GUARANTEED CROWDLENDING LOANS: A TOOL FOR ENTREPRENEURIAL FINANCE ECOSYSTEM SUSTAINABILITY

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Abstract

Crowdlending is a disruptive financial tool that has been increasingly requested by SME's to cover their capital needs. However, the growth of this technological development is being limited by the existing risk of default resulting in loss for lenders. To deal with this, funding platforms have started to offer more sustainable products such as the guaranteed loans. These special loans are backed by a Mutual Fund so Lenders minimise the risk of suffering the consequences of a default. This study aims to investigate the importance of factors related to loan characteristics, investor type and borrower's characteristics, in the crowdlending campaign success. To perform the analysis, we use Partial Least Squares (PLS) technique over a sample of 196 guaranteed loans from the pioneer platform in Spain offering that type of loans (MytripleA). Results indicate that the characteristics with greater influence in guaranteed crowdlending success are those related to the investors and the loans, while SME's factors seem not to have any impact. We consider that our results are interesting for both the funding platforms and the SME's seeking for funds.

Keywords: disruptive technologies, SME's, crowdlending, Peer-to-Business (P2B), guaranteed loans, success factors, Partial Least Squares (PLS).

JEL Classification: G23, G41, O33, Q55.

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Introduction

In the current digital economic context, it is significant to provide sustainable and innovative financial mechanisms to encourage the development of technologies (Veselovsky et al., 2018). Thus, digitalization context is forcing organizations to evaluate, innovate and adapt their business models (Bharadwaj et al., 2013). In particular, any amount of emerging digital innovations is taking place in the financial services industry. Experts attribute a fundamental impact on the industry to the new financial technology companies (Fintech) and blockchain technology (Beck et al., 2016; Dorfleitner and Braun, 2019). Fintech and blockchain facilitate access to new sources of financing and investment, operate in decentralized systems, avoid traditional intermediaries, reduce costs and inefficiencies, expand the number of private investors and address emerging customer demands by developing innovative solutions (Christensen 2013; Dorfleitner and Braun, 2019). The author Brett (2016) suggested that blockchain-based organizations should be explored as potential facilitators for building social finance. For this reason, crowdlending (or peer-to-peer lending) platforms have been called "natural candidates" for taking advantage of the blockchain infrastructure. It could replace financial intermediate services (Glaser, 2017).

In this line, Alternative Finance Markets have increased their volumes dramatically in recent years, due to the development of new technologies together with credit constraints. Latest Cambridge Centre of Alternative Finance report (Ziegler et al., 2019) points out that its total volume worldwide was around 370 billion euros.

The same report shows that crowdlending, Peer-to Peer (P2P) and Peer-to-Business (P2B), lead this market. Specifically, P2B crowdlending is playing a key role as an alternative financing for SME's fulfilling their capital needs to grow up their operations (Astrauskaitė and Paškevičius, 2018). Thus, replacing traditional financial intermediaries (Lehner, 2013).

Crowdlending will be used to refer to a form of community financing carried out in the form of loans from the lenders: the platform operator connects individuals or companies who wish to borrow funds from third parties, who are not banks or financial intermediaries (Schneuwly, 2014). Therefore, Crowdlending depends on the interaction of three entities: lenders or founders, borrowers and internet-based platforms (Belleflamme, Omrani and Peitz, 2015). Later, Lenz (2016) and Wonglimpiyarat (2018) defined the term as commercial version of debt Crowdfunding, which operates through an internet-based platform that acts as an intermediary and manages small investments that help finance a larger loan for companies or individuals. In exchange, lenders receive more interest in their investment.

There are several reasons that explain the success of crowdlending. On the one hand crowdlending drives borrowers to obtain credit with lower interest rates, raise funds rapidly, and without having to provide strong guarantee that would likely be requested by their trusted bank (Pignon, 2017). On the other hand, crowdlending platforms lead lenders to better investment returns than in a bank deposit (Lin, Prabhala and Viswanathan, 2013). It also allows individual lenders to combine their investments to finance various projects (Bruton et al., 2015).

In addition, crowdlending is considered a sustainable investment option with social and financial returns (Schweizer et al., 2017). The development of social conscience has also

been added, by sharing and making the available resources more efficient, which has generated a whole stream of the collaborative economy in which crowdfunding is framed.

