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Behavioural imperfections in the crowdfunding market

An empirical analysis of Dutch platforms with a lending-based model

Abstract: The crowdfunding market is characterized by information asymmetry and low participation thresholds. As a result, its partakers might have been engaging in imperfect behaviour. In an attempt to identify any anomalies, this paper finds that two behavioural imperfections are particularly salient: entrepreneurs wishing to borrow more should be willing to pay a higher interest rate, and the media coverage of platforms drives the popularity of projects. These results have important implications for entrepreneurs, platforms, and investors, and contribute to the existing body of literature by providing insight in the key determinants of behaviour in the crowdfunding market.

Keywords: crowdfunding, market efficiency, imperfect behaviour, loan pricing, project popularity

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1. Introduction

Over the last few years, the field of crowdfunding has received a growing amount of attention from researchers, attempting to grasp its fundamentals and analyse the role of the key participants in the market. Crowdfunding has evolved from an elementary instrument for the financing of artists in sectors such as music and art, to a universal source of capital for entrepreneurs in all kinds of industries. As it largely takes place online, information asymmetry – the lender has less information about the creditworthiness of the borrower than the borrower himself – complicates investors' decision making and makes room for uncertainty and inefficient behaviour (e.g., Freedman and Jin, 2008; Collier and Hampshire, 2010; Lin et al., 2013). Compelling consequences of this information asymmetry are moral hazard (Akerlof, 1970) and adverse selection (Stiglitz and Weiss, 1981). Emekter et al. (2015) argue that regular monitoring might reduce the impact of these agency problems, however this is impeded by the fact that borrowers and lenders meet trough the online channel instead of face to face.

Aside from the market structure that evokes the eminence of information asymmetry, one must take into account the fact that, in contrast to the screening process that entrepreneurs wishing to start a crowdfunding project generally are required to go through, investors undergo an ostensibly low degree of evaluation. This factor bears partial responsibility for the high extent of accessibility of crowdfunding as an investment opportunity. Typically, no extensive financial knowledge or investment experience is required to participate in a project. Combined with the fairly low threshold – one can often already take part with amounts that have three or even two digits – this might result in the exhibition of less sophisticated behaviour by the average investor in crowdfunding, compared to that of other types of investors.

Due to these tendencies, the three main participants in the crowdfunding market, entrepreneurs, platforms, and investors, might have been engaging in imperfect behaviour. By exploring the demeanour of the different parties, this paper desires to investigate whether this is the case. This is crucial, since the understanding of the mechanisms and dynamics of crowdfunding has yet to improve (Ahlers et al., 2015). Although related fields such as peer-to-peer lending, microfinance, venture capital, and bank financing already provide valuable insight in the important concepts, crowdfunding practitioners should still benefit from this study by using its outcomes to design strategies more effectively.

I answer the research question, which is whether imperfect behaviour is observable in the crowdfunding market, through empirical analysis. It is based on a market-covering sample that consists of projects of 18 Dutch platforms. These are the most important platforms that feature projects with a lending-based model[1]. I identify a dyad of essential outcomes that are determined at different stages of the funding process, which are loan pricing and project popularity. To determine whether or not the market participants exhibit imperfect behaviour, I create two null hypotheses: the efficient loan pricing hypothesis and the efficient investment hypothesis.

First, I study the impact of key credit-related project characteristics and a set of controls on loan pricing and project popularity. The results reveal two particular behavioural imperfections. Firstly, entrepreneurs wishing to borrow a higher amount on average have to pay a higher interest rate to investors. Secondly, the higher the media coverage of the platform that publishes the project, the more popular that project becomes. These two observed relations lack a cogent theoretical foundation and therefore deviate from completely efficient behaviour. As a result, both the efficient loan pricing hypothesis and the efficient investment hypothesis are rejected.

