's capital for loans with high social impact. Furthermore, partners who post more loans must submit additional documentation and a Kiva analyst conducts an on-site visit to conduct interviews with leadership, management, and borrowers (Kiva, 2021).

The loan process on Kiva can be divided into several phases: application phase, approval phase, public fundraising phase, repayment phase (if applicable). These phases are described below:

1. *Application Phase*: In terms of a loan application, there are two distribution models: partner model (in which borrowers apply to a local field partner) and direct model (in which borrowers apply directly through Kiva's website). However, direct loans currently are only available to businesses in the US and social enterprises internationally.
2. *Approval Phase*: After the loan application, local non-profits or lending institutions should approve the borrower's loan request (in case of partner model) and Kiva should approve the loans in a process called "social underwriting" (in case of the direct model). Direct loans borrowers can be endorsed by Kiva's trustees (entrepreneurs known and trusted by Kiva). The mentioned social underwriting process includes a private fundraising period of up to 15 days in which the borrower should gather a specific number of lenders (decided by Kiva) to prove its creditworthiness. Normally, Kiva asks for 10-25 lenders, but the average number of lenders required per loan amount in the private fundraising period is:

$1000-$2000 requires 14 lenders on average, $3000-$4000 requires 15 lenders on average, $5000-$7000 requires 17 lenders on average and $8000-$10000 requires 19 lenders on average. The actual number of people necessary for a certain loan will vary based on aspects such as the borrower's social media presence, borrower's credit score, and the quality of the campaign's photo and the campaign's description section. If at the end of the private fundraising period (15 days) the borrow has not the required number of lenders, the loan will expire.

3. *Public Fundraising Period*: After being approved and after the private fundraising period (in case of the direct model) loans are posted on Kiva's website and the period in which the loan is public on the website is called the "fundraising period" and it might vary depending on the loan but usually loans have a fundraising period up to 30 days. However, it is of great importance to refer that, depending on the case, the borrowers may access the money even before the loan is fully funded on Kiva's website. This pre-disbursed occurs for most field partner loans but, for direct loans, the money can only be disbursed after the loan has been fully funded on Kiva's website and, in this case, the funds will be sent to Kiva via PayPal and then Kiva will deposit repaid funds into Kiva's lender accounts. In the cases of pre-disbursement, the borrower receives the loan from the field partner, even if the campaign on Kiva's website did not achieve the required amount, which means that, in these cases, the crowdfunded money raised on Kiva is used to backfill the loan amount provided by the field partners. There are two models related to the raised amount: fixed model (in which the partners only receive the loans if the total amount has been fully funded and, if not, the loans will expire and the funds already raised are returned to lenders' accounts; typically, direct loans or partners loans that are not pre-disbursed uses this model) and flexible model (in which, even if the required amount was not fully raised, the field partners receive the amount raised at the end of the fundraising period and they will have to cover the rest of the loan amount with other sources).
4. *Repayment Phase*: The last part of this process is the repayment phase, in which the borrowers have a repayment schedule to repay their loans to the involved Kiva's lenders. although Kiva loans have a historical repayment rate of about 97%, Kiva does not guarantee repayment for any loans funded. Lenders should be aware that repayment of field partner loans depends on the borrower repaying the Field Partner, and also the Field Partner repaying Kiva. On the other hand, direct loans do not depend on field partners but that represents a different kind of risk as there is no field partner to follow up with the borrower and encourage or collect repayments, which represents a different kind of risk.

When a borrower is behind on paying back a loan, Field Partners and Kiva can be flexible and try to reschedule repayments on the delinquent loan to make it possible for the borrower to eventually repay. However, despite the mentioned efforts to avoid default loans, there are particular situations in which the borrowers are not able to repay and loans end in default. All the contributing lenders of default loans are notified by email that they will not receive their money back. In these cases, the field partners may decide not to lend to a specific individual again if they are not able to repay and direct loans' borrowers will not be allowed to apply for another loan on Kiva unless they have repaid previous loans. Therefore, Kiva lenders should be aware of the different types of associated risks that could lead to losing some or all the principal.

The major risks referred by Kiva (2021) are presented below:

- *Borrower risk for loans administered by a Field Partner*: The partner looks at a variety of factors (past loan history, loan purpose, group or village reputation, among others) before considering a borrower as creditworthy. However, many factors such as health issues, business issues, and other issues might culminate in borrowers defaulting.
- *Borrower risk for direct loans*: Lenders should be aware that direct loans involve a higher level of risk of default than loans administered through Field Partners for various reasons, including less monitoring and follow-up for collection of repayments as well as the stage of business. Also, loans are refunded if the borrower requests it or if, for instance, the borrower violates one of Kiva's policies such as inaccuracies found in the information provided to Kiva, duplicated borrower profile, violation of Kiva's community guidelines, or evidence of self-fundraising. All refunded loans become anonymous and that might be the reason for having missing data regarding the campaigns with this status.
- *Field Partner risk*: Even if a Kiva borrower can repay, Kiva lenders could still lose principal due to Field Partner issues such as bankruptcy (the Field Partner may go out of business and be unable to collect your loan), fraud (staff members at the Field Partner may embezzle funds) and Operational difficulties (the Field Partner may have some cash-flow or other challenges that could prevent repayment). Before working with a Field Partner, Kiva performs due diligence on the organization to help assess this risk.
- *Country risk*: It is important to consider 3 macro-level risks when lending internationally: the economic risk, the political risk, and the natural disaster risk. The economic risk is associated with the devaluation of the lending country currency,

meaning that the local governments and financial institutions have control over the exchange rate diminishing the value of the loan. The political risk is associated with the risk of lending to developing countries. Finally, natural disaster risk, meaning that due to natural unforeseen events, the probability of loan repayment might decrease. To minimize the risk of non-related loans Kiva set a limit of 10% of the total per country. This strategy also ensures that the loan portfolio on the website is diverse and allows to reach more people.

- *Currency risk*: Although Kiva's working currency is the U.S. dollar, many borrowers receive their loans in their local currency, which adds additional risks to lenders, especially in times when the U.S. dollar is strong. For loans with currency risk, lenders bear the risk of loss if the U.S. dollar appreciates against the local currency. Additionally, if the currency of the lender's country is not the U.S. dollar, there is an initial exchange risk associated with the fact that loans made through Kiva must be in U.S. dollars.
- *Kiva-related risk*: As much as any other organization, Kiva has a potential risk of not continuing its operations indefinitely. To improve the protection of lenders' funds in this circumstance and others, Kiva holds lender funds separately from its operational funds, meaning that when lenders have funds in their Kiva accounts (for example, funds that have been repaid), they are held into bank accounts.

Figure 3.1. illustrates the Kiva process between Kiva.org and its main stakeholders in simple terms.

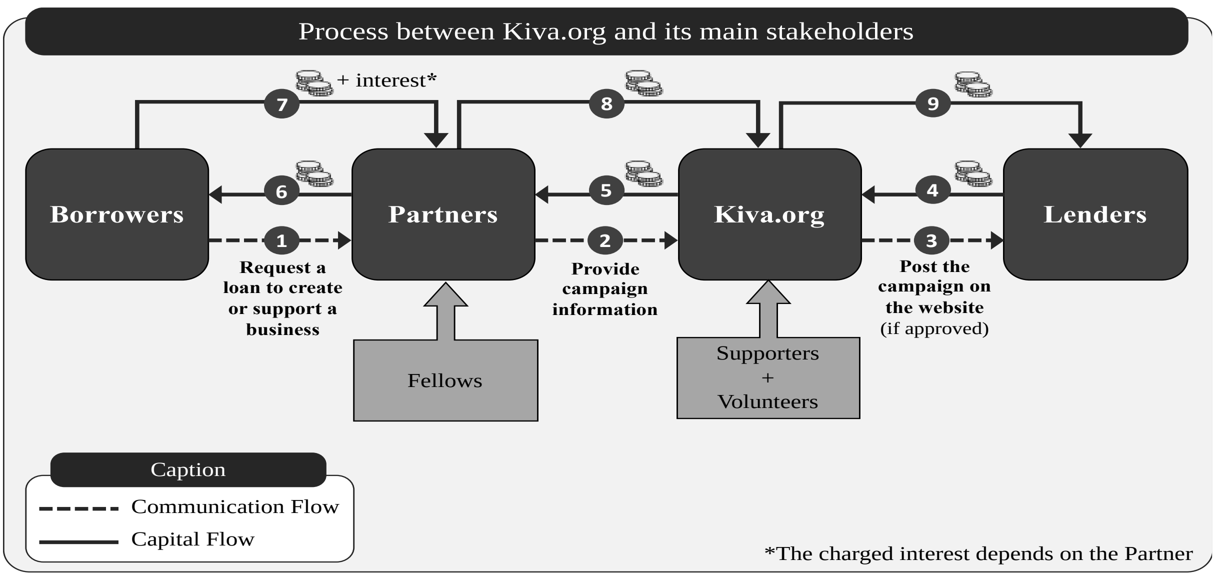

Figure 3.1 - Process between Kiva.org and its main stakeholders (Source: Own Research)

3.2. Research Design

This study followed a quantitative approach. In terms of the type of investigation, it is causal research since it aims to make an inference about the correlation between campaign characteristics and the campaign duration. In terms of the experimental design classification, this study followed a Quasi-Experimental design. Considering the research problem of this research, the dependent variable of the model was the Campaign_Duration, being the remaining variables (Ln_Amount, Description_Size, Loan_Term, Hashtags_Num, HDI, English, Rep.Monthly, Individual, Female, Agriculture) the independent ones. Table 3.1. contains the description of the mentioned variables.

Table 3.1 - Variables Description (Source: Own Research)

Variable Name	Variable Description	Variable Type
Campaign_Duration	Number of days between the campaign posted time and raised time	Scale
Ln_Amount*[1]	Logarithm of the campaign target amount	Scale
Description_Size	Number of words in the campaign's description	Scale
Loan_Term	The number of months it will take the borrower to repay the loan	Scale
Hashtags_Num	Number of hashtags associated to the campaign	Scale
HDI	Human Development Index of the borrower's country	Scale
English	Dummy variable of the borrower's original language: English = 1; Other = 0	Nominal
Rep.Monthly	Dummy variable of repayment frequency: Rep.Monthly = 1; Other*[2] = 0	Nominal
Individual	Dummy variable of borrower type: Individual =1; Group = 0	Nominal
Female	Dummy variable of borrower's gender: Female*[3] = 1; Other = 0	Nominal
Agriculture	Dummy variable of sector: Agriculture = 1; Other = 0	Nominal

*[1] The logarithm of the variable amount was calculated because the values of the target amount were large
*[2] The other repayment frequency options in Kiva.org are "bulk repayments" and "irregular repayments"
*[3] Female includes both female individual campaigns and female group campaigns

The population of this study is all the Kiva's campaigns, and two samples were used to answer the research problem: one sample with Kiva's campaigns of the last 4 years (2017-2020) and another sample only with the Kiva's campaigns posted during a recession year (2020).

3.3. Data Collection

To have an overview of what has been studied and insights to help to interpret secondary data more insightfully, external secondary data was gathered through scientific studies and books.

In this study, secondary data was used to answer the proposed research questions, resorting to the World Bank website and Kiva.org website. The World Bank website has information about the HDI, which will be useful to study the impact that the development of a country might have on the campaign's duration. On the other hand, Kiva.org is an online debt-based crowdfunding platform, that has the goal to empower borrowers financially, through microcredits from lenders and, thus, it has some information regarding its prosocial campaigns.

The snapshot database was collected from Kiva.org in CSV format, on the 14th of March 2021 at 17h08. However, it is important to refer that the snapshot was taken on the 6th of February 2021 at 00h47. That file contained all Kiva campaigns that occurred between 2005 and 2021, totalling 2,058,105 Kiva's campaigns. Since most studies of prosocial crowdfunding were previous to 2017, we decided to focus on campaigns between 2017 and 2020, to cover a more recent and less studied period, including a recession year, 2020. The first step after collecting the CSV file, was to delete (through queries) all the campaigns posted on Kiva's website (Kiva.org) outside that period which totalled 1,207,501 campaigns. After that, the CSV snapshot was converted into an Excel sheet and that new file was constituted by precisely 850,604 (as 2,058,105 - 1,207,501 = 850,604) Kiva's campaigns (loans).

After that, it was also necessary to do data cleaning. Thus, it was decided that all campaigns with a "fundraising" status (1712 campaigns) should not be included in this study since those campaigns were not completed at the time of the data collection. Furthermore, all the campaigns with "refunded" status (2805 campaigns), were not taken into account for two main motives: the meaning of "refunded" campaigns and the lack of information regarding these specific campaigns. In addition, we did not consider the direct loans because, at the date of the study development, only the United States and social enterprises internationally were allowed to do these types of loans in Kiva.org. Finally, all cases with empty values were deleted.

It was necessary to develop new variables from existing ones and also delete some variables not related to the topic. Furthermore, the variable "HDI" was obtained by associating the HDI data, collected from UNDP (n.d.), to each country of the samples (see Appendix D, Table D.1). Since there was no data available regarding HDI in 2020, for that specific year we considered the values from 2019. Also, because of data unavailability, we did not consider campaigns from Somalia and Puerto Rico.

Having this phase completed, the final Excel file was imported to SPSS to conduct the statistical analysis. However, before starting the statistical analysis, it was necessary to prepare the variables for SPSS. This preparation included the choice of the proper type for each variable (in this case, all the variables were numeric, except the "Posted Time" which was a date), the description of each variable (on a column called "Label", in variable view of the SPSS file) and the transformation of the value using "Automatic Recode".

3.4. Data Analysis

To test the hypotheses of this study, presented in section 2.3., we structured a model based on the variables presented before, in Table 3.1. and we applied it to two different samples: a sample that contained campaigns from the time interval 2017-2020, which in this study we called "regression 1", and a sample that contained campaigns exclusively of the year 2020, which in this study we will call "regression 2". Thus, the following formula represents the multiple linear regression model that we structured, in which β_0 represents the intercept, the remaining β represents the slope coefficients for each of the independent variables and u_e represents the model's error term (residuals):

$$\begin{gathered} Campaign\_Duration = \beta_0 + \beta Ln\_Amount + \beta Description\_Size + \beta Loan\_Term + Hashtags\ Num \\ + \beta HDI + \beta English + \beta Rep.Monthly + \beta Individual + \beta Female + \beta Agriculture + u_e \end{gathered} \tag{1}$$

To be able to analyse the results of the two regressions more accurately, we deleted outliers that could cause statistical problems when conducting the regressions. To do that, we considered as outliers all the cases in which the respective standardized residuals were outside the range [-3,3]. Therefore, for regression 1, we deleted 10689 outliers from the prepared dataset for the four years that contained 802,223 cases, which culminated in a final dataset of 791,534 cases. Similarly, for regression 2, we deleted 553 outliers from the prepared dataset for the year 2020 that contained 172,051, which culminated in a final dataset of 171498 cases.

After the outliers' removal, we proceeded to some descriptive statistics, to explore the sample before conducting the multiple linear regression. At this phase, we did a general description of all variables, both dependent and independent, and then we carried out a descriptive analysis that linked the independent variables with the dependent ones.

Then we assessed the assumptions related to multiple linear regression, which included the verification of sample size, linearity, no multicollinearity, independent residuals, residuals normality and homoscedasticity. One of these assumptions, homoscedasticity, was not confirmed. This problem was identified by evaluating the results of White's test (MacKinnon & White, 1985). To overcome the problem of heteroscedasticity, we first tried to transform the dependent variable into a logarithm. However, when we conducted again the White's test, the p-value was still 0.00. Therefore, we decided to consider parameter estimates with robust standard errors in our regression, obtained through the HC3 method (Davidson & Mackinnon, 1985) to finally test our hypothesis based on a significance level of 99% (α = 0.01).

4. Results and Discussion

4.1. Results

In this section, we present the descriptive statistics of the samples that we used in the study regressions and, after that, we present the inferential statistics.

4.1.1. Descriptive Statistics

This section was divided into two parts: descriptive statistics of sample and descriptive statistics of sample 2.

4.1.1.1. Descriptive Statistics of Sample 1

Regarding the descriptive statistics of sample 1 that we later used to conduct regression 1, it was possible to acknowledge an N = 791,534 and other information regarding statistical measures such as range, minimum, maximum, mean, standard deviation, variance, symmetry measures, are presented in Table 4.1, the mean and median of target amount is 729.50 US dollars and 425.00 US dollars, respectively.