However, the main weakness that crowdlending platforms have to face is the risk of borrower default resulting in the loss of lenders' investments. To deal with this, some platforms are guaranteeing repayment of principal and interest depending on their own liquidity or through a guarantee fund (Ahern, 2018). As a result, a new type of crowdlending is emerging and due to its novelty no empirical research studies have been found by the authors about guaranteed crowdlending loans (GCL). This type of crowdlending is characterised by having guarantees of refund of investors' capital, generating major confidence among investors who do not know very well the platform or associated projects.

One of the more significant research topics in crowdlending has been to identify the key factors of success for a loan request. This topic has been broadly researched in P2P and, in a less extent, in P2B. Among others, some of the factors conditioning lender decision pointed out by other authors are trust in the borrower (Han et al., 2108), herd behaviour (Liu and Zang, 2012), geographical proximity to the borrower (Lin and Viswanathan, 2016) and loan characteristics (Feng et al., 2015). However, there are several features in GCL that make necessary new research focused on it. For instance, borrower solvency is not a main point to consider in this particular case as the investment is guaranteed by a Mutual Fund. Neither, interest rate is relevant because in this model that rate use to be fixed as we will explain next in platform description subsection. So, under this new circumstance potential investors should choose which projects to finance based on other characteristics than interest rate or credit scoring, factors traditionally identified as key to the success of the projects (Yum, Lee, and Chae, 2012).

The aim of this paper is to identify which factors drive investors to choose the project they will support for GCL in order to better understand the decision making process of lenders in the use of this disruptive tool. To do so, we propose a model based on characteristics such as: the investors' professionalism, the loan's amount and term and the SME's expertise as crowdlending borrowers. To perform the analysis, we use Partial Least Squares (PLS), a technique of structural equation models based on variance (Roldán and Sánchez-Franco, 2012). To apply this model, we have compiled a sample of 196 SME's financed with guaranteed loans. The data has been obtained from MytripleA, which is the only crowdlending platform that offers GCL in Spain since 2015.

The rest of the paper is organised as follows: a theoretical background is introduced together with our research hypotheses follow by a brief methodological approach. The paper concludes with a discussion and conclusion section over the empirical results which will be set previously.

1. Review of the scientific literature and hypotheses development

Most of the studies based on crowdlending have been focused on P2P (Gao, Yu and Shiue, 2018; Nowak, Ross and Yencha, 2018; Yan, Lv and Hu, 2018). However, there is a paucity of research that examines the effects or role of P2B lending. The reason behind may be in its popularity and so in the data available. In 2017, P2P lending was again the most popular crowdfunding investment model in Europe. P2P consumer and business lending accounted

for 41% (€1.392 million) and 14% (€466.60 million), respectively of the total crowdfunding market. (Ziegler et al., 2019). Therefore, to study key factors in crowdlending success, it is necessary to consider also the P2P literature even if our study is based on P2B. In addition, authors who have identified some factors, P2B or P2P, use to do it in an isolated manner.

However, Moreno-Moreno, Berenguer and Sanchís-Pedregosa (2018) propose a theoretical framework identifying several types of success factors in crowdlending. To do so, the authors conduct a literature review on the field from 2011 to 2018. Their model identifies 10 success factors for crowdlending success. To perform our research, we have adapted that theoretical and general model to the Guaranteed Credit Loans (GCL) offered by the Spanish platform MytripleA. Despite the benefits of crowdlending, information asymmetry has been considered to be an important problem, as it affects the market's efficiency (Agrawal, Catalini and Goldfarb, 2014). Adhami, Gianfrate and Johan (2019), aware of this problem, conduct a study trying to evidence if the returns offered by crowdlending loans are consistent with their risks. For a dataset of 3,000 loans mediated on 68 European platforms, the authors show that the returns are inversely related to loan's riskiness. These authors even claim that the crowdfunding business model is not sustainable due to the high risk lenders assume. In this sense, guaranteed products such as the GCL offer great advantages for practitioners since they minimise one of the most important risks in crowdlending.

To alleviate those market inefficiencies, potential funders focus on a series of factors used as indicators to decide which crowdlending project to support. The loan characteristics have been traditionally identified as essential elements determining investment decisions because they are major determinants of the profit to be generated by the investment. There is a consensus on the impact that interest rates and credit ratings have in crowdlending success (Yum, Lee and Chae, 2012). In this sense, Cumming and Hornuff (2017), one of the few papers based on P2B crowdlending, demonstrated that the credit rating offered by the platform plays a key role in funding success. Despite these results, in our study, we will not consider either the interest rate or the credit rating when defining our model because all the guaranteed loans (GCL) in our sample offer the same return for investors and consequently have the same rating. We consider this is an opportunity to analyse in greater depth other factors that have been overshadowed continuously by ratings and interest rates like, for example, loan term and loan amount.