Second, I address the endogeneity concerns that might arise regarding the credit quality measurements. Investors advertise signs of risk aversion, as less risky projects – indicated by more favourable credit scores and lower interest rates – complete faster and draw higher average amounts. To test the extent to which the effect of credit risk on the dependent variables is driven by already available information, I calculate the predicted values of these measures, together with their residuals. After regressing loan pricing and the two aspects of project popularity onto these newly created variables, I find that the ratings add considerable value, since their effect mainly is a product of yet unobserved information. The platform's own credit score shows to be particularly informative, as it appears more meaningful than the ratings of external agencies.

Third, I shift the attention towards personal characteristics of the entrepreneur by scrutinizing the impact of the photo and gender of the entrepreneur on loan pricing and project popularity. Although I discover some signals of gender-based discrimination, concerning the completion speed of projects, the evidence is not consistent enough to justify any well-founded implications.

This paper contributes to the existing literature on crowdfunding and peer-to-peer lending by pinpointing and critically evaluating key characteristics, and identifying the deficiencies. Instead of targeting one type of participants, the demeanour of multiple partakers is examined. Importantly, the analysis deviates from the bulk of prior research by covering a substantial number of platforms rather than concentrating at one single platform. This is essential, as it facilitates the establishment of more generalizable statements. The findings of this study regarding behavioural imperfections in the crowdfunding market provide insight in its efficiency. In more traditional credit markets, the size of the loan does not necessarily impact the interest rate that is charged. To highlight one

[1] In crowdfunding, four different models are distinguishable: a donation-based model, a reward-based model, a lending-based model and an equity-based model (Pierrakis and Collins, 2013, Mollick, 2014).

example, Jiménez and Saurina (2004) find that larger loans are even associated with lower default probabilities. The authors explain this by arguing that these loans are screened and monitored more carefully. Since these processes are impeded by the online character of crowdfunding, an increase in the size of the loan might more pronouncedly be connected to an upsurge of credit risk. As platforms should let the interest rate be influenced by the size of the loan only through the credit score, it seems as though investors might demand a premium for this lack of monitoring opportunities. Besides this implication, the current study provides evidence for the impact of the media. Whereas the importance of social media has been addressed in prior research, not much attention has been given to the more traditional media channels, such as newspapers and magazines. By showing that the behaviour of investors is impacted by the media coverage of the platforms, I provide additional insights in the determinants of investor decisions.

This paper has important implications for all three main market participants: entrepreneurs, platforms, and investors. First of all, an important takeaway for entrepreneurs is that the size of the loan matters. Since setting a higher amount is accompanied by an increased interest rate, much consideration should be put into deciding which amount is targeted. As a result, the entrepreneur should not largely exceed the minimal amount that he or she thinks is necessary for the purpose. Second, platforms that wish to increase the popularity of their projects are advised to seek publicity. This does not just regard social media, but also more traditional channels such as newspapers and magazines. The results indicate that relatively small investors have a preference for platforms with higher brand awareness, either because they make a quality inference, or due to cautiousness or unconscious associations. Third, investors need to remember to differentiate factors that impact the expected return from characteristics that do not do this. For example, the age of the company or the media coverage of the platform should not matter, as these variables likely do not influence the credit quality. On the other hand, factors such as interest rate and maturity should be of concern to investors, since they contribute to the return that is expected to be made on the loan.

The remainder of this paper is structured as follows: Chapter 2 identifies and reviews the most important literature on crowdfunding and its related concepts. Based on this section, Chapter 3 formulates the hypotheses that will be tested in the empirical section. Chapter 4 describes the research setting, the selection and properties of the dataset, and the design of the model. Chapter 5, which covers the empirical analysis, provides a detailed description of the results. Finally, Chapter 6 concludes the findings and implications of this research, and suggests potential avenues for future studies.