Table 4.1 - Descriptive Statistics of the variables regarding sample 1 (Source: Own Research)

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Campaign_Duration	791534	75.85	0.00	75.85	13.36	12.51	156.53	1.13	0.00	0.37	0.01
Target_Amount_Ln	791534	9.90	3.22	13.12	6.11	0.92	0.84	0.43	0.00	0.26	0.01
Loan_Term	791534	144.00	2.00	146.00	12.95	6.36	40.48	3.25	0.00	26.46	0.01
Description_Size	791534	1521.00	0.00	1521.00	114.54	43.26	1871.08	0.96	0.00	2.27	0.01
Hashtags_Num	791534	53.00	0.00	53.00	2.58	2.31	5.34	1.46	0.00	5.76	0.01
HDI	791534	0.50	0.427	0.93	0.66	0.09	0.01	-0.08	0.00	-0.08	0.01
English	791534	1.00	0.00	1.00	0.73	0.44	0.20	-1.04	0.00	-0.93	0.01
Rep.Monthly	791534	1.00	0.00	1.00	0.87	0.34	0.11	-2.20	0.00	2.86	0.01
Individual	791534	1.00	0.00	1.00	0.87	0.34	0.11	-2.19	0.00	2.79	0.01
Female	791534	1.00	0.00	1.00	0.77	0.42	0.18	-1.29	0.00	-0.34	0.01
Agriculture	791534	1.00	0.00	1.00	0.28	0.45	0.20	0.97	0.00	-1.06	0.01
Valid N (listwise)	791534										

For this study, the descriptives of the dependent variable, Campaign_Duration, were considered as of particular interest since it is the focus of the study. Therefore, Table 4.1, shows that campaign durations range from 0 days to 75.85 days, being the mean approximately 13 days. The standard deviation is 12.51 and the variance is 156.53. In terms of symmetry, the dependent variable of this study had a Skewness of 1.13 and a Kurtosis of 0.37, which means that the variable is right skewed and has a leptokurtic distribution.

Furthermore, to have a better understanding of the categorical variables from sample 1, we built frequency tables and the respective charts of all the categories of the categorical variables and dummy variables used in regression 1.

Starting with the first group of frequency tables and respective charts of sample 1, we can see that English is the most frequent original language in sample 1, representing 73% of the sample, followed by Spanish, French, Russian, and lastly, Portuguese (see Appendix E, Table E.1 and Figure E.1). Female is the most frequent category regarding borrowers' gender in sample 1, representing 70.1% of the sample, followed by male, female group, mixed group, and lastly, male group (see Appendix E, Table E.2 and Figure E.2). Monthly repayments are the most frequent in sample 1, representing 87% of the sample, followed by bullet payments and, lastly irregular payments (see Appendix E, Table E.4 and Figure E.3). Agriculture sector is the most frequent sector in sample 1, representing 28.2%, followed by food, retail, housing, services, personal use, clothing, education, arts, health, transportation, construction, manufacturing, entertainment, and lastly, wholesale (see Appendix E, Table E.3 and Figure E.4). Finally, although we did not use the variable country in our regression 1, as we represented the countries by the respective HDIs, we generated a frequency table of the countries included in sample 1, to eventually explore the countries with other variables. Thus, we can see that the Philippines is the most frequent country of the sample, followed by Kenya, Cambodia, Uganda, El Salvador, and Tajikistan, representing together 52.8% of sample 1, which means that more than half of the campaigns belong to borrowers from these 5 countries, being the remaining 47.2% distributed by other 72 countries (see Appendix E, Table E.5).

Regarding the second group of frequency tables and respective charts (based on dummy variables) of sample 1, we can see that the most frequent category for each variable, presented in the previous paragraph, matches the respective dummy variable that we later used in regression 1 (see Appendix F, Table F.1 and Figure F.1; Table F.2 and Figure F.2; Table F.3 and Figure F.3; Table F.4 and Figure F.4). Furthermore, the remaining dummy variable, named "individual", represents 86.90% of sample 1 (see Appendix E, Table F.5 and Figure F.5).

The dependent variable was also linked to each of the independent variables, to provide a visual understanding of how campaigns' duration could vary depending on the independent variable. Table G.1 and Figure G.1 from Appendix G show that, in sample 1, campaigns with English as original language seem to be faster than other campaigns. Table G.2 and Figure G.2 from Appendix G show that, in sample 1, campaigns with monthly as repayment frequency seem to be slightly faster than other campaigns. Table G.3 and Figure G.3 from Appendix G show that, in sample 1, campaigns with Individual as borrower's type seem to be slower than other campaigns. Table G.4 and Figure G.4 from Appendix G show that, in sample 1, female campaigns seem to be faster than other campaigns. Table G.5 and Figure G.5 from Appendix G show that, in sample 1, campaigns with agriculture as a sector seem to be slower than other campaigns.

4.1.1.2. Descriptive Statistics of Sample 2

Concerning the descriptive statistics of sample 2 that we later used to conduct regression 2, it was possible to acknowledge an N = 171,498 and, once again, other information regarding statistical measures such as range, minimum, maximum, mean, standard deviation, variance, symmetry measures, are presented in Table 4.2. Although not showed in Table 4.2, the mean and median of target amount is 712.26 US dollars and 400.00 US dollars, respectively.

Table 4.2 - Descriptive analysis of the sample 2 excluding the outliers (Source: Own Research)

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Campaign_Duration	171498	88.42	0.01	88.43	19.44	17.75	315.13	0.79	0.01	-0.67	0.01
Target_Amount_Ln	171498	9.70	3.22	12.92	6.02	0.97	0.94	0.44	0.01	0.36	0.01
Loan_Term	171498	142.00	2.00	144.00	12.91	6.94	48.18	3.09	0.01	23.58	0.01
Description_Size	171498	518.00	0.00	518.00	109.56	42.72	1824.73	1.00	0.01	1.07	0.01
Hashtags_Num	171498	44.00	0.00	44.00	2.27	2.37	5.63	1.36	0.01	4.07	0.01
HDI	171498	0.492	0.434	0.93	0.66	0.09	0.01	-0.21	0.01	0.10	0.01
English	171498	1.00	0.00	1.00	0.71	0.45	0.21	-0.93	0.01	-1.13	0.01
Rep.Monthly	171498	1.00	0.00	1.00	0.84	0.37	0.13	-1.86	0.01	1.47	0.01
Individual	171498	1.00	0.00	1.00	0.90	0.30	0.09	-2.72	0.01	5.39	0.01
Female	171498	1.00	0.00	1.00	0.78	0.41	0.17	-1.36	0.01	-0.14	0.01
Agriculture	171498	1.00	0.00	1.00	0.32	0.47	0.22	0.76	0.01	-1.43	0.01
Valid N (listwise)	171498										

Once more, for this study, the descriptives of the dependent variable, Campaign_Duration, were considered as of particular interest since it is the focus of the study and, thus, Table 4.2, shows that campaign durations range from 0.01 days to 88.43 days, being the mean approximately 19 days, representing an apparent slight increase compared with the sample used for conduct regression 1. The standard deviation is 17.75 and the variance is 315.13. In terms of symmetry, the dependent variable of this study had a Skewness of 0.79 and a Kurtosis of -0.67, which means that the variable is moderately right skewed and has a platykurtic distribution.

Similar to what we did for sample 1, based on the same criteria, we built frequency tables and the respective charts.

Starting by the first group of frequency tables and respective charts of sample 2, we can see that English is, again, the most frequent original language in sample 2, representing 71.1% of the sample, followed by Spanish, by French, Russian, and lastly, Portuguese (see Appendix H, Table H.3 and Figure H.2). Female is, once again, the most frequent category regarding borrowers' gender in sample 2, representing 73.5% of the sample, followed by the male, mixed group, female group, and lastly, male group (see Appendix H, Table H.4 and Figure H.1). Monthly repayments are, again, the most frequent in sample 2, representing 84.1% of the sample, followed by bullet payments and, lastly irregular payments (see Appendix H, Table H.1, and Figure H.3). Agriculture sector is, once again, the most frequent sector in sample 2, representing 32.3%, followed by food, retail, housing, services, clothing, personal use, education, arts, health, transportation, construction, manufacturing, wholesale, and lastly, entertainment (see Appendix H, Table H.2 and Figure H.4). We generated a frequency table of the countries included in sample 2, as we did for sample 1. Thus, we can see that the Philippines is the most frequent country of the sample, followed by Kenya, Tajikistan, Ecuador, representing together 52.9% of sample 2, which means that more than half of the campaigns belong to borrowers from these 4 countries, being the remaining 47.1% distributed by other 57 countries (see Appendix H, Table H.5).

Regarding the second group of frequency tables and respective charts (based on dummy variables) of sample 2, we can see that the most frequent category for each variable, presented in the previous paragraph, matches the respective dummy variable that we later used in regression 2 (see appendix I, Table I.1 and Figure I.1; Table I.2 and Figure I.2; Table I.3 and Figure I.3; Table I.4 and Figure I.4). Furthermore, the remaining dummy variable, named "individual", represents 90.27% of sample 1 (see Appendix I, Table I.5, and Figure I.5).

It is important to mention that both samples (sample 1 and sample 2) contain data campaigns from 2020. However, the values are different because of the outliers that were deleted in each of them. In this study, regarding 2020, we focused our attention on sample 2, which was the sample from which we performed regression 2.

Table J.1 and Figure J.1 from Appendix J show that, in sample 2, campaigns with English as original language seem to be slightly slower than other campaigns. Table J.2 and Figure J.2 from Appendix J show that, in sample 2, campaigns with monthly as repayment frequency seem to be slower than other campaigns. Table J.3 and Figure J.3 from Appendix J show that, in sample 2, campaigns with Individual as borrower's type seem to be slower than other campaigns. Table J.4 and Figure J.4 from Appendix J show that, in sample 2, female campaigns seem to be faster than other campaigns. Table J.5 and Figure J.5 from Appendix J show that, in sample 2, campaigns with agriculture as a sector seem to be slightly faster than other campaigns.

4.1.2. Inferential Statistics

In this section, we will start by presenting the model assumptions diagnosis, to guarantee that the results obtained in our regressions are truly representative of the samples that we used and that those results are reliable. After that, we will present the results of the two multiple linear regressions that we conducted to answer our formulated defined in section 2.3.3.

4.1.2.1. Model Assumptions Diagnosis

Before conducting the two multiple linear regressions that we used to validate the hypothesis formulated in section 2.3.3., we proceeded to the model assumptions diagnosis. To validate the assumptions regarding regression 1, we used Tables Table K.1, Table K.2,Table K.3, Table K.4, andTable K.5 and Figure L.1, Figure L.2 and Figure L.3, from Appendices K and L, respectively. To validate the assumptions regarding regression 2, we used Table M.1,Table M.2,Table M.3,Table M.4, and Table M.5 and Figure N.1, Figure N.2, and Figure N.3, from Appendices M and N, respectively. The detailed diagnosis is the following:

a) *Sample Size* - Sample 1 contains 791,534 campaigns sample 2 contains 171,498 campaigns. Thus, both of our samples have a size greater than 30 and, thus, according to the Central Limit Theorem (CLT), we can predict the characteristics of a population accurately. Therefore, this assumption is validated for the two samples (Ross, 2017).

b) *Linearity* - To see if there is a substantially linear relationship between two or more variables, it is possible to take the linearity test using the ANOVA table in SPSS (Ainiyah et al., 2016). They observed that the degree to which the independent variable value follows a straight line is referred to as sig. linearity and the value of sig. deviation from linearity represents which of the data is used as linear. If sig. of linearity < significance level (α) and the sig. of deviation from linearity > significance level (α), then the linear regression can be used. However, our findings showed odd results (see Table K.1 and Table M.1 for regression 1 and 2, respectively) between these two tests as both linearity and deviation from linearity were less than 0.01 (α). To try to solve this issue we transformed the dependent variable into a logarithm, as suggested by Benoit (2011), but our finding remained odd (see Table K.2 and Table M.2 for Regression 1 and 2, respectively). Therefore, we used our original dependent variable to perform Ordinary Least Square (OLS) linear regression and we looked to the significance level of each variable, as proposed by Leong et al. (2018) and Suo (2019). According to these authors, if the p-value is less than 0.01 (α), then the relationship between variables can be sufficiently linear. In our study, each variable has a p-value of 0.000 (see Table K.1 and Table M.1 for regression

1 and 2, respectively), which is less than 0.01, meaning that through this method we can consider the relationship between variables sufficiently linear. Therefore, this assumption is validated for the two samples.

c) *No Multicollinearity* - Multicollinearity occurs when the multiple linear regression analysis includes several variables that are significantly correlated not only with the dependent variable but also to each other (Alin, 2010; Shrestha, 2020). To diagnose multicollinearity the variance inflation factor (VIF) and, its inverse, the tolerance, can both be used (Alin, 2010; Shrestha, 2020). The lower the tolerance, the more likely the variables are to be multicollinear. VIF = 1 implies that the independent variables are not associated with one another. There will be multicollinearity if VIF is between 5 and 10 (Shrestha, 2020). The results of the correlation tables of both samples (see Appendix K, Table K.3 and Appendix M, Table M.3) show that any independent variable is highly correlated with another independent variable and, in accordance with that, all the tolerance values of both samples are higher than 0.1 and all VIF values are less than 5 (see Appendix K, Table K.5 and see Appendix M, Table M.5). Therefore, this assumption is validated for the two samples.

d) *Independent Residuals* - The independence of residuals can be verified by the value of Durbin Watson. According to Jeong & Jung (2016), the residuals are independent if the Durbin Watson value is near to 2, more precisely between 1.5 and 2.5. Our results show that the Durbin Watson value for sample 1 is 1.974 (see Appendix K, Table K.4) and for sample 2 is 1.982 (see Appendix M, Table M.4). Therefore, this assumption is validated for the two samples.

e) *Residuals Normality* – The charts generated in both regressions suggest that there is no normality between the residuals (see Appendix L, Figure L.1 and Figure L.2 and see Appendix N, Figure N.1 and Figure N.2). However, according to Schmidt & Finan (2018), huge samples, as the ones we used in this study, do not need to have normal residuals. Therefore, we moved on to the next samples' assumptions.

f) *Homoscedasticity* - Homoscedasticity means that the variance of the regression predictors remains constant, and, on the other hand, heteroscedasticity means that the variance of the regression predictors is not constant (Knaub, 2007). Both scatterplots from regression 1 (see Appendix L, Figure L.3) and from regression 2 (see Appendix N, Figure N.3) suggest that we could be facing a heteroscedasticity problem. Thus, we conducted the White test for both regressions. The White test applied to sample 1 shows a p-value = 0.00, which is statistically significant considering $\alpha = 0.01$ (see Appendix O, Table O.1). Similarly, the

White test applied to sample 2 shows a p-value = 0.00, which is statistically significant considering $\alpha = 0.01$ (see Appendix O, Table O.2). Therefore, we confirmed the heteroscedasticity problem and, thus, the homoscedasticity assumption was not validated. To handle this problem, we decided to consider parameter estimates with robust standard errors, obtained through the HC3 method, instead of using the normal standard errors. According to Astivia & Zumbo (2019) the robust standard errors recognize the presence of non-constant variance and propose a different method for calculating the variance of the sample regression coefficients, and thus, it, is a solution to the heteroscedasticity problem. We chose to use the HC3 method because, according to Davidson & Mackinnon (1985) HC3 always outperforms HC2, which always outperforms HC1, which always outperforms HC0.

4.1.2.2. Model Results

As mentioned before in section 3.4, regression 1 was applied to the sample which included campaigns from the period 2017-2020 (sample 1). Both regressions allowed us to validate the hypotheses of this study on a confidence interval of 99% (α = 0.01).

ANOVA tables indicate if the regression equation explains a statistically significant fraction of the variability in the dependent variable based on the variability in the independent variables (Waghmare & Sakhale, 2015). The model is statistically significant when the p-value is less than 0.01, as we consider 99% our significance level. Thus, Table 4.3 and Table 4.4 show, respectively, that both models (regression 1 and regression 2) are statistically significant, meaning that our models statistically improved the ability to predict our dependent variable (campaign duration).

Table 4.3 - ANOVA Table from Regression 1 (Source: Own Research)

ANOVA (Regression 1)					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	18318706.82	10	1831870.682	13732.904	0.000
Residual	105583480.5	791523	133.393		
Total	123902187.3	791533			

Table 4.4 - ANOVA Table from Regression 2 (Source: Own Research)

ANOVA (Regression 2)					
Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	6650324.76	10	665032.476	2406.351	0.000
Residual	47393100.82	171487	276.366		
Total	54043425.58	171497			

The results of regression 1 are presented in Table 4.5 and the results of regression 2 are presented in Table 4.6.