Loan term has also been identified as a critical factor for potential investors. Related to loan term, Lin et al. (2013) pointed out that lenders use to prefer shorter periods in order to recover their money as soon as possible due to it drive better liquidity of their investment. In this line, the size of the loan request can also determine its attractiveness since many lenders would prefer small loans to large loans for risk management purposes (Feng, Fan and Yoon, 2015).

The second group of factors are compiled as borrower's characteristics. Borrowers in seek of funds use to drive their efforts to show an image of solvency in order to get their loans requests completed rapidly. To do that, they try to describe their company accurately offering as much relevant information as possible, so it seems to be a success factor (Dorfleitner et al., 2016). Following this idea, Lin, Prabhala and Viswanathan (2013) find that an extensive loan description with shorter sentences has a positive effect on funding success. Nevertheless, Dorfleitner et al. (2016) demonstrated an inversely u-shape impact; this means that too short

or too long texts decrease the probability that a loan is funded. For a sample of 590,000 loan listing P2P in China (Renrendai.com), Han et al. (2018) found that borrowers who use a longer sentence in loan description were less likely to be successful.

Additionally, to ensure their trustworthy appearance (Duarte, Siegel and Young, 2012) it has been pointed out that is key that borrowers share information like company size or their expertise in other campaigns (Feng, Fan and Yoon, 2015) with potential lenders. Borrowers with more experience in online borrowing are in a better position to design loans more efficiently. Nevertheless, for a dataset of 14,537 small American firm loan applications Kgoroedira, Burke and Van Stel (2019) find that lenders ignore business characteristics and focus on personal characteristics instead.

Finally, there are some lender" s factors influencing crowdlending success. Among them, previous authors have typically identified herd behaviour (Luo and Lin, 2013) or geographical proximity to the borrower (Lin and Viswanathan, 2016) as the most important. However, to differentiate between professional and individual (retail) investors have been highlighted as a point to study more closely due to their different criteria, choosing a project to invest considering financial a non-financial information. The type of investor for crowdlending determines how investment decisions are made. Professional investors seem to face the information asymmetries of the market better. As a result, they have theoretically advantage in making lending decisions (De la Torre, Pería and Schmukler, 2010). The inferior investment performance of individual retail investors compared to professional is documented (Barber and Odean, 2013; Cummins et al., 2018) For a dataset of loans from Funding Circle Platform in the period 2014-2016, Cummins et al. (2018) observe notable differences between the profile and performance of loans invested in by professional and retail investors.

Summarizing the above, there are many studies that have focused on factors that can affect the success of a crowdlending campaign. This study contributes to literature in several ways. First, it extends the research on the success factors by considering a specific sample of guaranteed loans (GCL). As far as we are concerned, there is no empirical evidence for a sample of guaranteed loans. The use of this sample is important because by removing credit ratings from our analysis we will have the opportunity to focus on other factors much less studied. Second, together with the loan's and the borrower's characteristics, we have included the type of investor in our model. With this idea we want to start exploring the role of the investor together with the key factors of crowdlending success.

2. Research methodology

2.1. Hypotheses development

Crowdlending depends on the interaction of three entities: borrowers, funders (investors) and platforms. The investors, once they registered the platform, have access to information on all project seeking for funds. This information is conditioning the investor's decisions making a project more or less attractive. Literature has identified different sets of information, but mainly it can be reduced to loan's and borrower's characteristics.

Likewise, factors such as the loan characteristics and the borrower's characteristics will affect the type of investor of the different projects. This is one of the ideas we want to explore in our study with our hypotheses. Because of that, we wonder if the loan and

borrower's (company) characteristics determine the type of investor. For this study, this construct refers to the proportion of professional investors since we have measured it the ratio professional investors/total investors). We are also interested in analysing if the type of investor mediates the relationship with both factors.

The aim of this paper is, for GCL, to explore the factors that drive investors to choose the project they will support. All of the projects that we consider in our sample have been successfully funded although not all have obtained the funds just as quickly nor have them been financed by the same number of investors. So, what we do is to measure the degree of attractiveness using the average investment computed as the ratio of the total funds raised divided by the number of investors (For this variable we follow Bento, Gianfrate and Groppo, 2019) and the funding days. Traditionally, funding success has been measured by using a binary variable that takes the value of either 1, when the fund goal is reached, or 0 when the funding goal is not reached (Han et al., 2018).