2. Theoretical background

Typically, the companies that address crowdfunding as a source of financing are small and medium-sized companies (SMEs). Research suggests that, within this large set of enterprises, financial constraints play an undeniable role. Some explanation is offered by a general limitation that SMEs often face, which is the presence of informational opacity: difficulties that potential investors have in obtaining firms' capacity and willingness to pay, determined by project viability and moral hazard, respectively (De la Torre et al., 2010). Since traditional providers of credit, such as banks, often base their decision to the utmost extent on quantitative and verifiable information, the companies that come across as more opaque might find themselves troubled in obtaining credit from these institutions. It has often been discussed in the literature whether the access to credit of SMEs is impeded by informational opacity. Cole et al. (2004) test if there are any differences in the way small and large banks make a lending decision. Their results demonstrate that more sizeable banks tend to base the decision to a larger extent on formal financial data, whereas smaller banks place more weight on the presence of pre-existing deposit relationships. Furthermore, the authors find that both age and size are positively related to banks' likelihood to approve a loan to the firm, a result that holds for both small and large banks. According to the classical view that age and size are related to opacity, this rules in favour of the idea that more opaque firms indeed face increased credit constraints. Similar outcomes are found by Beck et al. (2006), who perform a cross-country analysis, whereby examining over 10,000 firms from 80 countries. Their research is based on outcomes of the World Business Environment Survey (WBES), which contains a large number of questions on the nature and severity of obstacles to firm performance and growth. The authors find a significant influence of certain firm-specific factors on the access to credit: firms that are older, larger and foreign-owned appear to experience less difficulties in obtaining funds. Hyytinen and Pajarinen (2008) argue that too rapidly the association is made between opacity and both company age and size. As a proxy for opacity, they instead use rating disagreements[2]. The authors find that age is indeed related to opacity, but they are not able to gather any evidence in support of the relationship between size and opacity. They claim that their findings "do not challenge the generally accepted view that firm size is a reliable predictor of firms' financing obstacles in a broader cross-section and, in particular, that SMEs may as a group have a constrained access to

[2] The reasoning behind this, provided by Hyytinen and Pajarinen (2008), is as follows: if a small business is opaque and outsiders cannot easily determine its quality, credit information companies should disagree more often over the creditworthiness of that particular firm than over that of (otherwise similar but) less opaque firms. The measure was first introduced by Morgan (2002).

external finance". The results however suggest that changes in the size of a specific firm are related to its opacity in a different way than changes in the age of that firm.

After they started to make use of small business credit scoring systems, banks have gained a better understanding of the credit quality of opaque companies. Berger and Udell (2006) argue that the aggregate level of lending to opaque U.S.-based SMEs has increased due to the use of such systems. Before these technologies, such companies were even less likely to obtain bank loans. Reasonably, the rating that is received has impact on the access to credit of the firm, as it functions as an indication for its creditworthiness. The literature on bank lending illustrates that this is indeed the case. Brown et al. (2012), who analyse a sample of 9,715 German start-ups, show that banks have the propensity to focus their attention on negative signals from companies' credit ratings when making lending decisions. This is entailed by their finding that solely bad ratings have a significant negative impact on the availability of credit, whereas no dissimilarities appear to exist between fair and good ratings in their effect on access to external funds. In line with this work, Robb and Robinson (2014) examine a sample of newly founded companies and find that the firms that are assigned a good rating, have access to a considerably greater amount of external credit, compared to their lower rated peers. Machauer and Weber (1998) demonstrate that borrowers with a lower credit rating pay higher premia over the daily interbank money rate, compared to borrowers with a more favourable rating. Similarly, Lehmann and Neuberger (2000) report a negative and significant relationship between the borrower's credit score and the interest rate that is charged by the bank. Furthermore, the authors reveal that an improvement of the rating lowers the probability that a loan is disapproved by the bank.