Table 4.5 - Regression 1 with Robust Standard Errors (Source: Own Research)

Parameter Estimates with Robust Standard Errors – Sample 1						
Parameter	B	Robust Std. Error[a]	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-8.476	0.135	-62.984	0.000	-8.74	-8.212
Target_Amount_Ln	2.689	0.018	146.96	0.000	2.653	2.725
Loan_Term	0.14	0.003	46.525	0.000	0.134	0.146
Description_Size	-0.009	0.000	-28.04	0.000	-0.01	-0.009
Hashtags_Num	1.184	0.007	161.434	0.000	1.17	1.199
HDI	-3.76	0.148	-25.385	0.000	-4.05	-3.469
English	-0.142	0.032	-4.508	0.000	-0.204	-0.08
Rep.Monthly	2.151	0.045	48.081	0.000	2.063	2.239
Individual	4.474	0.043	104.751	0.000	4.391	4.558
Female	-2.545	0.035	-73.582	0.000	-2.612	-2.477
Agriculture	1.392	0.033	42.567	0.000	1.328	1.456
a. HC3 Method						

Table 4.6- Regression 2 with Robust Standard Errors (Source: Own Research)

Parameter Estimates with Robust Standard Errors - Sample 2						
Parameter	B	Robust Std. Error[a]	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-12.913	0.456	-28.338	0.000	-13.807	-12.02
Target_Amount_Ln	1.126	0.066	17.147	0.000	0.997	1.254
Loan_Term	-0.009	0.008	-1.218	0.223	-0.024	0.006
Description_Size	-0.025	0.001	-23.375	0.000	-0.027	-0.023
Hashtags_Num	2.114	0.024	89.913	0.000	2.068	2.161
HDI	25.839	0.442	58.435	0.000	24.972	26.705
English	2.218	0.092	24.041	0.000	2.038	2.399
Rep.Monthly	4.445	0.125	35.549	0.000	4.20	4.69
Individual	2.568	0.159	16.116	0.000	2.256	2.88
Female	-1.859	0.112	-16.63	0.000	-2.078	-1.64
Agriculture	1.127	0.094	11.935	0.000	0.942	1.312
a. HC3 Method						

The intercept of the multiple linear regression model based on the general sample is equal to -8.476, with a robust standard error of 0.135. The t value is -62.984 and the level of significance is 0,00, which means that the intercept is statistically significant (p-value < 0.01). Regarding the multiple linear regression model based on the sample of campaigns posted during 2020, its intercept is equal to -12.913, with a robust standard error of 0.456. The t value is -28.338 and the significance value is 0.00, which means that the intercept is statistically significant (p-value < 0.01).

For the general sample, the variable Target_Amount_Ln has a coefficient of 2.689, has a robust standardized error of 0.018, has a t value of 146.960 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the sample to reject hypothesis 1. Thus, hypothesis 1 was accepted. Regarding the sample of campaigns posted during 2020, the variable Target_Amount_Ln has a coefficient of 1.126, has a robust standardized error of 0.066, has a t value of 17.147 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, once again, there is no statistical evidence from the second sample to reject hypothesis 1. Thus, hypothesis 1 was also accepted.

The variable Loan_Term has a coefficient of 0.140, has a robust standardized error of 0.003, has a t value of 46.525 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the sample to reject hypothesis 2. Thus, hypothesis 2 was accepted. Regarding the sample of campaigns posted during 2020, the variable Loan_Term has a coefficient of -0.009, has a robust standardized error of 0.008 and has a t value of -1.218. In terms of significance, the p-value is equal to 0.223 which is higher than 0.05, meaning that Loan_Term coefficient is not statistically significant for the model.

The variable Description_Size has a coefficient of -0.009, has a robust standardized error of 0.000, has a t value of -28.040 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the sample to reject hypothesis 3. Thus, hypothesis 3 was accepted. Regarding the sample of campaigns posted during 2020, the variable Description_Size has a coefficient of -0.025, has a robust standardized error of 0.001, has a t value of -23.375 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, once again, there is no statistical evidence from the second sample to reject hypothesis 3. Thus, hypothesis 3 was accepted.

The variable Hashtags_Num has a coefficient of 1.184 has a robust standardized error of 0.007, has a t value of 161.434 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, hypothesis 4 was rejected. Regarding the sample of campaigns posted during 2020, the variable Hashtags_Num has a coefficient of 2.114 has a robust standardized error of 0.024, has a t value of 89.913 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, hypothesis 4 was rejected once again.

The variable HDI has a coefficient of -3.760, has a robust standardized error of 0.148, has a t value of -25.385 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, hypothesis 5 was rejected. Regarding the sample of campaigns posted during 2020, the variable HDI has a coefficient of 25.839, has a robust standardized error of 0.442, has a t value of 58.435 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the second sample to reject hypothesis 5. Thus, hypothesis 5 was accepted.

The dummy variable English has a coefficient of -0.142, has a robust standardized error of 0.032, has a t value of -4.508 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, hypothesis 6 was accepted. Regarding the sample of campaigns posted during 2020, the dummy variable English has a coefficient of 2.218, has a robust standardized error of 0.092, has a t value of 24.041 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the second sample to reject hypothesis 6. Thus, hypothesis 6 was rejected.

The dummy variable Rep_Monthly has a coefficient of 2.151, has a robust standardized error of 0.045, has a t value of 48.081 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, hypothesis 7 was rejected. Regarding the sample of campaigns posted during 2020, the dummy variable Rep_Monthly has a coefficient of 4.445, has a robust standardized error of 0.125, has a t value of 35.549 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, hypothesis 7 was also rejected using the second sample.

The dummy variable Individual has a coefficient of 4.474, has a robust standardized error of 0.043, has a t value of 104.751 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the sample to reject hypothesis 8. Thus, hypothesis 8 was accepted. Regarding the sample of campaigns posted during 2020, the dummy variable Individual has a coefficient of 2.568, has a robust standardized error of 0.159, has a t value of 16.116 and it is statistically significant (p-value = 0.00 which is < 0.01). Therefore, there is no statistical evidence from the second sample to reject hypothesis 8. Thus, hypothesis 8 was accepted.

The dummy variable Female has a coefficient of -2.545, has a robust standardized error of 0.035, has a t value of -73.582 and it is statistically significant (p-value = 0.00 which is < 0.01). Therefore, there is no statistical evidence from the sample to reject hypothesis 9. Thus, hypothesis 9 was accepted. Regarding the sample of campaigns posted during 2020, the dummy variable Female has a coefficient of -1.859, has a robust standardized error of 0.112, has a t value of -16.630 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, once again, there is no statistical evidence from the second sample to reject hypothesis 2. Thus, hypothesis 9 was accepted.

The dummy variable Agriculture has a coefficient of 1.392, has a robust standardized error of 0.033, has a t value of 42.567 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, there is no statistical evidence from the sample to reject hypothesis 10. Thus, hypothesis 10 was accepted. Regarding the sample of campaigns posted during 2020, the dummy variable Agriculture has a coefficient of 1.127, has a robust standardized error of 0.094, has a t value of 11.935 and it is statistically significant (p-value = 0.00 which is <0.01). Therefore, once again, there is no statistical evidence from the second sample to reject hypothesis 10. Thus, hypothesis 10 was accepted.

4.1.3. Validation of the Hypothesized Conceptual Framework

Overall, our results allowed us to validate the hypothesized conceptual framework presented in section 2.3.4. of this study and illustrated in Figure 2.1. Thus, the validated conceptual framework based on regression 1 is illustrated in Figure 4.1. Similarly, the validated conceptual framework based on regression 2 is illustrated in Figure 4.2.

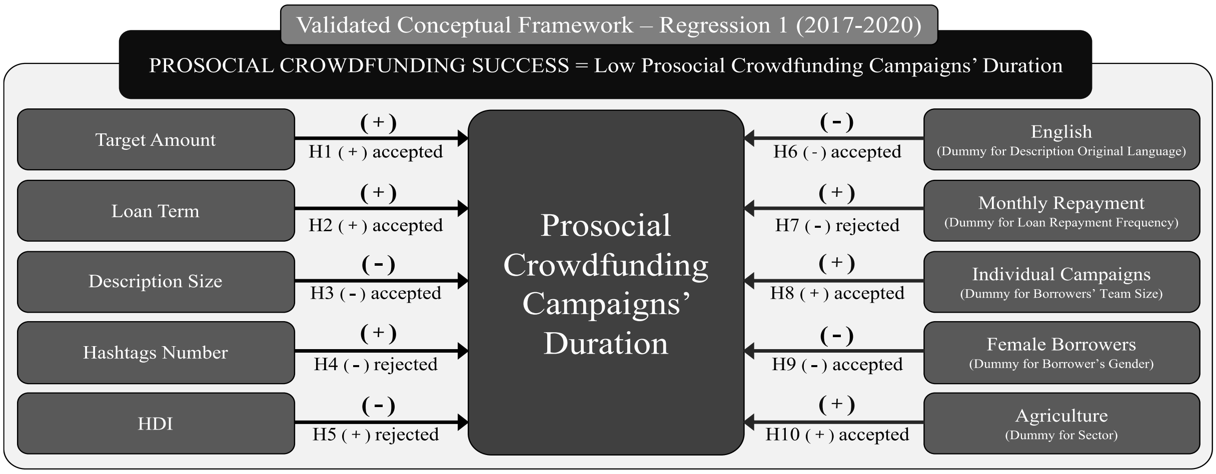

Figure 4.1 - Validated Conceptual Framework based on Regression 2 (Source: Own Research)

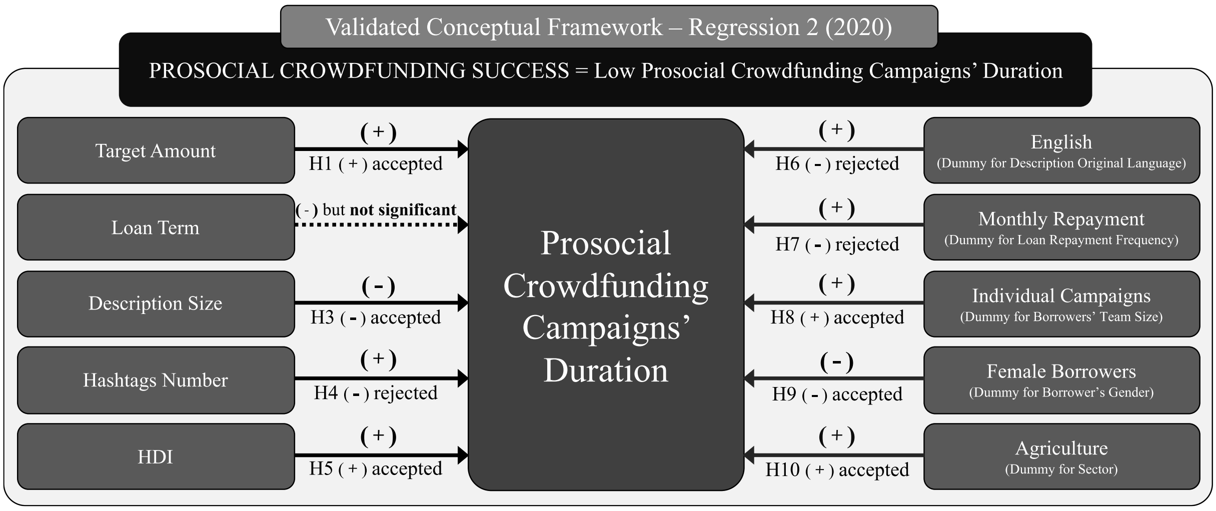

Figure 4.2 - Validated Conceptual Framework based on Regression 1 (Source: Own Research)

In summary, we identified three differences in terms of hypotheses validation between the two regressions. Those 3 differences refer to H2, H5, and H6 and they are presented in Table 4.7.

Table 4.7 - Hypotheses Validation' Differences between the two Regressions Applied (Source: Own Research)

Hypotheses Validation' differences between the two regressions applied			
Variables	Hypotheses	Hypotheses Validation - Regression 1	Hypotheses Validation - Regression 2
Loan Term	**H2 (+)**	H2 (+) accepted	Not significant
HDI	**H5 (+)**	H5 (+) rejected	H5 (+) accepted
English	**H6 (-)**	H6 (-) accepted	H6 (-) rejected

4.2. Discussion

This section includes a discussion of key findings regarding the created multiple linear models, comparing the results with the previous literature presented in chapter 1 of this study.

Several crowdfunding studies have used campaign duration as a proxy for success. We used this approach measuring the number of days since the first day of the campaign until the day the target amount is achieved. Thus, regression 1 allowed us to test the hypotheses formulated in chapter 2. Furthermore, we applied the same model to a sample that only included campaigns posted in 2020 on Kiva.org (regression 2). This allowed us to make some considerations regarding the impact of the 2020 year in campaigns' duration, taking into account that, in 2020, the world faced a global economic recession caused by a pandemic, known as the Covid-19 pandemic.

H1 was about the impact of the target amount on the campaign duration. When testing the H1 through regression 1, we found that the target amount has a significant and positive impact on the campaigns' duration (see table 4.5), which means that higher target amounts are associated with slower campaigns. This result is in accordance with Gama et al. (2021), who concluded that larger loans receive funding slower than smaller loans. This is also in accordance with Ly & Mason (2012a), that concluded that if there is an increase in the requested loan amount by one standard deviation, the campaign duration increases 76%. When testing H1 through regression 2, we obtained similar results (see table 4.6), meaning that the H1 was also accepted for the sample that only contained campaigns from 2020. Therefore, it seems that Covid-19 pandemic did not affect the target amount effect. A possible justification is the fact that the target amount is fixed, regardless of the lender's behaviour, so it seems reasonable to think that larger amounts take more time to be achieved, even in economic recessions.

H2 was about the impact of the loan term on the campaign duration. When testing H2 through regression 1, we found that the loan term has a significant and positive impact on the campaigns' duration (see table 4.5), which means that longer loan terms are associated with slower campaigns. This result is in accordance with the study conducted by Ly & Mason (2012b), which concluded that campaigns with longer loan terms are 26% slower than the other. As also suggested by Ly & Mason (2012b), our results might be explained by the eventual impatience that lenders feel in receiving the repayment. However, when we tested H2 through regression 2, the results were surprising since they indicated that, exclusively in an economic recession year, 2020, the loan term has no significant impact on the campaigns' durations (see table 4.6). Based on the idea suggested by Visconti (2011). that during recessions, the high interest rates, the default probability, and the high repayment difficulties intensify the probability of increasing the credit risk, we expected that the loan term had an even higher impact on lender's decision due to the economic recession. Since it was not the case, a possible explanation for this could be to assume that lenders are not so impatient to recover the money they lent during economic recessions because they might feel a higher willingness to help during these periods of more uncertainty, even if the risk of default is higher.

H3 was about the impact of the description size on the campaign duration. When testing H3 through regression 1, we found that the description size has a significant and negative impact on the campaigns' duration (see table 4.5), which means that longer descriptions are associated with faster campaigns and, therefore, we accepted H3. This result is in accordance with Dorfleitner et al. (2016) who concluded that if the description text is increased ceteris paribus by one standard deviation the funding probability increases by 5.2%. As reported by Formanowicz et al. (2017), the number of prosocial words used in a project's description contributes to campaign success, as it helps to achieve the project's financial goals by attracting a larger number of supporters, as according to Proelss et al. (2021) donors prefer details over shorter descriptions. Proelss et al. (2021) also stated that poorly understandable campaign descriptions, usually too technical or too short, are negatively correlated with funding speed, which is in line with our results. When testing the H3 through regression 2, the results also showed that longer descriptions are associated with faster campaigns (see table 4.6). Therefore, it is possible that, in recession years, lenders continue to be curious about the details of the campaigns.

H4 was about the impact of the number of hashtags on the campaign duration. When testing H4 through regression 1 (see table 4.5), we found that the number of hashtags has a significant and positive impact on the campaigns' duration, which means that the higher number of hashtags, the slower the campaigns will be. However, taking into account that, according to Yu & Zhu (2015), hashtags facilitate the search by other relevant users of online publications and that, according to Rauschnabel et al. (2019), hashtags contribute to engaging to trendy topics and provide more character to the postings, we were expecting that a higher number of hashtags would help more lenders to find the campaigns within the crowdfunding platforms and, thus, to participate on them by providing a microloan to the borrowers. When testing H4 through regression 2 we found similar results (see table 4.6) and, therefore, we rejected H4 once again.

H5 was about the impact of the HDI on the campaign duration. When testing H5 through regression 1, we found that the HDI of the borrower's country has a significant and negative impact on the campaigns' duration (see table 4.5), which means that higher HDIs are associated with faster campaigns. These results do not corroborate our expectation based on the study developed by Chen et al. (2019) that concluded that is more likely that the lenders prefer to lend to borrowers they perceive to be needier. On the other hand, our results are aligned with Linh (2019) that stated that lenders find borrowers from developed countries more trustworthy than borrowers that come from poor or developing countries, typically with lower HDIs. When testing H5 through regression 2, we concluded the opposite of what we concluded in regression 1, meaning that in the new conditions, higher HDIs are associated with slower campaigns (see table 4.6), which is in line with Linh (2019). This could have several explanations and one of them might be the fact that lenders do prefer to help borrowers they perceive to be needier but only in recession periods.

H6 was about the impact of the borrower's original language on the campaign duration. When testing H6 through regression 1, we found that the campaigns with English as the borrower's original language are associated with a significant and negative impact on the campaigns' duration (see table 4.5), which means that campaigns with English as original language are associated with faster campaigns. This is in line with our expectations and, thus, we accepted H6. According to Chen et al. (2019), the supporters tend to make loans to people from the same ethnicity and the same gender as them and Guiso et al. (2009) concluded that shared language has significant positive effects on trust formation and bilateral trade. Furthermore, Burtch et al. (2014) stated that, despite campaigns are translated into English, lenders may prefer to lend money to borrowers who speak the same language, which is in line with our expectation. If the majority of lenders are from English speaking countries, it is reasonable to admit that they prefer to lend to campaigns with English as original language. However, H6 was rejected when we used the sample of regression 2 (see table 4.6), which suggests that, during economic recession years such as 2020, campaigns originally written in English were less attractive to lenders, which in turn might indicate that perhaps there were more lenders from non-English speaking countries or that the lenders considered the non-English speaking borrowers more in need during the pandemic situation of Covid-19.