In line with the above, our conceptual model is shown in (figure no. 1), together with the following hypotheses:

- H1(-): The characteristics of the loan influence the success of the crowdlending campaign
- H2(+): The characteristics of the borrowers influence the success of the crowdlending campaign
- H3(+): The characteristics of the loan have influence on the type of investor.
- H4(+): The characteristics of the borrowers have influence on the type of investor.
- H5(+): The type of investor influences the success of the crowdlending campaign
- H6 (+): Investor type mediates the relationship between loan characteristics and crowdlending campaign success
- H7 (+): Investor type mediates the relationship between Borrower's characteristics and crowdlending campaign success
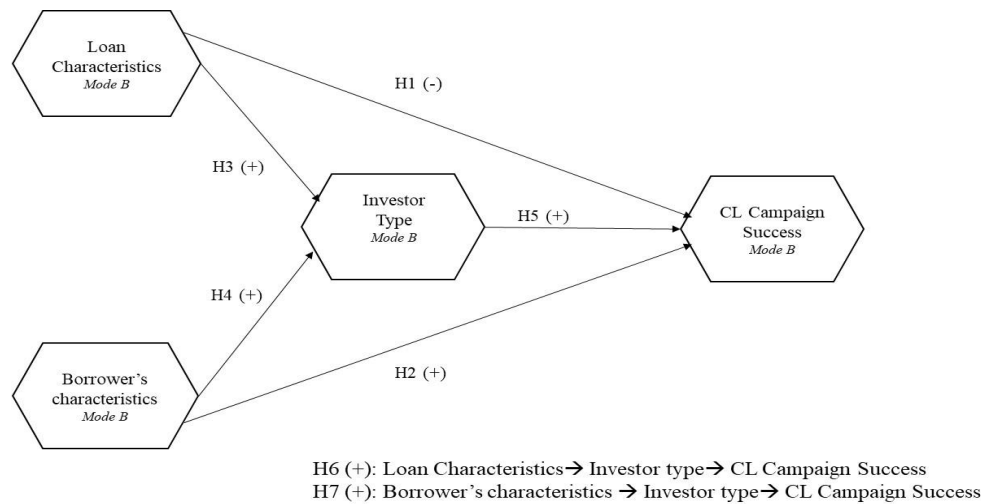

H6 (+): Loan Characteristics→ Investor type→ CL Campaign Success
H7 (+): Borrower's characteristics → Investor type→ CL Campaign Success

Figure no. 1. Model and hypotheses

Source: Own elaboration

2.2. Platform description

Data have been collected from MytripleA, a leading P2B lending platform in Spain. MytripleA was founded in 2013 in order to create a marketplace where companies can obtain financing directly from private investors. To date, this P2B platform has intermediated 1,400 loans for a total amount of 73,700,000 euros. This success in the Spanish market is based not only in having been one of the pioneer P2B lending platforms but also in having been the first to offer guarantee crowdlending loans.

The Guaranteed Crowdlending Loan has the advantage of having the guarantee of a Mutual Fund that covers 100% of the invested capital and ordinary interests. All investors for this product receive a 2% return, which is an attractive yield considering the current level of interest rates. That explains the popularity of this type of loan. The minimum amount to invest is 50 euros and the interests are paid on a monthly basis. For the purpose of our study, it is also a very interesting product because it allows us to focus on loan characteristic's different from credit rating or interest rates. As far as we are concern there have been no crowdfunding studies based on guaranteed loans.

2.3. Data collection, sample and measures

A secondary database of companies that have sought funding through a Crowdfunding platform, MyTripleA, has been employed. The database consisted of 769 companies, but companies seeking financing to pay for their circulation have been eliminated. Therefore, a final sample of 196 companies has been available.