Hence, financial constraints due to informational opacity and poor ratings may daunt firms to apply for credit at financial institutions such as banks. As a result, they might consult other sources of financing, such as crowdfunding. Blaseg and Koetter (2015) scrutinize a group of young German ventures, of which a portion employs crowdfunding as a means of capital collection. The remaining portion of the group uses other sources of funding. The authors are interested in knowing which factors drive the propensity to choose for crowdfunding as opposed to other credit sources, and find that the companies dealing with larger credit constraints are more likely to apply for the former. To be specific, these companies are characterized by poorer ratings, smaller size and lower tangibility. The result that the choice for crowdfunding is associated with increased credit constraints, is in line with research done by Schwienbacher and Larralde (2012), who state that company size and the absence of historical financial data create an obstacle in the form of information asymmetry for potential investors. As a result, traditional sources of credit such as bank loans or venture capital might become somewhat difficult to obtain, which leads capital seeking companies to explore new possibilities such as crowdfunding. The question arises whether or not these companies are truly successful in collecting funds from 'the crowd', and what other factors drive funding success. The literature seems to be divided on this topic. Recent evidence, to a large extent reviewed by Kuppuswamy and Bayus (2015), indicates that determinants of success include credit quality (Herzenstein, 2011b; Hildebrand et al., 2014), social networks (Lin et al., 2013; Mollick, 2014), others' prior bids (Herzenstein et al., 2011a; Agrawal et al., 2015), the project narrative (Herzenstein, 2011b), personal borrower characteristics (Ravina, 2012; Ly and Mason, 2012a), competition (Ly and Mason, 2012b), geographical distance (Mollick, 2014; Agrawal et al., 2015), and the presence of financial roadmaps, risk factors, board experience and the number of board members (Ahlers et al., 2015).

Research in the field of peer-to-peer lending[3] provides some more comprehensive insight in the underlying mechanisms and the role of the main actors. In general, the literature in this field limits its research to one peer-to-peer lending platform, such as the U.S.-based platforms Prosper.com and Lending Club, or their Chinese counterpart PPDai.com. Typically, these platforms assign a rating to each project, which is expected to reflect the borrower's credit quality. By a considerable number of studies, this rating is found to be a salient driver of investor behaviour. A comparison can be made to the previously described research on bank lending: The difference is that the middleman – the bank – is removed from the process, as the funds of investors flow directly to the entrepreneur. The lending decision is no longer made by the bank, but instead investors decide whether or not money is lent to the entrepreneur. Similar to the bank, investors derive the entrepreneur's creditworthiness from the credit score. For example, Freedman and Jin (2008) scrutinize a sample of listings that were placed on Prosper.com between January 2006 and July 2008. The authors stress the obstacles emerging from information asymmetry inflicted upon lenders. Since Prosper.com only displays credit grade categories and does not make actual credit scores available, investors are unable to assess borrowers' creditworthiness in an accurate manner. It is shown that, over time, there are more listings towards the lower end of each grade category. The authors report that the funding success of listings is influenced by the credit grade that the borrower receives: the higher this rating, the more likely it is that the loan is fully funded. The authors are not the only ones to report a significant influence of credit ratings on funding success[4]. Feng et al. (2015) show that the credit grade does not solely have influence on whether or not a listing is successfully funded, but also on funding time, i.e. the speed with which the listing is

[3] Crowdfunding and peer-to-peer lending are intertwined. The latter denotes loans from individuals and entrepreneurs that are funded by 'the crowd', whereby the middleman is removed from the process. The latter comprises, as explained earlier, four different types: donations, non-financial rewards, debt, and equity. Therefore, insights from peer-to-peer lending are well applicable to the field of crowdfunding.

[4] See Klafft (2008), Lin (2009), Iyer et al. (2009), Li et al. (2011), and Hildebrand et al. (2014), among others.

funded, and the number of bids that the project receives. The results display a positive relationship between the rating and the popularity of the project: a higher credit grade leads to a lower funding time and an increased number of received bids.

Another characteristic that is shown to be subject to projects' credit grades is the interest rate that borrowers pay on their loan. As investors use the rating as a tool for evaluating the borrower's credit quality, this relationship appears self-evident: increased risk should be compensated by an interest rate premium. Unsurprisingly, a negative and significant relationship between credit grade and loan pricing is found by a number of studies, including the research of Freedman and Jin (2008), Barasinka and Schäfer (2010), Lin et al. (2013), and Hildebrand et al. (2014). Interestingly, through observing the interest rates that are offered by investors, Iyer et al. (2009) find evidence for the ability of investors to infer a third of the variation in borrowers' creditworthiness, measured by their credit score. The authors demonstrate that a positive shift in the credit score of a borrower, within the same credit category, leads to higher offered interest rates. Since investors only have information on the category and do not have access to the exact credit score itself, the finding displays that they are able to infer changes in the creditworthiness of borrowers. Furthermore, the authors provide evidence that investors' inference is to a larger extent driven by more formal, *hard* information[5] than by non-standard, *soft* information[6]. The impact of the latter type of information becomes, however, more pronounced for lower rated listings, as opposed to the ones with better credit scores. Hence, investors that are faced with poorly rated borrowers appear to increasingly depend on soft information.