H7 was about the impact of the repayment frequency on the campaign duration. When testing H7 through regression 1, we found that the monthly repayments have a significant and positive impact on the campaigns' duration (see table 4.5), which means that campaigns with a monthly repayment frequency are slower campaigns. This result contradicts our expectation based on the study developed by Feigenberg & Pande (2013) that shows that a development program that stimulates repeat interactions can contribute to increasing long-term relationships and enhancing social capital among members of a community in a very short period of time. In accordance with that, when we applied regression 2, we also rejected H7 (see table 4.6). This might indicate that during economic recession years, lenders also prefer to lend to campaigns in which the repayment frequency is not monthly.

H8 was about the impact of individual campaigns on the campaign duration. When testing H8 through regression 1, we found that individual campaigns have a significant and positive impact on the campaigns' duration (see table 4.5), which means that individual campaigns are associated with slower campaigns, as expected. When we tested H8 through regression 2, the results were in accordance with our expectations as well (see table 4.6). These results suggest that lenders may think that joint responsibility might, in fact, potentially contribute to peer monitoring as well as reduce the rate of strategic defaults and enhance their ability to recover the invested amount, as suggested by Armendáriz De Aghion (1999). On the other hand, this contradicts the results reached by Ly & Mason (2012b), who found that campaigns from groups of borrowers were funded slower than individual loans by 84%. This also contradicts the findings of the study developed by Desai & Kharas (2018), in which Kiva's lenders prefer to fund individual borrowers than group borrowers. However, it might be possible that these differences are related to the different contexts in which the studies were developed. While our study was based on campaigns posted between 2017 and 2020 and the sample was very large, the study conducted by Desai & Kharas (2018) used a smaller sample of campaigns posted between 2006 and 2010. The crowdfunding market changed over the years and the lenders' motivation might have changed as well.

H9 was about the impact of gender on the campaign duration. When testing H9 through regression 1, we found that females have a significant and positive impact on the campaigns' duration (see table 4.5), which means that female campaigns are associated with shorter durations. Also, when we tested H9 through regression 2, we found similar results (see table 4.6). This result ties well with previous studies. Dorfleitner et al. (2021) concluded that investors prefer to lend female borrowers and Proelss et al. (2021) concluded that campaigns about treatments for female (infant) patients were faster than campaigns about treatments for male (infant) patients. Gama et al. (2021) concluded that campaigns from female microentrepreneurs are faster than campaigns from male microentrepreneurs. Jancenelle et al. (2019) revealed that, on average, female campaigns are funded 38% faster than male campaigns and Ly & Mason (2012a) showed that 76% of the loans were made to individual women borrowers or groups of women, being the average speed of projects involving women (groups or individuals) 2,751 min, while the average of the projects speed with male borrowers was 4,871 min. In accordance with that, Badding & Heller (2012) concluded that loans to female campaigns are funded approximately 30% faster than compared to male campaigns. Anderson & Saxton (2016) also concluded that female campaigns that include photos with women and males are 23.7% slower compared to the ones that do not include males in the campaign photo. Yunus & Jolis (1999) encourage to lend to woman and that seems to be in accordance with lenders preference when choosing the borrower that they want to support.

H10 was about the impact of the sector agriculture on the campaign duration. When testing H10 through regression 1 (see table 4.6), we found that the agriculture sector has a significant and positive impact on the campaign duration, which means that higher target amounts are associated with slower campaigns. This result is in accordance with Gama et al. (2021) showed empirically that modern sector campaigns are faster than traditional sector campaigns and, according to Lavopa & Szirmai (2018), small-scale subsistence agriculture activities belong to the traditional sector When testing the first hypothesis through regression 2 we obtained similar results (see table 4.6), which might indicate that, even during economic recession years, lenders prefer to lend to campaigns not linked to agriculture.

4.2.1. Practical Implications

Our study has several practical implications. The findings of our study helped to address the problem of understanding how campaign characteristics might influence the duration of prosocial crowdfunding campaigns. According to our results from regression 1, the description size, the HDI of the borrowers' country, the fact that the original language of the campaign is English, and the fact of the borrower's gender is female, are prosocial crowdfunding success factors. According to our results from regression 2, only the fact of the borrower's gender is female and longer descriptions represent prosocial crowdfunding success factors.

Therefore, this study allows that microfinance institutions and other interested organizations be aware that lenders prefer to support prosocial crowdfunding campaigns with those characteristics. On the other hand, it allows them to focus on strategies that might minimize the negative impact of some campaign's characteristics, which, according to our results, are high target amounts, high loan terms, hashtags number, monthly repayments, individual campaigns, and agriculture-related campaigns. In consequence, this might increase the speed of the campaigns in reaching the defined target amounts, and, consequently, they might be able to help financially excluded people in a faster way to become entrepreneurs and sustainably generate income.

This study is also useful for prosocial crowdfunding platforms, specially Kiva.org. since it provides conclusions regarding campaigns' duration based on a very large sample in recent years. These platforms might focus their attention on the factors that are associated with longer campaigns, to make suggestions to the campaign owners, usually the microfinance institutions, to increase the chance of mitigating risks associated with campaigns' information and borrowers' profiles. Also, this study might be useful for these platforms as it highlights some differences regarding two different samples, being one of them a sample of campaigns posted in a year of an economic recession caused by Covid-19. Furthermore, prosocial crowdfunding platforms might highlight the campaigns that, according to our regression model, are less likely to succeed in a fast way on their websites, by changing the website organization and loan categories. This could also decrease the number of campaigns that do not achieve the target amount because of a lack of time to convince lenders to support them.

Governments might use the information contained in this study in favour of the poor and financially excluded people who, perhaps, would like to change their financial situation through entrepreneurship. This means that our study contributes to incentive Governments to define new public and private policies to combat poverty, especially the ones that focus on the variables that we concluded are associated with faster campaigns. For example, since agricultural campaigns are associated with slower campaigns, Governments could encourage the population to create more businesses not related to agriculture.

The scientific community interested in this study's research problem will benefit from our results as it represents an advance in the knowledge of prosocial crowdfunding's success based on campaigns' duration, which allowed us to identify other additional possibilities to explore regarding this field. Some results of this study contradicted previous studies and, thus, it deserves further attention in the future, and some paths for future research will be presented in section 5.2 of this study. Moreover, as Covid-19 seems to have had some impact on the duration of prosocial crowdfunding campaigns, the scientific community could explore that more in-depth.

This study might also contribute to lenders as they might want to be aware of the campaigns' durations associated with 2020, which might contribute to their willingness to help even more financially excluded entrepreneurs obtain the microcredit they need to speed up the campaigns and recover from the pandemic economic situation.

All of these practical implications together might help, in a certain way, to achieve the primary goal of the United Nations of eradicating poverty until 2030 by providing access to credit in a faster way, which might boost entrepreneurship among financially excluded people for them to have the chance to have a more sustainable and healthier financial life.

5. Conclusions, Limitations & Paths for Future Research

In this chapter, we present the conclusions and limitations of the study and paths for future research.

5.1. Conclusions

The eradication of poverty by 2030 is the main priority of the United Nations and all the initiatives that contribute to that goal are welcome. Many organizations, such as NGOs, have tried to cope with it by helping the most disadvantaged people. This help might come from donations and microcredit. However, one of the main obstacles to fundraising by NGOs is the fact that funders fear that their money is not being used to solve the actual problems of beneficiaries and could be diverted by less than honest intermediaries, increasing the perceived risk of either donating or lending.

In an increasingly technological world, the possibility of crowdfunding emerged, which allowed solving some serious problems such as information asymmetry. Furthermore, crowdfunding made it easier to donate and lend and it also made it possible to reduce the risk of borrowing large amounts of money, distributing the risk of lending to people among various supporters. This allowed to reduce the interest charged to the borrowers by the MFIs and other organizations that contribute to financial inclusion of disadvantaged people over the world.

Prosocial Crowdfunding is a specific type of lending-based crowdfunding and it is of particular interest since it allows empowering disadvantaged people, mainly from developing countries, helping them access interest-free credit for starting a business in a faster way since the campaigns are advertised online on crowdfunding platforms such as Kiva.org. The idea of lending instead of just donating is revolutionary as it represents a mindset change for poor people. With loans, they have the responsibility to repay the amount they received and that motivates them to apply for the money in a business that will generate a return, allowing them to repay the loan and to generate income in a sustainable way to reduce or evade poverty. This allows lower interest rates as compared to traditional microcredit. Furthermore, prosocial crowdfunding also contributes to decreasing the administrative complexity of microcredit. The transaction value of crowdfunding increased from 965.6 million US dollars to 969.9 million US dollars between 2017 and 2020 (Statista, 2021a) and the crowdfunding market is projected to increase from 12.27 billion US dollars to 25.8 billion US dollars between 2020 and 2027 (Statista, 2021b), attracting a rising interest from researchers to this still insufficiently understood field.

Several studies about the success of the crowdfunding campaigns, including prosocial crowdfunding, have attempted to measure crowdfunding campaigns' success. Some articles consider that successful campaigns are the ones that achieve the target amount. Other articles go further and have focused on studying how quickly the target value is reached. Considering the urgency in eradicating poverty until 2030, the present study focused on this second approach.

This study seems to be one of the first studies addressing prosocial crowdfunding success with a sample with more than 700000 campaigns, which allowed us to have a clear understanding of prosocial crowdfunding success. We used data provided by Kiva.org regarding the years 2017, 2018, 2019 and 2020, to answer our research questions taking into account recent data. Once 2020 was a recession year because of Covid-19, we tested the formulated hypotheses using two different samples: one sample with campaigns posted on period 2017-2020 and another sample with campaigns posted exclusively in 2020.

We applied two multiple linear regressions and, based on regression 1, we concluded that campaigns with higher loan terms, campaigns with a higher number of hashtags, campaigns with monthly repayment periods, individual campaigns, and agriculture campaigns are associated to slower campaigns and that campaigns with longer description size, campaigns with higher HDIs, campaigns with English as original language and female campaigns are associated to faster campaigns. The results obtained in regression 2 confirmed the results of regression 1, except for loan amount, HDI, and English as the original language. The loan amount stopped being significant, meaning that loan amount has not impact on the lender's decision in campaigns from 2020, a recession year. On the other hand, based on the results from regression 2, higher HDI and English as original language are associated with slower campaigns. These results suggest that Covid-19 might have had an impact on lenders' decisions.

Our results contributed to building some additional knowledge regarding factors that might influence the prosocial campaigns' duration and this was especially relevant because this means that the involved stakeholders might change their future crowdfunding approach according to our results.

We see this study as an additional step towards understanding promising tools for the eradication of poverty and we encourage future studies in this field in order to make the crowdfunding process can more efficient and pervasive.

5.2. Limitations and Paths for Future Research

In this section, we present some limitations of the study and some recommendations to be considered in the future.

One of the limitations of the study is the fact that we have not used the real HDI for the year 2020 because that data was not available by the time of the development of the present study. Instead, for that year, we considered the 2019 HDI. Although the changes of HDI between the two years might have been smooth, we suggest future studies to address this question when the mentioned data is available. In addition to that, we did not consider campaigns from Somalia and Puerto Rico as, by the time when the present study was developed, there was no HDI data available regarding those two countries for the periods in the study. Thus, we suggest that future studies include these countries in the sample when the required data is available.

In this study, we included campaigns from 2020 in the sample that we used for regression 1, allowing us to study the prosocial crowdfunding campaigns from the last 4 years posted in Kiva.org. However, including the year of 2020 in regression 1 did not allow us to understand the data behaviour excluding the economic recession year (2020). Therefore, we suggest that future research consider the mentioned issue in order to be possible to compare the lender's behaviour in years of economic growth or years of economic stability with years of economic recession.

Our study focused on campaigns with field partners involved in the crowdfunding process (partner model), since the direct model, is currently available in only one country. However, perhaps when the direct model is available to more countries, it could be interesting to compare the crowdfunding success between partner model and direct model.

Future research might also focus on the reasons behind the results of loan terms not being statistically significant during 2020, as concluded in this study.

Since our results showed that, regarding campaigns from 2017 to 2020, the HDI has a significant impact on the campaigns' durations, it could be interesting to study if the variables have a different impact on the campaign duration, depending on the group of countries, such as LDC, ODC, and DC.

The original language of the borrowers is also a variable that could be considered in future studies as it had a different behaviour in the sample from the recession year compared with the sample with campaigns from 2017 to 2020. Hence, we suggest that future studies focus on this variable, to understand why having English as the original language of the borrower is not a success factor during a recession year. Furthermore, we concluded that campaigns with English as original language are faster than the others in the first sample but whether this has to do with the nationality of lenders remains an open question. Therefore, another path for future research is to relate our results regarding borrowers' language to the lenders' language.

Another topic that could be explored in the future is the fact that there are different formats of prosocial crowdfunding. Kiva was the crowdfunding platform used in this study and it follows the format 1 suggested in section 2.3.1. of this study. As explained in that section, this format allows lenders to choose the campaigns and the borrowers they will support, allowing higher transparency regarding loan information, including information regarding default loans. Format 3 also allows the backers to choose the campaigns they want to support but they donate instead of lending, and it could be interesting to assess the success in terms of campaigns' duration between Format 3 and Format 1.

As demonstrated in this study, microcredit is part of prosocial crowdfunding. However, we did not compare microcredit with prosocial crowdfunding in an isolated way. Thus, we suggest future research to address this comparison, to allow a better understanding of the advantages of prosocial crowdfunding, suggested in previous literature, in comparison with traditional microcredit. In line with this idea, we suggest that future studies explore the differences in speed of providing credit to financially excluded people, who aspire to be entrepreneurs able to live a sustainable financial life, between traditional microcredit and prosocial crowdfunding.

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Appendices

Appendix A - Sustainable Development Goals Proposed by United Nations

Figure A.1 - Sustainable Development Goals (Source: United Nations, 2015)

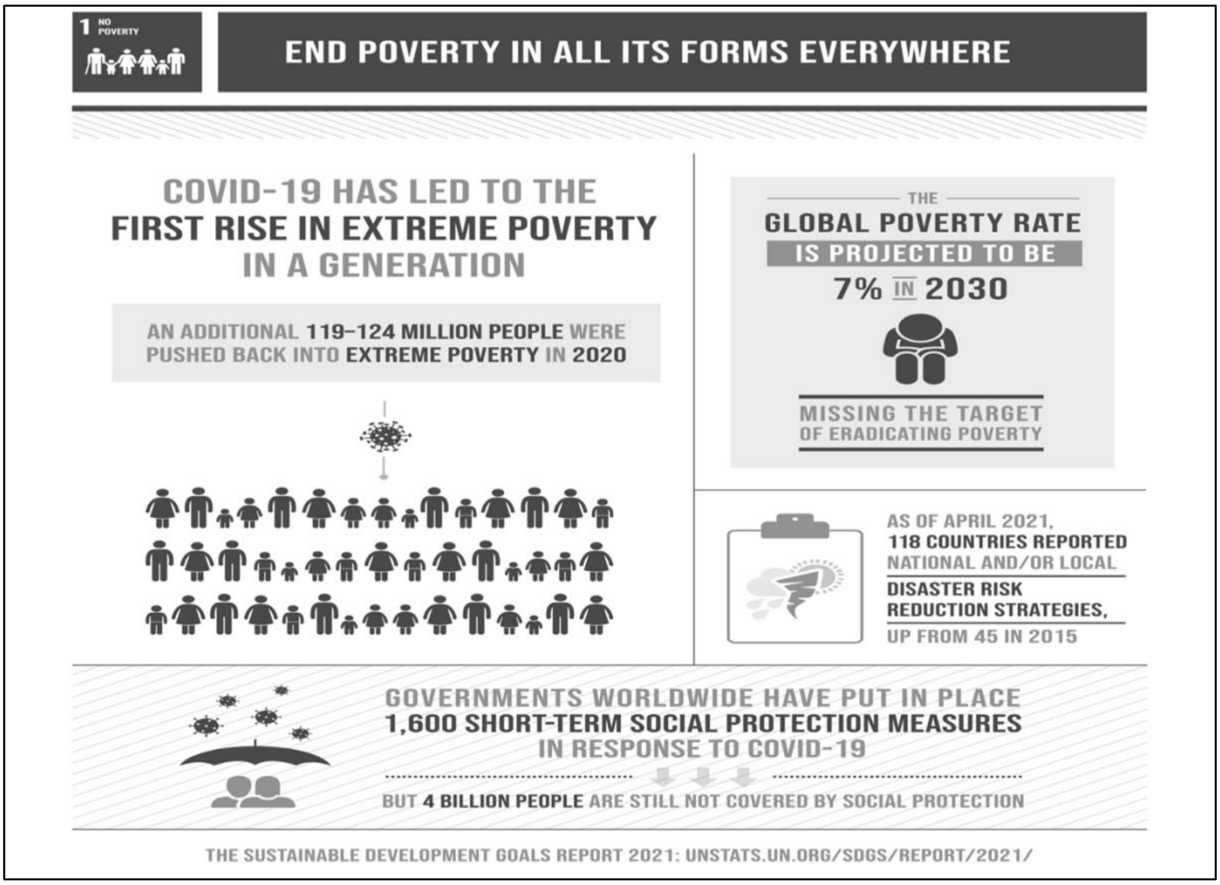

Figure A.2 - Impact of Covid-19 in the sustainable goal of eradicating poverty (Source: United Nations, 2021b)