We use the tool G*Power 3.1 to confirm the adequacy of the sample size (Erdfelder et al., 2009). The analysis test a priori evidences that, to obtain a power of 0.95, being alpha 0.05 and 3 being the number of predictors (Loan characteristics, borrower's characteristics and type of investor), a minimum sample size of 70 cases is required. Thus, the final sample (n=196) meets the initial sample size requirements (see (figure no. 2)).
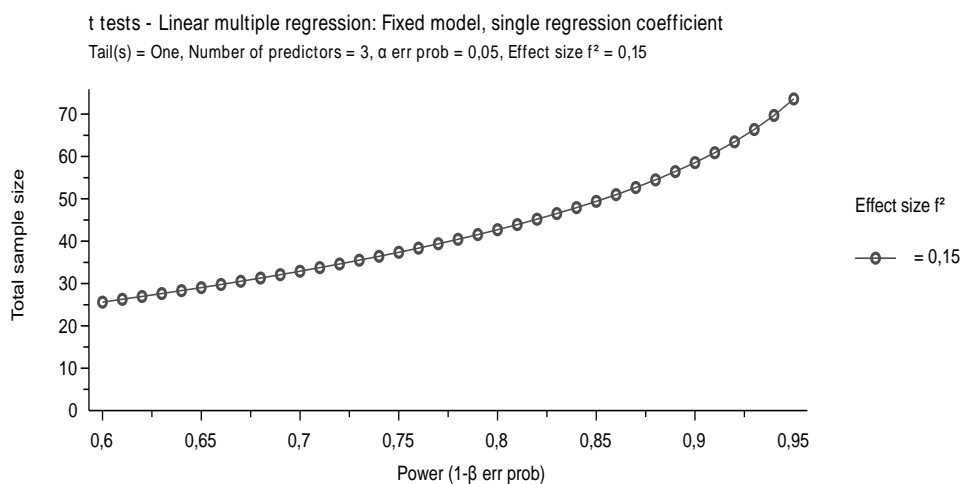

Figure no. 2. A priori power analysis plot
*Source: G*Power 3.1*

The constructs used in this work are: Borrower's characteristics, loan characteristics, type of investor, Crowdlending campaign success. These variables are composed of the following indicators: Borrower's characteristics: Borrowers expertise, Number of employees (Size) and Breadth of description (Info offered in the platform).

- Loan characteristics: Loan Term and Loan Amount
- Type of Investor: Type of investor
- Crowdlending campaign success: Average ticket and funding period

It should be noted that some items of the loan characteristics construct are constant such as: 2% interest rate, the rating will be Mutual Fund, and the monthly repayment rate. Thus, the characteristics of the loan that we are going to study are term and amount.

Among all the variables, loan term, loan amount and funding period has been calculated directly while average ticket and type of investor have been calculated indirectly. The average ticket item has been calculated using the quotient between the loan amount and the number of investors. And to calculate the type of investor, the number of accredited investors was divided by the total number of investors to obtain the percentage or proportion.

Next, the table no.1 shows the main descriptive statisticians of the items.

Table no. 1. Descriptive statistics

	Mean	Min	Max	Standard Deviation	Kurtosis	Skewness
Loan term (days)	1,487.00	365	2.922	401.55	-0.01	0.42
Loan Amount (euros)	116,345.66	10.000	736.000	100,025.22	9.477	2.43
Funding period (days)	231.90	-58	2.296	408.89	10.63	3.14
Average ticket (unit)	31,568.14	435	400.000	65,688.96	9.90	3.04
Type of investor (%)	35.91	0	100	25.79	0.51	-0.63
Description (Unit-Number of characters)	874.00	30	2.978	400.82	6.80	2.01
Number of employees (unit)	26.10	0	285	40.40	19.34	3.91
Expertise (unit)	1.27	1	4	0.62	7.43	2.68

Source: Own elaboration

2.4. Data analysis

The hypotheses proposed in this study have been tested using the Partial Least Squares (PLS) tool, a technique of models of structural equations based on variance (Roldan and Sanchez-Franco, 2012; Richter et al., 2016)). This technique is used to analyse complex interrelationships that involve a wide range of variables and indicators, whether direct, indirect mediators or moderators (Hair et al., 2017).

The PLS technique allows simultaneous evaluation of the reliability and validity of the measures of the theoretical constructs (outer model), as well as the estimation of the relationships between these constructs (inner model) (Barroso, Cepeda and Roldán, 2010). The use of the PLS methodology is justified for the following reasons: (1) the present study is oriented towards the prediction of the key or dependent variable (Chin, 2010); (2) our research model is complex, both for the type of variables it contains and for the

hypothesised relationships (in this study we will analyse 5 direct relationships and 2 mediations); and (3) the model uses variables modelled as compounds (composite constructions) and estimated in Mode B (regression weights). To test the model, the "SmartPLS 3.2.7" software, developed by Ringle, Wende and Becker (2015).

3. Results

In general, a study using the PLS methodology contains two clearly differentiated sections:

• Analysis of the measurement model to determine whether indicators (manifest variables) correctly measure constructs (latent variables).

• Analysis of the structural model to determine if the hypothesised relationships between the constructs are significant.

In addition, we will incorporate a complementary analysis, Importance Performance Map Analysis (IPMA), to know which constructs and items are most important and have the best performance when determining an objective construct.