Appendix B - Summary of Selected Prosocial Crowdfunding Studies

Table B.1 - Summary of Selected Prosocial Crowdfunding Studies (Source: Own Research)

Reference	Methodology	Hypotheses and Hypothesis Validation
Gama et al. (2021)	**Sample Size:** 1,005,414 campaigns **Timeframe:** 2011-2018 **Target:** Not specified **Platform:** Kiva.org **Type:** Prossocial lending **Method:** Tobit Regression Model, Eicker–Huber–White Robust Standard Errors	**H1 Accepted:** Modern sector campaigns achieve quicker funding speeds than traditional sector campaigns in crowdfunding microfinance **H2 Accepted:** Female microentrepreneurs achieve quicker funding speeds than male microentrepreneurs. **H3 Rejected:** Female microentrepreneurs negatively moderate the modern sector's effect on funding speed **H4 Accepted:** Small loans achieve quicker funding speeds than large loans. **H5 Rejected:** When directed towards modern sector activities, larger loan campaigns achieve quicker funding.
Proelss et al. (2021)	**Sample Size:** 4677 campaigns **Timeframe:** Not specified **Target:** Not specified **Platform:** Watsi.org **Type:** Donation **Method:** Poisson Regression & Logistic Regression	**H1 Accepted:** Age is negatively correlated with funding speed. **H2 Accepted:** Treatments for female (infant) patients are funded more quickly. **H3 Rejected:** Smiling patient pictures (lower level of donor sympathy) are negatively correlated with funding speed **H4 Accepted:** Religious holidays and Sundays increase the likelihood of charitable giving and increase funding speed **H5 Rejected:** The severity of a patient's condition is positively correlated with funding speed **H6 Accepted:** Public Profile Donors are less likely to donate if a donation by a Public Profile Donor has already been made **H7 Accepted:** Public Profile Donors are less likely to donate if the average reputation of previous donors is higher.
Jancenelle et al. (2019)	**Sample Size:** 127,597 campaigns **Timeframe**: 2006 - 2010 **Target:** Business loans **Platform:** Kiva.org **Type:** Prosocial lending **Method:** Two-Level Hierarchical Regression	**H1 Accepted:** The cultural alignment between a borrower's own level of temporal awareness and the average level of temporal awareness exhibited in his or her own country is positively related to funding time. **H2 Accepted:** The cultural alignment between a borrower's own level of commonality and the average level of commonality exhibited in his or her own country is positively related to funding time
Anderson & Saxton (2016)	**Sample Size:** 323 campaigns **Timeframe:** 2009 **Target:** Asian women entrepreneurs **Platform:** Kiva.org **Type:** Prossocial Lending **Method:** Ordinary Least Squares	**H1 Rejected:** Genuine enjoyment smiles are negatively related to the length of time it takes women microentrepreneurs to be fully funded. **H2a Accepted:** Inclusion of a baby in the loan-request photo is negatively associated with the length of time it takes women entrepreneurs to get fully funded. **H2b Rejected:** Inclusion of a preadolescent child (age 1 to 11) in the loan-request photo is negatively associated with the length of time it takes women entrepreneurs to get fully funded, though to a lesser degree than babies. **H2c Accepted:** Inclusion of a man or husband in the loan-request photo is positively associated with the length of time it takes women entrepreneurs to get fully funded. **H3 Accepted:** Inclusion of material wealth indications in the loan-request photo is positively associated with the length of time it takes women entrepreneurs to get fully funded.
Heller & Badding (2012)	**Sample Size:** 289,501 campaigns **Timeframe:** 2006 - 2010 **Target:** Not specified **Platform:** Kiva.org **Type:** Prossocial Lending **Method:** Simple Ordinary Least Square	**H1 Accepted:** The time it takes for a given loan to be funded will depend on borrower (i), loan (j) and time or period-specific (k) characteristics. - **Conclusion 1:** Female borrowers are associated with faster campaigns. - **Conclusion 2:** The campaigns' speed is associated to the borrowers' region of residence (Borrowers from Sub-Saharan Africa are associated with faster campaigns). - **Conclusion 3:** Higher loan amounts are associated with slower campaigns. - **Conclusion 4:** The campaigns' speed is associated to the loan sector (Loans related to agriculture sector are associated with slower campaigns). - **Conclusion 5:** The existence of a picture is associated with slower campaigns. - **Conclusion 6:** Higher exchange rates are associated with slower campaigns. - **Conclusion 7:** MFI-level with high default risk are associated with slower campaigns. - **Conclusion 8:** The Kiva's relative popularity is associated with faster campaigns. - **Conclusion 9:** A higher number of available loans on the Kiva website during the time period that a loan is funded is associated with slower campaigns.
Dorfleitner et al. (2016)	**Size:** 6121 campaigns **Timeframe:** 2011 - 2017 **Target:** US inhabitants **Platform:** Kiva.org **Type:** Prossocial Lending **Method:** Logistic Regression	**H1 Accepted: (Trustee endorsement)** The existence of a trustee is positively related to funding success **H2 Accepted: (Trust)** Signals in the descriptive texts that emphasize trustworthiness regarding the repayment are positively associated with funding success **H3 Accepted: (Empowerment)** A description text indicating empowerment possibilities is positively related to funding success. **H4 Partially Accepted: (Vulnerability)** If the description text indicates that a borrower is more vulnerable, the probability of funding is higher

Appendix C - Least Developed Countries List

Table C.1 - Least Developed Countries List (Source: Own Research)

Least Developed Countries	
1. Afghanistan	**24.** Madagascar
2. Angola	**25.** Malawi
3. Bangladesh	**26.** Mali
4. Benin	**27.** Mauritania
5. Bhutan	**28.** Mozambique
6. Burkina Faso	**29.** Myanmar
7. Burundi	**30.** Nepal
8. Cambodia	**31.** Niger
9. Central African Republic	**32.** Rwanda
10. Chad	**33.** Sao Tome and Principe
11. Comoros	**34.** Senegal
12. Democratic Republic of the Congo	**35.** Sierra Leone
13. Djibouti	**36.** Solomon Islands
14. Eritrea	**37.** Somalia
15. Ethiopia	**38.** South Sudan
16. Gambia	**39.** Sudan
17. Guinea	**40.** Timor-Leste
18. Guinea-Bissau	**41.** Togo
19. Haiti	**42.** Tuvalu
20. Kiribati	**43.** Uganda
21. Lao People’s Democratic Republic	**44.** United Republic of Tanzania
22. Lesotho	**45.** Yemen
23. Liberia	**46.** Zambia

Appendix D - Human Development Index by Year

Table D.1 - Human Development Index by Year (Source: Own Research)

Country	2017	2018	2019	2020*	Country	2017	2018	2019	2020*
Albania	0.790	0.792	0.795	0.795	Mexico	0.771	0.776	0.779	0.779
Armenia	0.769	0.771	0.776	0.776	Moldova	0.743	0.746	0.750	0.750
Bangladesh	0.616	0.625	0.632	0.632	Mozambique	0.446	0.452	0.456	0.456
Belize	0.714	0.714	0.716	0.716	Myanmar (Burma)	0.572	0.579	0.583	0.583
Bhutan	0.646	0.649	0.654	0.654	Namibia	0.644	0.645	0.646	0.646
Bolivia	0.710	0.714	0.718	0.718	Nepal	0.588	0.596	0.602	0.602
Brazil	0.761	0.762	0.765	0.765	Nicaragua	0.726	0.727	0.728	0.728
Burkina Faso	0.439	0.443	0.452	0.452	Nigeria	0.531	0.534	0.539	0.539
Burundi	0.434	0.431	0.433	0.433	Pakistan	0.550	0.552	0.557	0.557
Cambodia	0.582	0.585	0.594	0.594	Palestine	0.706	0.708	0.708	0.708
Cameroon	0.557	0.560	0.563	0.563	Panama	0.811	0.812	0.815	0.815
China	0.750	0.755	0.761	0.761	Papua New Guinea	0.549	0.549	0.555	0.555
Colombia	0.763	0.764	0.767	0.767	Paraguay	0.924	0.925	0.926	0.926
Congo	0.574	0.573	0.574	0.574	Peru	0.767	0.771	0.777	0.777
Costa Rica	0.804	0.808	0.810	0.810	Philippines	0.708	0.711	0.718	0.718
Dominican Republic	0.746	0.751	0.756	0.756	Rwanda	0.535	0.540	0.543	0.543
Ecuador	0.760	0.762	0.759	0.759	Samoa	0.710	0.709	0.715	0.715
Egypt	0.661	0.659	0.660	0.660	Senegal	0.512	0.516	0.512	0.512
El Salvador	0.671	0.670	0.673	0.673	Sierra Leone	0.443	0.447	0.452	0.452
Fiji	0.740	0.742	0.743	0.743	Solomon Islands	0.562	0.564	0.567	0.567
Georgia	0.799	0.805	0.812	0.812	South Africa	0.705	0.707	0.709	0.709
Ghana	0.602	0.606	0.611	0.611	Tajikistan	0.657	0.661	0.668	0.668
Guatemala	0.655	0.657	0.663	0.663	Tanzania	0.523	0.524	0.529	0.529
Haiti	0.505	0.508	0.510	0.510	Thailand	0.765	0.772	0.777	0.777
Honduras	0.630	0.633	0.634	0.634	The Democratic republic of the congo	0.475	0.478	0.480	0.480
India	0.640	0.642	0.645	0.645	Timor-Leste	0.599	0.599	0.606	0.606
Indonesia	0.707	0.712	0.718	0.718	Togo	0.506	0.510	0.515	0.515
Israel	0.913	0.916	0.919	0.919	Tonga	0.723	0.723	0.725	0.725
Jordan	0.726	0.728	0.729	0.729	Turkey	0.814	0.817	0.820	0.820
Kenya	0.595	0.699	0.601	0.601	Uganda	0.532	0.538	0.544	0.544
Kosovo	0.798	0.803	0.806	0.806	Ukraine	0.771	0.774	0.779	0.779
Kyrgyzstan	0.698	0.701	0.707	0.707	United States	0.924	0.925	0.926	0.926
Lao People's Democratic Republic	0.608	0.609	0.613	0.613	Uruguay	0.814	0.816	0.817	0.817
Lebanon	0.748	0.747	0.744	0.744	Vanuatu	0.601	0.603	0.609	0.609
Lesotho	0.517	0.522	0.527	0.527	Vietnam	0.696	0.700	0.704	0.704
Liberia	0.481	0.480	0.480	0.480	Yemen	0.467	0.468	0.470	0.470
Madagascar	0.526	0.527	0.528	0.528	Zambia	0.578	0.582	0.584	0.584
Malawi	0.473	0.478	0.483	0.483	Zimbabwe	0.563	0.569	0.571	0.571
Mali	0.427	0.431	0.434	0.434	**Mean**	0.647	0.650	0.653	0.653

Appendix E - Frequencies of Categorical Variables in Sample 1

Table E.1 - Frequency Table of Description's Original Language from Sample 1 (Source: Own Research)

Frequency Table - Description's Original Language				
	Frequency	%	Valid %	Cumulative %
English	577666	73.0	73.0	73.0
Spanish	142837	18.0	18.0	91.0
French	46446	5.9	5.9	96.9
Russian	19596	2.5	2.5	99.4
Portuguese	4989	0.6	0.6	100.0
Total	791534	100.0	100.0	

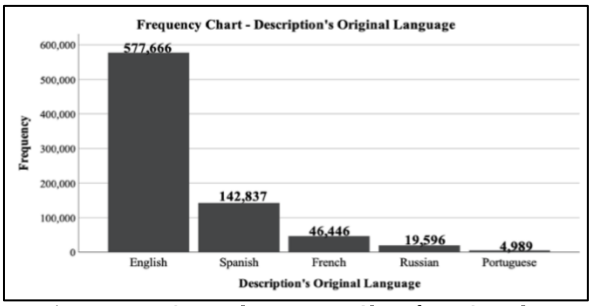

Figure E.1 - Original Language Chart from Sample 1 (Source: Own Research)

Table E.2 - Frequency Table of Borrowers' Gender from Sample 1 (Source: Own Research)

Frequency Table - Borrowers' Gender				
	Frequency	%	Valid %	Cumulative %
Female	555196	70.1	70.1	70.1
Male	132668	16.8	16.8	86.9
Female Group	54969	6.9	6.9	93.8
Mixed Group	45590	5.8	5.8	99.6
Male Group	3111	0.4	0.4	100.0
Total	791534	100.0	100.0	

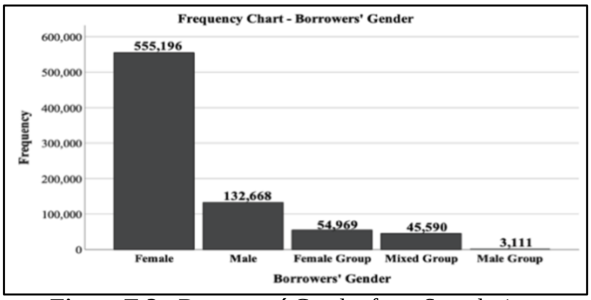

Figure E.2 - Borrowers´ Gender from Sample 1 (Source: Own Research)

Table E.3 - Frequency Table of Repayment Frequency from Sample 1 (Source: Own Research)

Frequency Table - Repayment Frequency				
	Frequency	%	Valid %	Cumulative %
Monthly	688870	87.0	87.0	87.0
Bullet	68644	8.7	8.7	95.7
Irregular	34020	4.3	4.3	100.0
Total	791534	100.0	100.0	

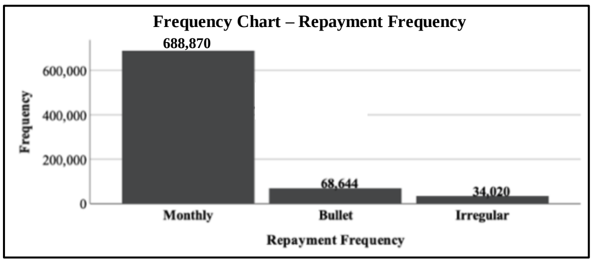

Figure E.3 - Repayment Frequency Chart from Sample 1 (Source: Own Research)

Table E.4 - Frequency Table of Sectors from Sample 1 (Source: Own Research)

Frequency Table - Sector				
	Frequency	%	Valid %	Cumulative %
Agriculture	222849	28.2	28.2	28.2
Food	161529	20.4	20.4	48.6
Retail	130547	16.5	16.5	65.1
Housing	54190	6.8	6.8	71.9
Services	47680	6.00	6,00	77.9
Personal Use	43610	5.5	5.5	83.4
Clothing	35899	4.5	4.5	87.9
Education	35343	4.5	4.5	92.4
Arts	17704	2.2	2.2	94.6
Health	14755	1.9	1.9	96.5
Transportation	12852	1.6	1.6	98.1
Construction	7002	0.9	0.9	99
Manufacturing	6339	0.8	0.8	99.8
Entertainment	659	0.1	0.1	99.9
Wholesale	576	0.1	0.1	100
Total	791534	0.0	0,00	

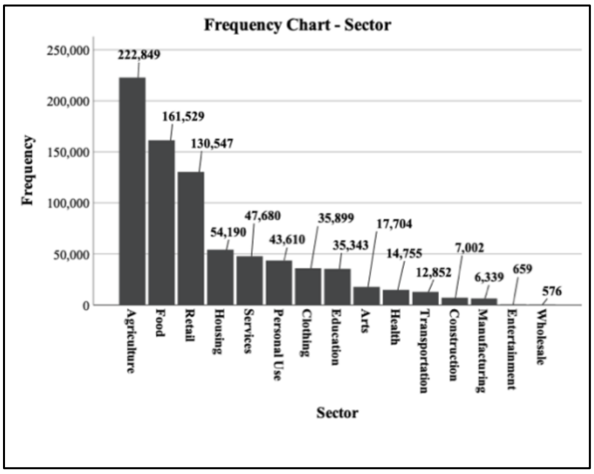

Figure E.4 - Sector Chart from Sample 1 (Source: Own Research)

Table E.5 - Frequency Table of Countries in Sample 1 (Source: Own Research)