3.1. Measurement model

In the measurement model, it is necessary to analyse first the weights of the items or variables manifested at the time of forming the constructs and the potential multicollinearity. Weights offer evidence on how each of the indicators contributes to the respective composite (type of construct, loan characteristics, borrower characteristics, Crowdlending campaign success), allowing that each indicator is classified according to their contribution (Hair et al., 2014). Note that the items 'funding period' and 'description' have negative weights. The items with the highest weights are type of investor, loan amount and average ticket.

On the other hand, it is necessary to verify that there are no multicollinearity problems. To this end, it must be verified that the Variance Inflation Factor (VIF) is below 3.3 (Petter, Straub and Rai, 2007) and 5.0 (Ringle, Wende and Becker, 2015). Multicollinearity could be a concern if VIF levels exceed the critical levels indicated. In our case, all items have a VIF below this critical level, which leads us to affirm that there are no multicollinearity problems (table no. 2).

Table no. 2. Measurement model

Construct/item	Weight	VIF
Type of investor		
Type of investor	1.000	1.000
Loan characteristics		
Loan term	0.458	1.001
Loan amount	0.877	1.001
Borrower characteristics		
Expertise	0.997	1.037
Description	-0.212	1.036
Number of employees (Size)	0.275	1.010
Crowdlending campaign success		
Funding period	-0.156	1.010
Average ticket	1.004	1.010

Source: Own elaboration

3.2. Structural model

Once the measurement model has been analysed and validated, the structural model is evaluated (see (table no. 3)). For it, a bootstrapping (5000 resamples) technique was used to generate the standard errors, t-statistics, p-values and 95% bias corrected confidence intervals (BCCI) that enable the assessment of the statistical significance for relationship raised in this study (Hair et al., 2014).

First of all, we must analyse the explained variance of the endogenous variables through the level of R^2. The value of $R^2_{success}$ fulfils the criterion of Falk and Miller (1992) because overcome the minimum value of 0.10, which indicates that with this value the model reaches an adequate level of explanatory power. In contrast, the value of $R^2_{investortype}$ does not meet it.

As previously commented, (table no. 4) shows the results of the significance analysis for the research hypotheses posed in the model, which is evaluated by means of the p-value value, t-value statistic and the confidence interval (95% BCCI). The analysis of the significance of the Path coefficients through the bootstrapping procedure shows that the hypotheses put forward are statistically significant, with the exception of H2 (Borrower's Characteristics on CL Campaign Success) and H7 (Borrower's characteristics on Investor type on CL Campaign Success). We can, therefore, conclude that the proposed hypotheses (H1, H3, H4, H5, H6), in the light of the research results, find empirical support.

For the loan characteristics affecting the success of the crowdlending campaign (CC) we do find support. This relationship was our hypothesis 1, which is consistent with the existing literature. Following Lin et al. (2013) and Feng, Fan and Yoon (2015) the loan's amount and term influences the funding days and the average investment of the CC. Recently, the study of the authors Slimane and Rousseau (2020) also confirmed that financial characteristics are essential elements that affect the CC success. Also, we do find support for hypothesis 3 and loan's characteristics influence the proportion of professional investors (type of investor). This confirms the idea that each investor type is different for decision making.

Nevertheless, for the borrower's characteristics affecting the CC success (hypothesis 2), we do not find evidence. It seems that the borrower's expertise and the length description of the company info has no effect on the funding days or the number of investors. This unexpected result is contrary to Dorfleitner et al. (2016) and Feng, Fan and Yoon (2015) results, but follows that of Kgoroedira, Burke and Van Stel (2019) who pointed out that lenders ignore business characteristics and concentrate on personal characteristics. Maybe is caused by the sample itself, due to the fact that the loans we use to test our hypothesis are guaranteed (GCL) so the borrower's characteristics are not as relevant for the investment decision. However, for hypothesis 4, relating the borrower's characteristics with the proportion of professional investors, we do find evidence of influence. This result confirms that investors pay attention to different things about borrowers when it comes to investing.

The relationship of the type of investor with the CC success has been studied directly, through hypothesis 5 and as a mediator for the loan's and borrower's factors (hypothesis 6 and 7 respectively).

For the direct relation, as expected we do find support. This reflects the fact that professional investors influence the success of the CC, so the type of investor is important

for this GCL campaigns. This result suggests that professional investors could be more interested in GCL than retail investors and the explanation could be that professional investors are attracted to GCL as part of their diversification strategy. This result is consistent with that of Moreno-Moreno, Sanchís-Pedregosa and Berenguer (2019) who find that retail investors in crowdlending show preference for riskier projects.