Country	Frequency	%	Cumulative %	Country	Frequency	%	Cumulative %
Philippines	194904	24.6	24.6	United States	3970	0.5	94.3
Kenya	96727	12.2	36.8	Armenia	3726	0.5	94.8
Cambodia	35258	4.5	41.3	Mozambique	3636	0.5	95.2
Uganda	31041	3.9	45.2	Fiji	2927	0.4	95.6
El Salvador	30549	3.9	49.1	Georgia	2897	0.4	96.0
Tajikistan	29269	3.7	52.8	Cameroon	2789	0.4	96.3
Ecuador	25752	3.3	56.0	Solomon Islands	2542	0.3	96.7
Colombia	24684	3.1	59.1	Myanmar (Burma)	2507	0.3	97.0
Pakistan	21656	2.7	61.9	Costa Rica	2287	0.3	97.3
Peru	18300	2.3	64.2	Lesotho	2188	0.3	97.5
India	15901	2.0	66.2	Albania	2177	0.3	97.8
Vietnam	15640	2.0	68.2	Tonga	2173	0.3	98.1
Madagascar	14186	1.8	70.0	Malawi	2011	0.3	98.3
Paraguay	13902	1.8	71.7	Zambia	1795	0.2	98.6
Nicaragua	13201	1.7	73.4	Turkey	1631	0.2	98.8
Lebanon	12941	1.6	75.0	Mali	1536	0.2	99.0
Liberia	11289	1.4	76.5	Brazil	1520	0.2	99.2
Togo	9815	1.2	77.7	Moldova	1406	0.2	99.3
Nigeria	9002	1.1	78.8	Dominican Republic	994	0.1	99.5
Samoa	8950	1.1	80.0	Kosovo	892	0.1	99.6
Tanzania	8193	1.0	81.0	Lao People's Democratic Republic	775	0.1	99.7
Honduras	7761	1.0	82.0	Nepal	735	0.1	99.8
Palestine	7008	0.9	82.9	Thailand	435	0.1	99.8
Ghana	6698	0.8	83.7	Ukraine	317	0.0	99.9
Kyrgyzstan	6665	0.8	84.6	Papua New Guinea	269	0.0	99.9
Guatemala	6472	0.8	85.4	Yemen	267	0.0	99.9
Rwanda	6273	0.8	86.2	Panama	198	0.0	100.0
Sierra Leone	5946	0.8	86.9	Israel	190	0.0	100.0
Indonesia	5917	0.7	87.7	Vanuatu	75	0.0	100.0
Timor-Leste	5586	0.7	88.4	Burundi	27	0.0	100.0
Jordan	5572	0.7	89.1	Namibia	23	0.0	100.0
Zimbabwe	5483	0.7	89.8	Belize	9	0.0	100.0
Burkina Faso	5328	0.7	90.4	South Africa	9	0.0	100.0
Haiti	4813	0.6	91.0	Bangladesh	1	0.0	100.0
Senegal	4767	0.6	91.7	Bhutan	1	0.0	100.0
The Democratic Republic of the Congo	4619	0.6	92.2	China	1	0.0	100.0
Bolivia	4431	0.6	92.8	Congo	1	0.0	100.0
Mexico	4075	0.5	93.3	Uruguay	1	0.0	100.0
Egypt	4022	0.5	93.8	Total	791534	100.0	100.0

Appendix F - Frequencies of Dummy Variables used in Regression 1

Table F.1- Frequency Table of Description's Original Language Dummy from Sample 1 (Source: Own Research)

Frequency Table - Description's Original Language				
	Frequency	%	Valid %	Cumulative %
English	577666	73.00	72.98	72.98
Other	213868	27.00	27.02	100.00
Total	791534	100.00	100.00	100.00

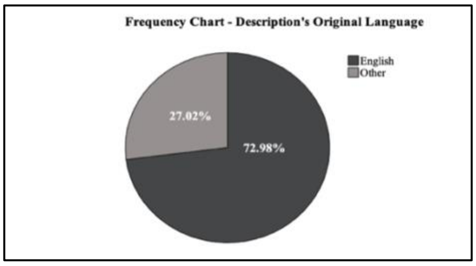

Figure F.1 - Original Language Chart Dummy from Sample 1 (Source: Own Research)

Table F.2 - Frequency Table of Repayment Frequency Dummy from Sample 1 (Source: Own Research)

Frequency Table - Repayment Frequency				
	Frequency	%	Valid %	Cumulative %
Monthly	688870	87.00	87.03	87.03
Other	102664	13.00	12.97	100.00
Total	791534	100.00	100.00	100.00

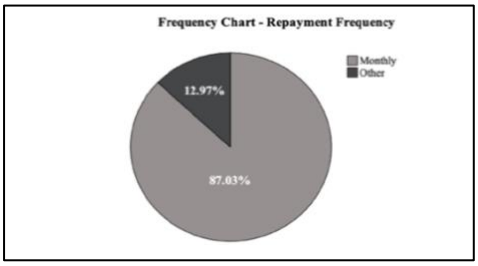

Figure F.2 - Repayment Frequency Chart from Sample 1 (Source: Own Research)

Table F.3 - Frequency Table of Sector Dummy from Sample 1 (Source: Own Research)

Frequency Table - Sector				
	Frequency	%	Valid %	Cumulative %
Agriculture	222849	28.20	28.15	28.15
Other	568685	71.80	71.85	100.00
Total	791534	100.00	100.00	100.00

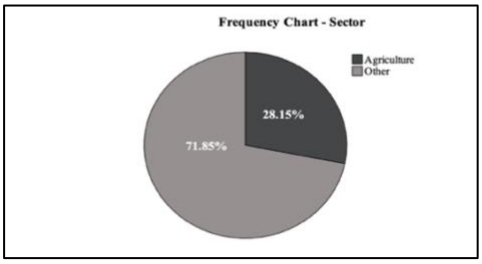

Figure F.3 - Sector Chart from Sample 1 (Source: Own Research)

Table F.4 - Frequency Table of Borrower's Gender Dummy from Sample 1 (Source: Own Research)

Frequency Table - Borrowers' Team				
	Frequency	%	Valid %	Cumulative %
Individual	687864	86.90	86.90	86.90
Group	103670	13.10	13.10	100.00
Total	791534	100.00	100.00	100.00

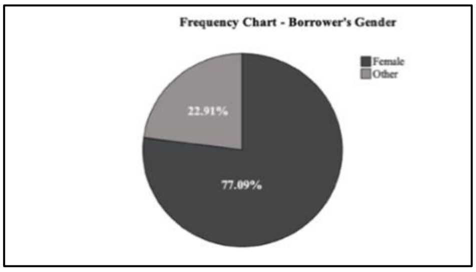

Figure F.4 - Borrower's Gender Chart from Sample 1 (Source: Own Research)

Table F.5 - Frequency Table of Borrowers' Team Dummy from Sample 1 (Source: Own Research)

Frequency Table - Borrowers' Team				
	Frequency	%	Valid %	Cumulative %
Individual	687864	86,90	86,90	86,90
Group	103670	13,10	13,10	100,00
Total	791534	100,00	100,00	100,00

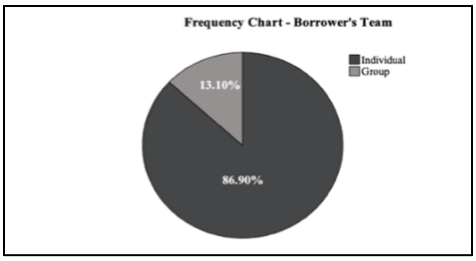

Figure F.5 - Borrowers' Team Chart from Sample 1 (Source: Own Research)

Appendix G - Independent Variables vs Dependent Variable (Sample 1)

Table G.1 - Average Campaign Duration by Original Language, Sample 1 (Source: Own Research)

Average Campaign Duration by Original Language	Posted_Year				
	2017	**2018**	**2019**	**2020**	**Total**
Other	13.8	13.59	13.9	18.22	14.77
English	12.43	10.4	12.2	17.5	12.83
Total	12.77	11.22	12.68	17.71	13.36

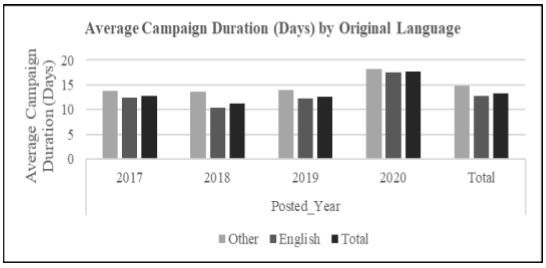

Figure G.1 - Average Campaign Duration by Borrower's Type, Sample 1 (Source: Own Research)

Table G.2 - Average Campaign Duration by Repayment Frequency, Sample 1 (Source: Own Research)

Average Campaign Duration by Repayment Frequency	Posted_Year				
	2017	**2018**	**2019**	**2020**	**Total**
Other	16.1	12.05	11.36	15.24	13.85
Monthly	12.26	11.12	12.86	18.19	13.28
Total	12.77	11.22	12.68	17.71	13.36

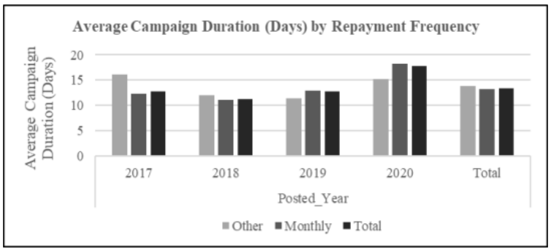

Figure G.2 - Average Campaign Duration by Repayment Frequency, Sample 1 (Source: Own Research)

Table G.3 - Average Campaign Duration by Borrower's Team, Sample 1 (Source: Own Research)

Average Campaign Duration by Borrower's Team	Posted_Year				
	2017	**2018**	**2019**	**2020**	**Total**
Group	12.78	11.25	10.61	17.69	12.65
Individual	12.77	11.22	12.96	17.71	13.47
Total	12.77	11.22	12.68	17.71	13.36

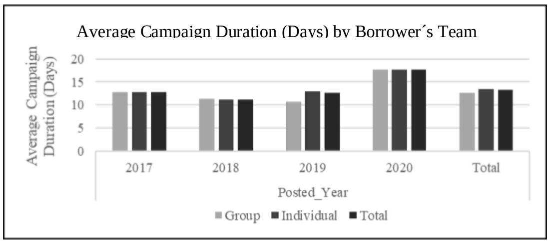

Figure G.3 - Average Campaign Duration by Borrower's Type, Sample 1 (Source: Own Research)

Table G.4 - Average Campaign Duration by Borrower´s Gender, Sample 1 (Source: Own Research)

Average Campaign Duration by Borrower's Gender	Posted_Year				
	2017	**2018**	**2019**	**2020**	**Total**
Other	16.36	14.7	14.6	19.55	16.11
Female	11.68	10.17	12.13	17.18	12.54
Total	12.77	11.22	12.68	17.71	13.36

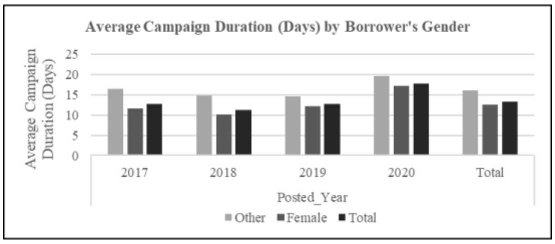

Figure G.4 - Average Campaign Duration by Borrower´s Gender, Sample 1 (Source: Own Research)

Table G.5 - Average Campaign Duration by Sector, Sample 1 (Source: Own Research)

Average Campaign Duration by Sector	Posted_Year				
	2017	**2018**	**2019**	**2020**	**Total**
Other	12.12	10.87	12.36	17.73	12.94
Agriculture	14.53	12.14	13.59	17.66	14.43
Total	12.77	11.22	12.68	17.71	13.36

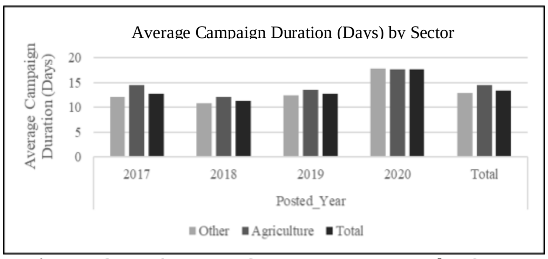

Figure G.5 - Average Campaign Duration by Sector, Sample 2 (Source: Own Research)

Appendix H - Frequencies of Categorical Variables in Sample 2

Table H.1 - Frequency Table of Description's Original Language from Sample 2 (Source: Own Research)

Frequency Table - Description's Original Language				
	Frequency	%	Valid %	Cumulative %
English	121938	71.1	71.1	71.1
Spanish	29017	16.9	16.9	88.0
French	13880	8.1	8.1	96.1
Russian	5447	3.2	3.2	99.3
Portuguese	1216	0.7	0.7	100.0
Total	171498	100.0	100.0	

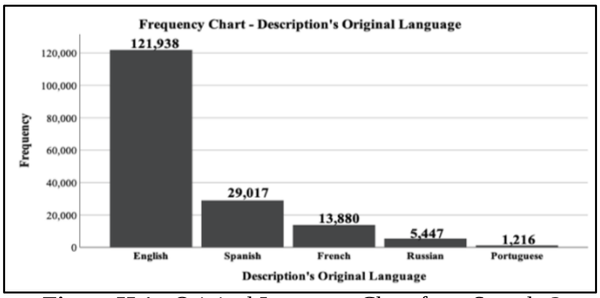

Figure H.1 - Original Language Chart from Sample 2 (Source: Own Research)

Table H.2 - Frequency Table of Borrower's Gender from Sample 2 (Source: Own Research)

Frequency Table - Borrowers' Gender				
	Frequency	%	Valid %	Cumulative %
Female	126134	73.5	73.5	73.5
Male	28678	16.8	16.8	90.3
Mixed Group	8199	4.8	4.8	95.1
Female Group	7940	4.6	4.6	99.7
Male Group	547	0.3	0.3	100.0
Total	171498	100.0	100.0	

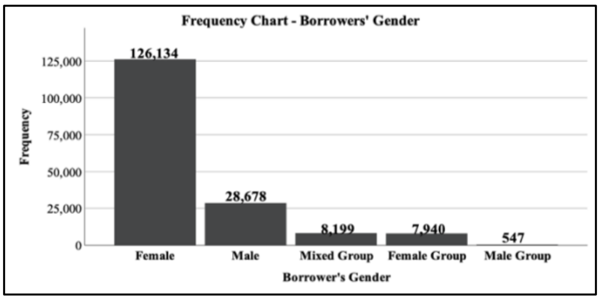

Figure H.2 - Borrowers' Gender Chart from Sample 2 (Source: Own Research)

Table H.3 - Frequency Table of Repayment Frequency from Sample 2 (Source: Own Research)

Frequency Table - Repayment Frequency				
	Frequency	%	Valid %	Cumulative %
Monthly	144176	84.1	84.1	84.1
Bullet	16511	9.6	9.6	93.7
Irregular	10811	6.3	6.3	100.0
Total	171498	100.0	100.0	

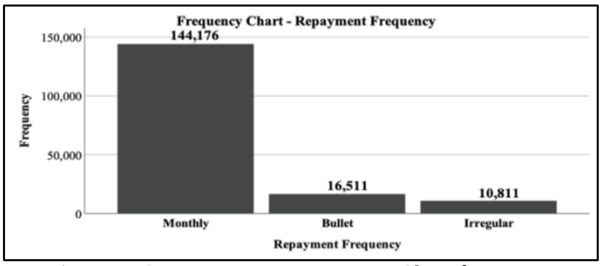

Figure H.3 - Repayment Frequency Chart from Sample 2 (Source: Own Research)

Table H.4 - Frequency Table of Sectors from Sample 2 (Source: Own Research)

Frequency Table - Sector				
	Frequency	%	Valid %	Cumulative %
Agriculture	55346	32.3	32.3	32.3
Food	38079	22.2	22.2	54.5
Retail	32788	19.1	19.1	73.6
Housing	8667	5.1	5.1	78.7
Services	7730	4.4	4.4	83.1
Clothing	7153	4.2	4.2	87.3
Personal Use	6502	3.8	3.8	91.1
Education	5370	3.1	3.1	94.2
Arts	2979	1.7	1.7	95.9
Health	2716	1.6	1.6	97.5
Transportation	1645	1.0	1.0	98.5
Construction	1288	0.7	0.7	99.2
Manufacturing	1057	0.6	0.6	99.8
Wholesale	92	0.1	0.1	99.9
Entertainment	86	0.1	0.1	100.0
Total	171498	100.0	100.0	

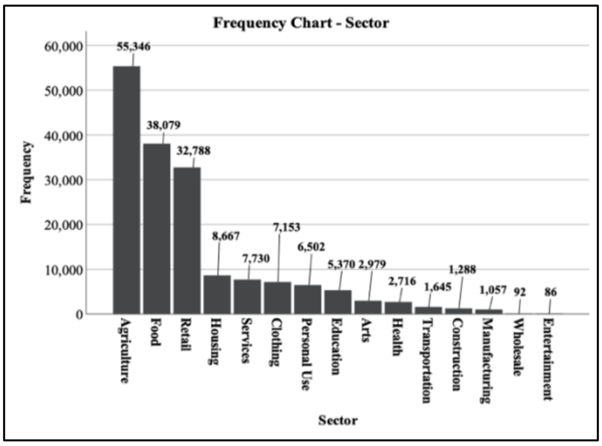

Figure H.4 - Sectors Chart from Sample 2 (Source: Own Research)

Table H.5 - Frequency Table of Countries in Sample 2 (Source: Own Research)

Country	Frequency	%	Cumulative %	Country	Frequency	%	Cumulative %
Philippines	52110	30.4	30.4	Tonga	911	0.5	92.3
Kenya	24275	14.2	44.5	Sierra Leone	850	0.5	92.8
Tajikistan	7584	4.4	49.0	Zambia	833	0.5	93.3
Ecuador	6681	3.9	52.9	Bolivia	828	0.5	93.8
Uganda	5795	3.4	56.2	Haiti	817	0.5	94.3
Cambodia	5740	3.3	59.6	Lesotho	793	0.5	94.7
El Salvador	5408	3.2	62.7	Mozambique	786	0.5	95.2
Nicaragua	5038	2.9	65.7	Egypt	783	0.5	95.7
Madagascar	4962	2.9	68.6	Costa Rica	770	0.4	96.1
Paraguay	3180	1.9	70.4	Fiji	727	0.4	96.5
Colombia	3072	1.8	72.2	Albania	672	0.4	96.9
Vietnam	2622	1.5	73.7	Pakistan	612	0.4	97.3
Togo	2600	1.5	75.3	Solomon Islands	608	0.4	97.6
Liberia	2520	1.5	76.7	India	566	0.3	98.0
Kyrgyzstan	2254	1.3	78.0	Georgia	533	0.3	98.3
Nigeria	2057	1.2	79.2	Moldova	487	0.3	98.6
Burkina Faso	1842	1.1	80.3	Brazil	462	0.3	98.8
Indonesia	1803	1.1	81.4	Mali	336	0.2	99.0
Rwanda	1769	1.0	82.4	Cameroon	244	0.1	99.2
Peru	1747	1.0	83.4	Malawi	233	0.1	99.3
Samoa	1670	1.0	84.4	Kosovo	204	0.1	99.4
The Democratic Republic of the Congo	1634	1.0	85.3	Thailand	192	0.1	99.5
Timor-Leste	1563	0.9	86.3	Turkey	179	0.1	99.6
Senegal	1448	0.8	87.1	Dominican Republic	176	0.1	99.7
Jordan	1318	0.8	87.9	Papua New Guinea	133	0.1	99.8
Honduras	1295	0.8	88.6	Nepal	99	0.1	99.9
Guatemala	1263	0.7	89.4	Panama	99	0.1	99.9
Palestine	1165	0.7	90.0	Vanuatu	75	0.0	100.0
United States	1019	0.6	90.6	Israel	45	0.0	100.0
Ghana	1017	0.6	91.2	Armenia	5	0.0	100.0
Mexico	989	0.6	91.8	Total	171498	100.0	100.0

Appendix I - Frequencies of Dummy Variables used in Regression 2

Table I.1 - Frequency Table of Description's Original Language Dummy from Sample 2 (Source: Own Research)

Frequency Table - Description's Original Language				
	Frequency	%	Valid %	Cumulative %
English	121938	71.10	71.10	71.10
Other	49560	28.90	28.90	100.00
Total	171498	100.00	100.00	100.00

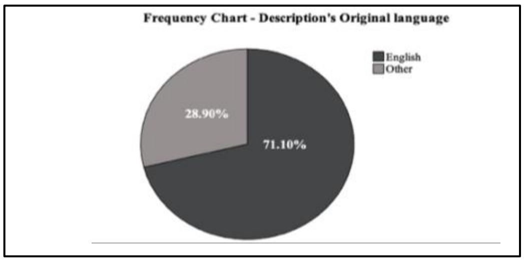

Figure I.1 - Original Language Dummy Chart from Sample 2 (Source: Own Research)

Table I.2 - Frequency Table of Repayment Frequency Dummy from Sample 2 (Source: Own Research)

Frequency Table - Repayment Frequency				
	Frequency	%	Valid %	Cumulative %
Monthly	144176	84.10	84.07	84.07
Other	27322	15.90	15.93	100.00
Total	171498	100.00	100.00	100.00

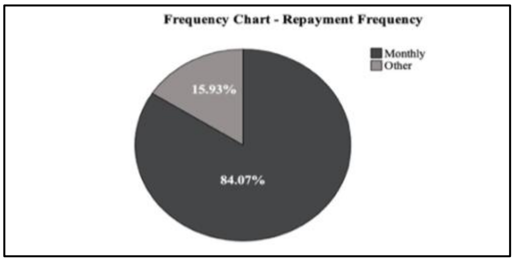

Figure I.2 - Repayment Frequency Dummy Chart from Sample 2 (Source: Own Research)

Table I.3 - Frequency Table of Sector Dummy from Sample 2 (Source: Own Research)

Frequency Table - Sector				
	Frequency	%	Valid %	Cumulative %
Agriculture	55346	32.30	32.27	32.27
Other	116152	67.70	67.73	100.00
Total	171498	100.00	100.00	100.00

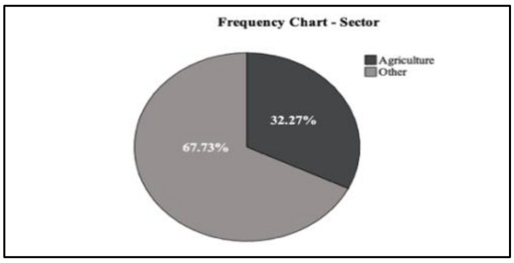

Figure I.3 - Sector Dummy Chart from Sample 2 (Source: Own Research)

Table I.4 - Frequency Table of Borrower's Gender Dummy from Sample 2 (Source: Own Research)

Frequency Table - Borrower's Gender				
	Frequency	%	Valid %	Cumulative %
Female	134074	78.20	78.18	78.18
Other	37424	21.80	21.82	100.00
Total	171498	100.00	100.00	100.00

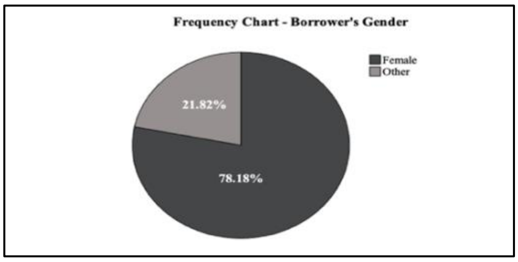

Figure I.4 - Borrower's Gender Dummy Chart from Sample 2 (Source: Own Research)

Table I.5 - Frequency Table of Borrowers' Team Dummy from Sample 2 (Source: Own Research)

Frequency Table - Borrowers' Team				
	Frequency	%	Valid %	Cumulative %
Individual	154812	90.30	90.27	90.27
Group	16686	9.70	9.73	100.00
Total	171498	100.00	100.00	100.00

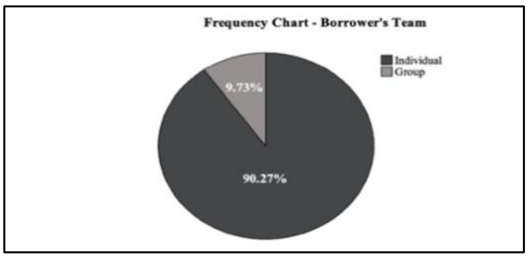

Figure I.5 - Borrowers' Team Dummy Chart from Sample 2 (Source: Own Research)

Appendix J - Independent Variables vs Dependent Variable (Sample 2)

Table J.1 - Average Campaign Duration by Original Language, Sample 2 (Source: Own Research)

Average Campaign Duration by Original Language	Posted Year
	2020
Other	19.22
English	19.53
Total	19.44

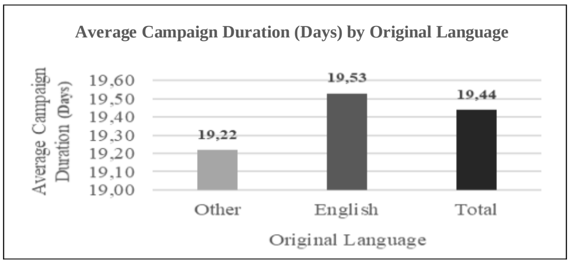

Figure J.1 - Average Campaign Duration by Original Language, Sample 2 (Source: Own Research)

Table J.2 - Average Campaign Duration by Repayment Frequency, Sample 2 (Source: Own Research)

Average Campaign Duration by Repayment Frequency	Posted Year
	2020
Other	16.07
Monthly	20.08
Total	19.44

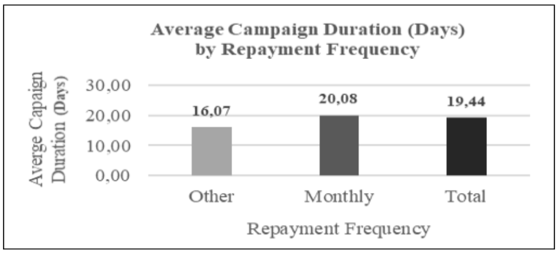

Figure J.2 - Average Campaign Duration by Repayment Frequency, Sample 2 (Source: Own Research)

Table J.3 - Average Campaign Duration by Borrower's Team, Sample 2 (Source: Own Research)

Average Campaign Duration by Borrower's Team	Posted Year
	2020
Group	18.63
Individual	19.53
Total	19.44

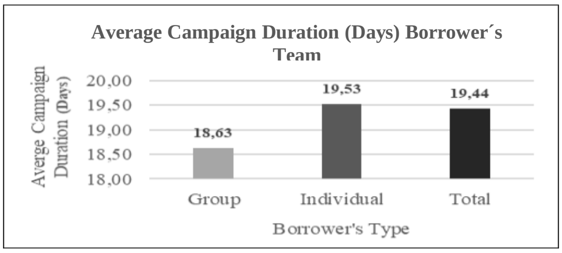

Figure J.3 - Average Campaign Duration by Sector, Sample 2 (Source: Own Research)

Table J.4 - Average Campaign Duration by Borrower's Gender, Sample 2 (Source: Own Research)

Average Campaign Duration by Borrower's Gender	Posted Year
	2020
Other	20.29
Female	19.20
Total	19.44

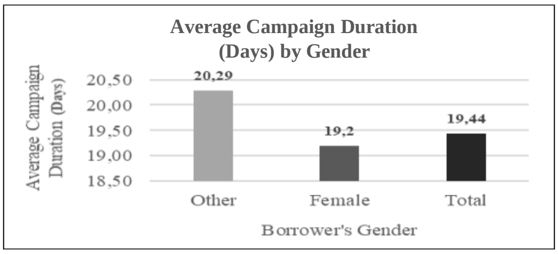

Figure J.4 - Average Campaign Duration by Borrower's Gender, Sample 2 (Source: Own Research)

Table J.5 - Average Campaign Duration by Sector, Sample 2 (Source: Own Research)

Average Campaign Duration by Sector	Posted Year
	2020
Other	19.58
Agriculture	19.14
Total	19.44

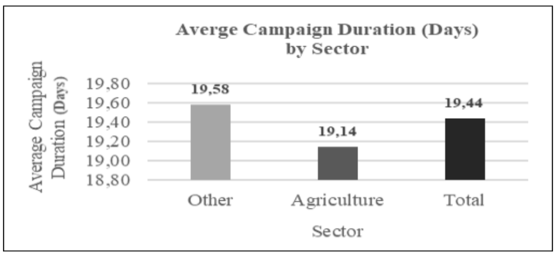

Figure J.5 - Average Campaign Duration by Borrower's Team, Sample 2 (Source: Own Research)

Appendix K - Assumptions Regression 1 Support Tables

Table K.1 - Linearity Test Applied to Continuous Variables from Sample 1 (Source: Own Research)

Linearity Test Applied to Continuous Variables from Sample 1									
Variables		ANOVA Test for Linearity				OLS (Linear Regression)			
Dependent Variable	Independent Variable	Linearity Test	P-value	Sig.	Remark	Linearity Test	P-value	Sig.	Remark
Campaign_ Duration	Target_ Amount_Ln	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	Loan_ Term	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	Description_ Size	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	Hashtags_ Num	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	HDI	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					

Table K.2 - Linearity Test Applied to Continuous Variables from Sample 1 & Dependent Variable as a Logarithm (Source: Own Research)

Linearity Test Applied to Continuous Variables from Sample 1 & Dependent Variable as a Logarithm					
Variables		ANOVA Test for Linearity			
Dependent Variable	Independent Variable	Linearity Test	P-value	Sig.	Remark
Ln_Campaign_Duration	Target_Amount_Ln	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	Loan_Term	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	Description_Size	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	Hashtags_Num	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	HDI	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	

Table K.3 - Pearson Correlation between Variables from Regression 1 (Source: Own Research)

Pearson Correlation (Regression 1)											
	Campaign _Duration	Target_ Amount_ Ln	Loan_ Term	Description _Size	Hashta_ Num	HDI	English	Rep. Monthly	Individual	Female	Agriculture
Campaign_ Duration	1	0.27	0.209	0.051	0.307	0.03	-0.069	-0.015	0.022	-0.12	0.054
Target_ Amount_Ln	0.27	1	0.267	0.227	0.433	0.188	-0.285	-0.078	-0.32	-0.146	0.006
Loan_Term	0.209	0.267	1	0.158	0.297	0.098	-0.006	-0.105	0.214	-0.061	0.058
Description_ Size	0.051	0.227	0.158	1	0.148	-0.157	0.021	-0.159	-0.114	-0.072	0.155
Hashtags_ Num	0.307	0.433	0.297	0.148	1	-0.026	-0.056	-0.147	-0.19	-0.165	0.058
HDI	0.03	0.188	0.098	-0.157	-0.026	1	-0.167	0.148	0.137	0.098	-0.062
English	-0.069	-0.285	-0.006	0.021	-0.056	-0.167	1	0.064	0.071	0.124	-0.008
Rep. Monthly	-0.015	-0.078	-0.105	-0.159	-0.147	0.148	0.064	1	0.2	0.286	-0.368
Individual	0.022	-0.32	0.214	-0.114	-0.19	0.137	0.071	0.2	1	0.222	-0.025
Female	-0.12	-0.146	-0.061	-0.072	-0.165	0.098	0.124	0.286	0.222	1	-0.151
Agriculture	0.054	0.006	0.058	0.155	0.058	-0.062	-0.008	-0.368	-0.025	-0.151	1

Table K.4 - Model Summary of Regression 1 (Source: Own Research)

Model Summary (Regression 1)									
R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
0.385	0.148	0.148	11.54958	0.148	13732.904	10	791523	0.000	1.974

Table K.5 - Standardized Coefficients of Regression 1 (Source: Own Research)

Coefficients (Regression 1)									
Unstandardized Coefficients			Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
Model	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
(Constant)	-8.476	0.147	-	-57.782	0.000	-8.764	-8.189	-	-
Target_ Amount_Ln	2.689	0.018	0.197	145.654	0.000	2.653	2.726	0.586	1.706
Loan_Term	0.14	0.002	0.071	59.442	0.000	0.135	0.145	0.751	1.331
Description_Size	-0.009	0	-0.033	-29.366	0.000	-0.01	-0.009	0.869	1.151
Hashtags_ Num	1.184	0.007	0.219	181.906	0.000	1.172	1.197	0.744	1.344
HDI	-3.76	0.151	-0.028	-24.877	0.000	-4.056	-3.463	0.85	1.177
English	-0.142	0.031	-0.005	-4.563	0.000	-0.204	-0.081	0.878	1.139
Rep.Monthly	2.151	0.044	0.058	48.557	0.000	2.064	2.238	0.761	1.314
Individual	4.474	0.046	0.121	98.141	0.000	4.385	4.564	0.712	1.404
Female	-2.545	0.033	-0.085	-76.494	0.000	-2.61	-2.479	0.862	1.16
Agriculture	1.392	0.031	0.05	44.383	0.000	1.331	1.454	0.847	1.181

Appendix L - Charts from Regression 1

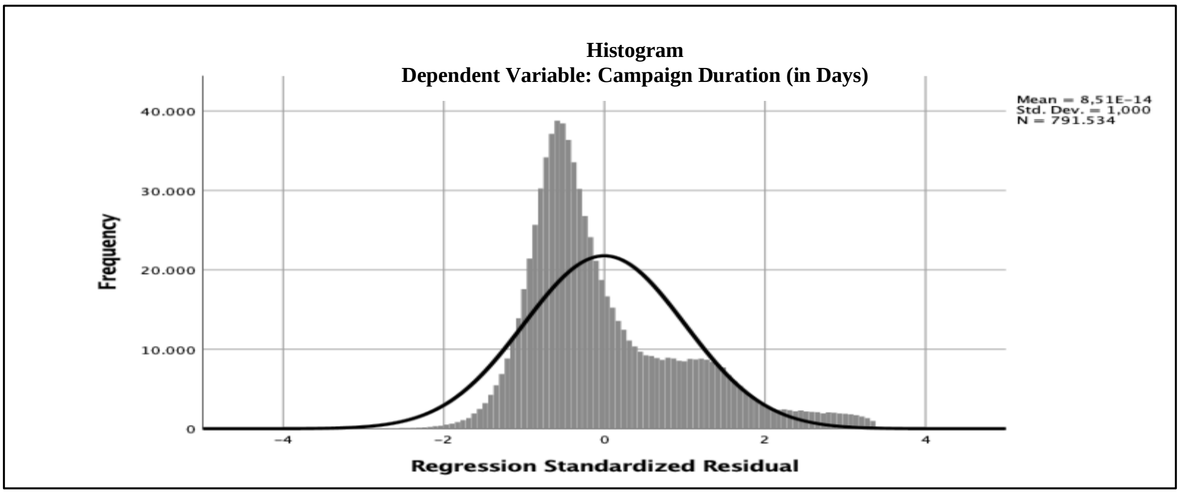

Figure L.1 - Histogram of Standardized Residuals of Regression 1 (Source: Own Research)