Regarding the mediating role of the investor type, we obtain different results depending on the factors analysed. For hypothesis 6, we do find support meaning that the loan's characteristics seem to influence the CC success also indirectly through the investor type. For the borrower's characteristics (hypothesis 7) we do not find support for this indirect relationship with CC success.

Table no. 3. Structural model

Relationships	$R^2_{success} = 0.336$					
	$R^2_{Investortype} = 0.068$					
	Path coefficient	t-Value	p-Value	95% BCCI		Support
Direct effects						
H1 (-): Loan Characteristics → CL Campaign Success	0.483	6.782	0.000	0.364	0.577	yes
H2 (+): Borrower's Characteristics → CL Campaign Success	0.135	1.348	0.088	-0.025	0.303	no
H3 (+): Loan Characteristics →Investor type	0.189	3.381	0.000	0.091	0.269	yes
H4 (+): Borrower's Characteristics → Investor type	-0.198	1.748	0.040	-0.313	0.122	yes
H5 (+): Type of investor→ CL Campaign Success	0.255	2.263	0.011	0.045	0.398	yes
Indirect effects						
H6 (+): Loan Characteristics→ Investor type→ CL Campaign Success	0.048	1.875	0.034	0.007	0.089	yes
H7 (+): Borrower's characteristics →Investor type→ CL Campaign Success	-0.0508	1.369	0.085	-0.101	0.015	no

Source: Own elaboration

3.3. Importance Performance Map Analysis (IPMA)

The Importance Performance Map Analysis (IPMA) allows us to know which constructs and items are most important and have higher performance when determining an objective construct, the construct we are trying to predict (Ringle and Sarstedt, 2016). Therefore, IPMA allows for prioritising the variables (loan characteristics, borrower's characteristics and type of investor) and items (type of investor, loan term, loan amount, expertise, description, number of employees, funding period and average ticket) to improve the targeted variable (success of the Crowdlending campaign). Figure no. 3 and figure no. 4 present some graphs that will allow us to analyse these relationships from a more practical and intuitive approach. The first graph will focus on the constructs and the second one on the items.

The first graph (figure no. 3) shows which constructions are most important and have the highest performance. To do this, two lines have been incorporated, one horizontal (performance) and another vertical (importance) that represent the average values of both dimensions and that, opposed both axes, give rise to four zones or areas (Ringle and Sarstedt, 2016). This analysis reveals that the constructs loan characteristics and the type of investor are those that have the greatest importance and performance. On the opposite quadrant, we find the borrower's characteristics with low importance and performance.
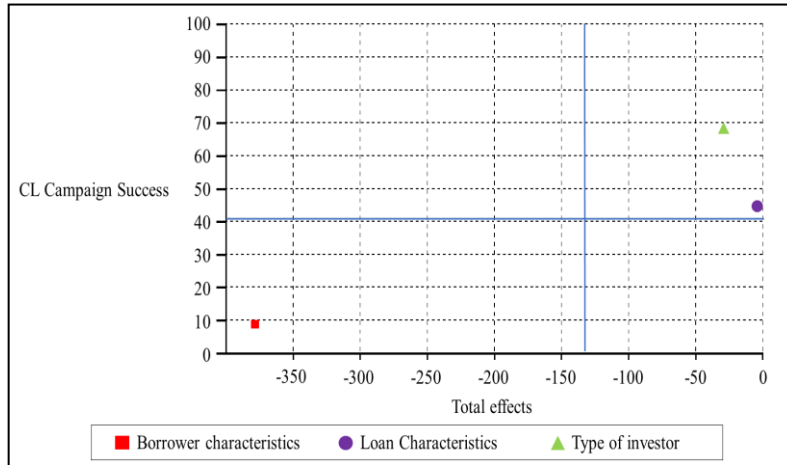

Figure no. 3. The IPMA map – constructs level
Source: Ringle and Sarstedt, 2016

On the other hand, we can see the graph of the items (figure no. 4). In this case, the items term, investor type and description have a high performance and importance. However, the items loan amount and number of employees (size) have higher importance but a lower performance for success. The IPMA manifest that expertise of companies is not a relevant item as its importance and performance are low.
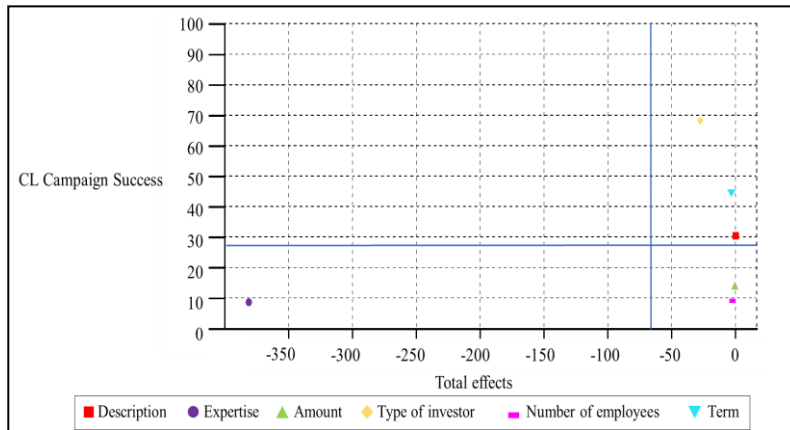

Figure no. 4. The IPMA map – indicators level
Source: Ringle and Sarstedt, 2016

Conclusions

Trying to shed some light on success factors for P2B crowdlending campaigns, we have focused on loans backed by a reciprocal guarantee society. These especial loans eliminate the possibility of borrower's default, so neither the borrower's solvency nor the interest rate is relevant as a characteristic affecting the success of the campaign. The use of this sample is a contribution itself because these loans provide the market with a great advantage of minimising its main risk. As far as we are concerned, this is the first study that uses a sample of guaranteed crowdlending loans (GCL) in order to study key factors of success in P2B crowdlending. So, since credit scoring traditionally has been identified as key to the success of the projects (Yum, Lee and Chae, 2012), this sample offers the possibility to study different factors.

The factors that we have studied come from the characteristics of different sources: the loans, the borrowers and the investors (lenders). All three affect the success of the crowdfunding campaign. In order to test this, we have developed a set of hypotheses based on these assumptions.

With our study we have confirmed that loan characteristics do have impact on Crowdlending (CL) campaign success and, also, influence the proportion of professional investors. These findings confirm the idea that each investor type has different preferences regarding the loan characteristics.

However, for the borrower's characteristics we do not find support of impact on CL success. This result, however, could be caused by the sample used in the study, where all loans are guaranteed and so the borrower's characteristics are not that relevant for investment decision.

For the investor type, we found that professional investors influence the success of the campaign, which suggests that this type of investor seems to be interested in guaranteed loans as part of their diversification strategy.

We can also conclude that, the variables included in the model explain the success of CL campaign. The explanatory power, measured by the variance of dependent variables, $R^2_{success} = 0,336$ confirms that. Nevertheless, since all models are simplifications, they cannot include all the existing variables. To explain the remaining variability, the study could have included other variables such as the gender of the investor, investor's psychological characteristics, crowdfunding company reputation, money destination of the loan, sector of activity of the borrower, etc. All these variables could serve as a basis for future work.

It is also remarkably interesting to comment the Importance Performance Map Analysis (IPMA) for the constructs in our model. This analysis reveal that the constructs loan characteristics and the type of investor are those that have the greatest importance and performance. On the opposite, we find the borrower's characteristics with low importance and performance, so less decisive when determining success.

This work makes several theoretical contributions. Our study proposes a definition of the emerging term Garanteed Crowdlending Loans. Moreover, our results provide evidence that loan characteristics affects (directly and indirectly) crowdlending campaign success. We observe a positive relation between loan and borrower's characteristics with investor type. Like so, type of investor on crowdlending campaign success. However, the effects of borrower's characteristics on CL campaign success was non-significant.

In the light of the results obtained a series of practical implications are proposed: These findings may be useful for understanding the attractiveness for certain projects. This information would help businesses to modify specific loan characteristics to make their loans more attractive or could even lead companies to consider a different financial option. Finally, it could also help platforms select and adapt project parameters to secure their success.

As with any empirical study, this one also has limitations that offer opportunities for further research. Firstly, this work takes place within a specific geographical context (Spain). Also, we have employed a data from a Crowdfunding platform, MyTripleA and focusing only on the success of his crowdlending campaigns (leaving out the other types of Crowdfunding). Therefore, researchers should be carefully while generalising these findings to other countries and institutions across the globe. Probably these results could not be generalized without regarding specific country traits, which can be a guideline for future research.

Secondly, this study employs the constructs loan characteristics, investor type, borrower's characteristics and crowdlending campaign success. As we previously commented, some other variables could be used to created constructs to explain the campaign success.

Third, future studies could focus on a comparative analysis between the companies and loans with different rating credit rating agencies, it might provide interesting findings in future. Lastly, a deeper study based on the moderating or mediating role of qualitative aspects of investors seems to be needed in order to get better Knowledge of the drivers and barriers of investment decisions.

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