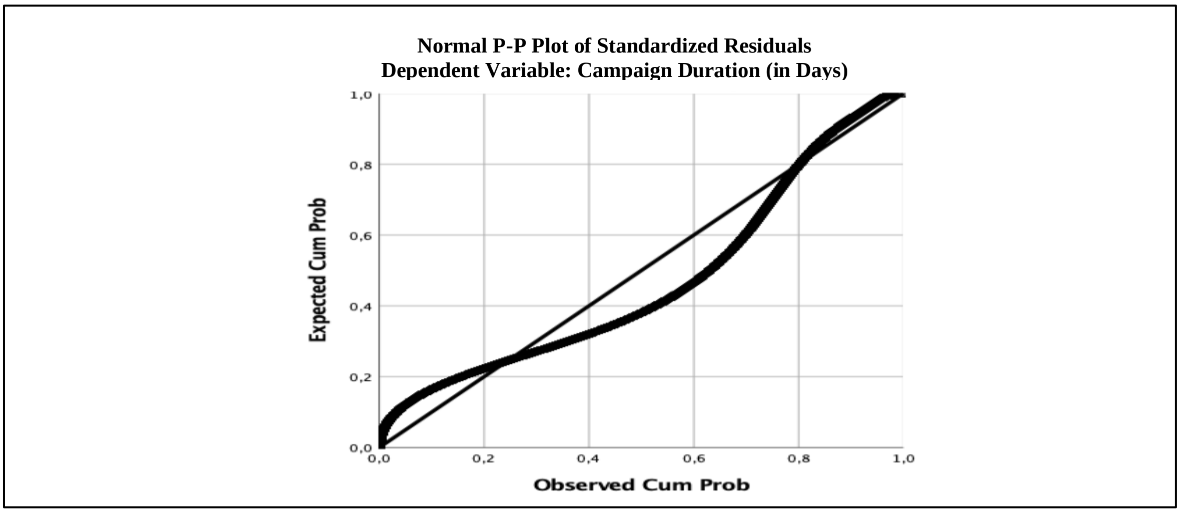

Figure L.2 - Normal P-P Plot of Standardized Residuals from Regression 1 (Source: Own Research)

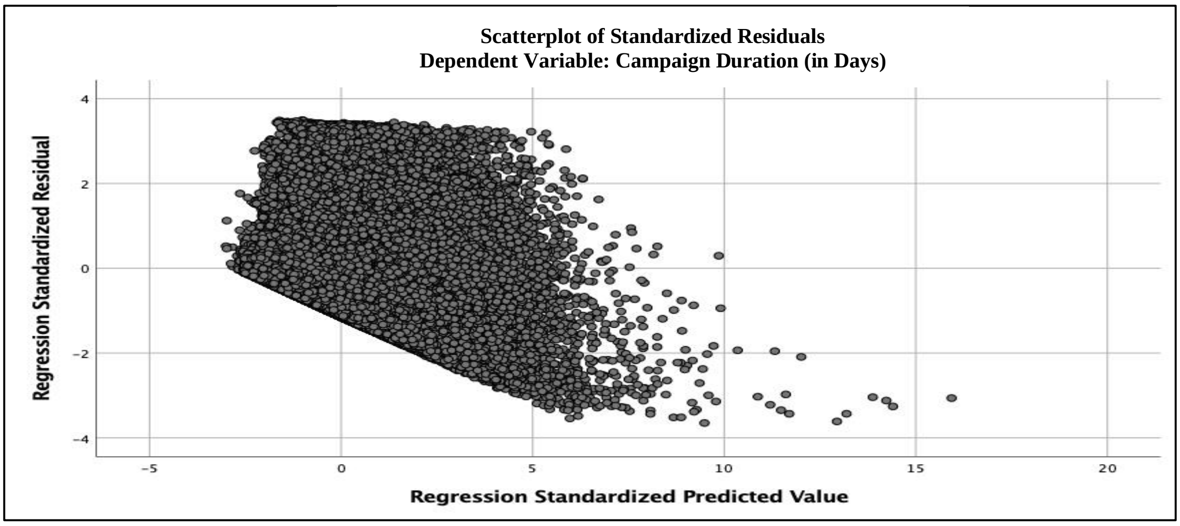

Figure L.3 - Scatterplot of Standardized Residuals from Regression 1 (Source: Own Research)

Appendix M - Regression 2 Support Tables

Table M.1 - Linearity Test Applied to Continuous Variables from Sample 2 (Source: Own Research)

Linearity Test Applied to Continuous Variables from Sample 2									
Variables		ANOVA Test for Linearity				OLS (Linear Regression)			
Dependent Variable	Independent Variable	Linearity Test	P-value	Sig.	Remark	Linearity Test	P-value	Sig.	Remark
Campaign _ Duration	Target_Amount_Ln	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	Loan_Term	Linearity	0.000	<0.01	Odd Result	OLS	0.223	>0.01	Not Linear
		Deviation from Linearity	0.000	<0.01					
	Description_Size	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	Hashtags_Num	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					
	HDI	Linearity	0.000	<0.01	Odd Result	OLS	0.000	<0.01	Linear
		Deviation from Linearity	0.000	<0.01					

Table M.2 - Linearity Test Applied to Continuous Variables from Sample 2 & Dependent Variable as a Logarithm (Source: Own Research)

Linearity Test Applied to Continuous Variables from Sample 2 & Dependent Variable as a Logarithm					
Variables		ANOVA Test for Linearity			
Dependent Variable	Independent Variable	Linearity Test	P-value	Sig.	Remark
Ln_Campaign_Duration	Target_Amount_Ln	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	Loan_Term	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	Description_Size	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	Hashtags_Num	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	
	HDI	Linearity	0.000	<0.01	Odd Result
		Deviation from Linearity	0.000	<0.01	

Table M.3 - Pearson Correlation between Variables from Regression 2 (Source: Own Research)

Pearson Correlation (Regression 2)											
	Campaign _Duration	Target_ Amount_ Ln	Loan_ Term	Description _Size	Hashtag_ Num	HDI	English	Rep. Monthly	Individual	Female	Agriculture
Campaign_ Duration	1	0.164	0.092	-0.027	0.285	0.161	0.008	0.083	0.015	-0.025	-0.012
Target_ Amount_Ln	0.164	1	0.338	0.306	0.49	0.122	-0.297	-0.062	-0.344	-0.144	-0.041
Loan_Term	0.092	0.338	1	0.185	0.299	0.052	-0.039	-0.173	0.156	-0.115	0.045
Description_ Size	-0.027	0.306	0.185	1	0.19	-0.116	-0.05	-0.205	-0.242	-0.118	0.145
Hashtags_ Num	0.285	0.49	0.299	0.19	1	0.015	-0.119	-0.118	-0.176	-0.163	0.033
HDI	0.161	0.122	0.052	-0.116	0.015	1	-0.049	0.2	0.088	0.174	-0.114
English	0.008	-0.297	-0.039	-0.05	-0.119	-0.049	1	0.049	0.163	0.135	0.024
Rep. Monthly	0.083	-0.062	-0.173	-0.205	-0.118	0.2	0.049	1	0.208	0.31	-0.331
Individual	0.015	-0.344	0.156	-0.242	-0.176	0.088	0.163	0.208	1	0.243	-0.029
Female	-0.025	-0.144	-0.115	-0.118	-0.163	0.174	0.135	0.31	0.243	1	-0.153
Agriculture	-0.012	-0.041	0.045	0.145	0.033	-0.114	0.024	-0.331	-0.029	-0.153	1

Table M.4 - Model Summary of Regression 2 (Source: Own Research)

Model Summary (Regression 2)									
R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
0.351	0.123	0.123	16.62425	0.123	2406.351	10	171487	0.000	1.982

Table M.5 - Standardized Coefficients of Regression 2 (Source: Own Research)

Coefficients (Regression 1)									
Unstandardized Coefficients			Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
Model	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
(Constant)	-12.913	0.461		-28.029	0.000	-13.816	-12.01		
Target_ Amount_Ln	1.126	0.056	0.062	20.017	0.000	1.015	1.236	0.54	1.85
Loan_Term	-0.009	0.007	-0.004	-1.357	0.175	-0.023	0.004	0.722	1.386
Description_ Size	-0.025	0.001	-0.061	-24.423	0.000	-0.027	-0.023	0.825	1.213
Hashtags_ Num	2.114	0.02	0.283	106.628	0.000	2.076	2.153	0.728	1.373
HDI	25.839	0.458	0.134	56.364	0.000	24.94	26.737	0.901	1.109
English	2.218	0.094	0.057	23.667	0.000	2.035	2.402	0.893	1.12
Rep.Monthly	4.445	0.127	0.092	35.078	0.000	4.197	4.694	0.749	1.335
Individual	2.568	0.162	0.043	15.831	0.000	2.25	2.886	0.697	1.434
Female	-1.859	0.107	-0.043	-17.427	0.000	-2.068	-1.65	0.83	1.205
Agriculture	1.127	0.092	0.03	12.236	0.000	0.947	1.308	0.869	1.151

Appendix N - Charts from Regression 2

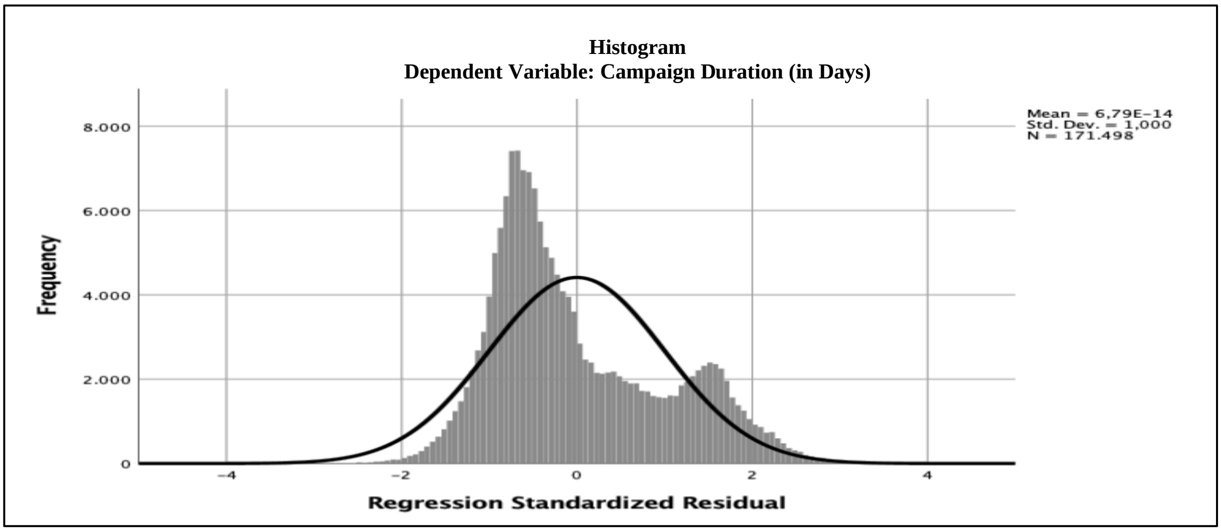

Figure N.1 - Histogram of Standardized Residuals of Regression 2 (Source: Own Research)

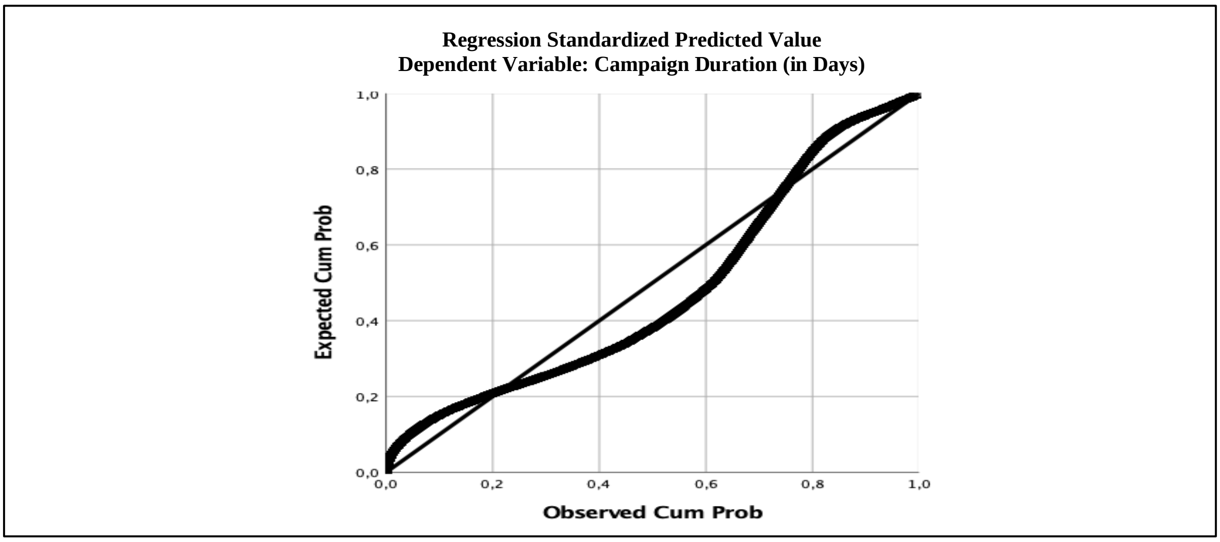

Figure N.2 - Normal P-P Plot of Standardized Residuals from Regression 2 (Source: Own Research)

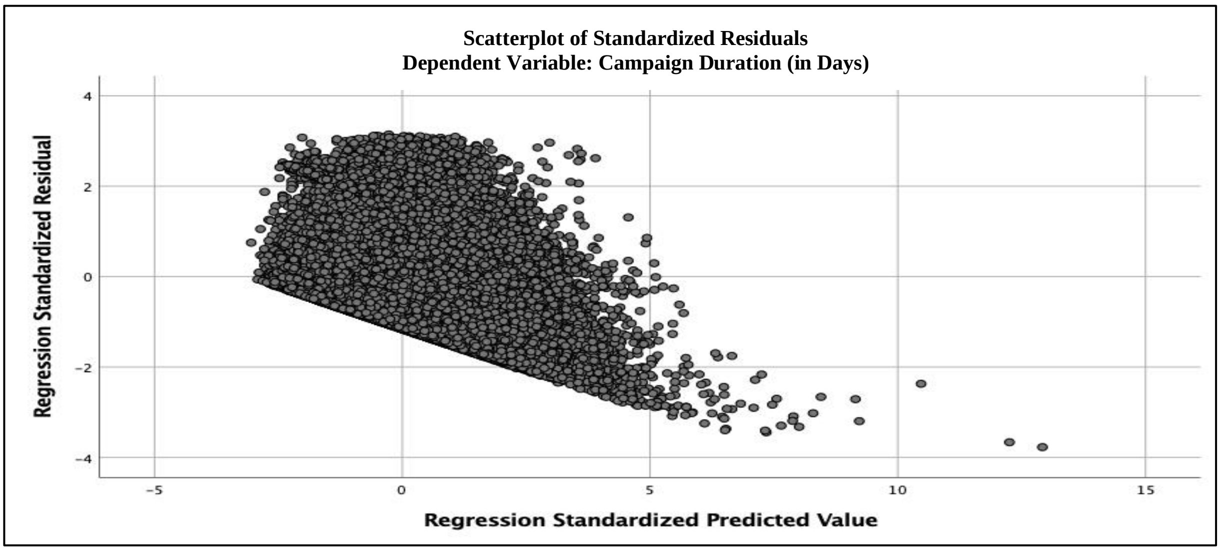

Figure N.3 - Scatterplot of Standardized Residuals from Regression 2 (Source: Own Research)

Appendix O - White Test for Heteroscedasticity Detection

Table O.1 - White Test for Heteroscedasticity Detection applied to Regression 1 (Source: Own Research)

White Test for Heteroscedasticity Detection – Regression 1		
Chi-Square	df	Sig.
52596.547	60	0.000

Table O.2 - White Test for Heteroscedasticity Detection applied to Regression 2 (Source: Own Research)

White Test for Heteroscedasticity Detection – Regression 2		
Chi-Square	df	Sig.
27604.397	60	0.000