The focus is not limited to ratings, as also other project attributes drive the behaviour of investors. Plainly hard information has a significant impact: research finds that, in general, investors prefer projects with high interest rates (controlled for the credit score), low maturity, and low targeted amounts. Furthermore, evidence is found for the influence of several soft factors such as loan purpose, occupation, age, marital status, homeownership, and social capital, and for the impact of other borrower characteristics (e.g., Freedman and Jin, 2008; Barasinka and Schäfer, 2010; Puro et al., 2010; Li et al., 2011; Pope and Sydnor, 2011; Duarte et al., 2012; Ravina, 2012).

While reviewing the literature on peer-to-peer lending, I encounter two potential caveats. First, as I already mentioned, every study limits its analysis to a single platform. This withholds any statement on between-platform differences and developments. A comparative study on online peer-to-peer lending practices in the United States and China, performed by Chen and Han (2012),

[5] Hard information concerns variables that are tangible and easy to screen. Examples of such variables are the targeted amount and the maturity of the loan.

[6] Soft information signifies more subjective and often non-financial information, such as the purpose of the loan or the borrower's age.

illustrates that Chinese lenders rely more on soft information compared to their American peers. Moreover, the study mentions that when the borrower is assigned a poor credit score, lenders in general depend on soft information such as the borrower's social capital. This literature review does not provide profound empirical insights in discrepancies across major platforms, however. Second, the loans that are considered in each study are to a considerable extent of a private nature. This is due to the fact that platforms such as Prosper.com and PPDai.com do not only publish entrepreneurial loans, but also attract a large number of individual capital seekers. Since investors might demonstrate deviating behaviour when considering business loans as opposed to situations wherein the borrower is a private person, it is possible that results differ when only business loans are considered.

3. Hypotheses

Imagine a loan being issued under fully efficient market conditions. Agency costs are limited and all relevant public information is immediately absorbed by the interest rate. A person that is considering to invest in the loan should exclusively care about the expected return. If he judges the loan to be relatively risky, based on all the to him available information, he wants this risk to be compensated by a relatively high interest rate. If this is not the case, he will forfeit the opportunity as he will likely be able to find a similar loan yielding a higher expected return elsewhere. In reality, the crowdfunding market probably is not fully efficient and information asymmetry plays an active role. Still, the risk-return trade-off is a mechanism that is applied by investors in their decision making (Fama and MacBeth, 1973). From the viewpoint of the borrower, the interest rate can be seen as the price that is paid for borrowing a certain amount, hence it would be in his or her advantage to minimize the rate. If it were too low, however, the borrower might have trouble attracting the attention of the lender. Therefore, the interest rate is expected to ultimately move toward an equilibrium that is low enough to prevent the borrower from exploring other investment opportunities, and high enough to persuade the lender to invest in the loan. In the field of peer-to-peer lending, the research underlines the trade-off: higher risk is associated with higher interest rates. Here, the risk is principally symbolized by the credit score that is assigned to the borrower. Presumably, this rating is not a perfect measure of credit risk, since it only adopts a limited number of values. Besides, the presence of information asymmetry likely suggests that platforms are unable to infer all of the project's credit risk and translate it into a rating. Still, as advocated by Iyer et al. (2009), the credit score is the best available proxy for the ex-ante default probability of a loan, which measures the borrower's creditworthiness. Its impact on the interest rate should therefore be preeminent. I predict that the interest rate depends on a few additional factors. First of all, investors might want to be compensated for maturity-related risk. Since a longer duration increases risk, I expect that some risk premium is observable for loans with a longer maturity. As a second, perhaps less pronounced factor, one can think of a project characteristic that is not accounted for in the credit rating: the purpose of the loan. Some relevant signals can be derived from this characteristic, since it indicates the stage of development in which the company finds itself. For instance, a loan with the goal of covering start-up costs indicates a whole different position in the development cycle than one that is meant for the financing of growth. In a fully efficient crowdfunding market, the interest rate of a project should not be notably impacted by other characteristics than the ones discussed. The rationale behind this is that any additional credit risk-affecting attributes should be reflected in the credit score of the project. Therefore, I will refer to my first hypothesis as the *efficient loan pricing hypothesis*:

H1: The interest rate solely depends on specific credit-related project characteristics

As pointed out by the literature, investors take the interest rate into account when they decide whether or not they wish to invest in a project. Together with the maturity and the invested amount, this factor determines the return that is received throughout the duration of the loan, assuming funds of the borrower remain sufficient. Since a full pay-out is not guaranteed due to default risk, the *expected* return needs to be considered. Logically, as the credit score is assumed to signal credit risk, this factor should therefore be taken into account by investors as well. Since the interest rate should move together with the credit score, however, the impact of the two characteristics should not significantly diverge. To summarize, I expect that the four loan characteristics – interest rate, maturity, targeted amount and credit score – drive the behaviour of investors. Since the credit score is expected to absorb all credit-related information, other attributes of the project should not be of considerable importance to return-driven investors. I neglect the so-called 5Fs – founders, family, friends, fans, and fools (e.g., Harrison, 2013) – since I argue that in the lending type of crowdfunding their influence is limited, and assume that their presence does not fluctuate significantly across projects. Taking the foregoing into consideration, I present my second hypothesis as the *efficient investment hypothesis*:

H2: Funding success solely depends on pure loan characteristics

Whether or not the two hypotheses are confirmed in the empirical section, provides insight in the efficiency of crowdfunding as an industry, and the sophistication of the main participants. In a properly performing market, both hypotheses should be confirmed, indicating that it is functioning optimally. If this is not the case, then apparently some biases persist that prevent the market from exploiting its full potential.

4. Data and method

4.1 Research setting

The empirical model used in this paper is roughly based on the analysis performed by Feng et al. (2015). The authors choose to encompass three measures of funding success: whether or not a project raised the amount that was targeted, the number of days the project required to raise its targeted amount, and the number of investors that made a bid on the project. Since there is insufficient access to data regarding their first measure of funding success, I do not include a dummy variable stating whether or not a project managed to raise its targeted amount as a measure. The other two variables, however, are feasible proxies for funding success in my model. I argue that, instead of using this term, 'project popularity' better grasps the essence of the concept. A lower completion time does not necessarily mean that the funding of the project is more successful: in fact, this shows that the project is more *popular* amongst investors. To give an example, consider two projects, which both raised the amount that they targeted on beforehand. Assume that both projects are equal in size. Project A completed its funding in two days, whereas project B needed four days to raise its targeted amount. This does not mean that project A is more successful than project B: both succeeded in raising the amount they desired. Compared to project B, project A attracted investors at a higher speed, which only highlights that it is more popular among investors. The same logic applies to the number of investors in the project. Consider again the same two projects. Project A attracted fifty investors, whereas project B attracted one hundred investors. Again, project A is not necessarily more successful. Instead, on average it attracted investors that provided a smaller amount. In other words, the project attracted smaller investors. As a result, a higher number of investors were able to participate in the project, compared to project B. Hence, this number provides an indication of the popularity of the project rather than reflecting the funding success. Likely, the completion time and the number of investors are dependent on the size of the project. The rationale behind this is elementary: Larger projects are prone to yield a higher number of investors compared to projects that are smaller (assuming that similar investments are made in both project types). Using the same argumentation, larger projects are expected to require more time to raise the aspired amount of funds compared to their smaller peers. This evidently calls for some form of control for size, which can be done in two ways. The first option denotes the inclusion of the project's targeted amount as a separate control variable. This action ensures that the effect of project size on the number of investors and the completion time is captured entirely. The second option regards altering the variables by building in a control for size. The variables would then be transformed: number of investors becomes average investment, and completion time is turned into relative completion time. I favour adding the targeted amount as a control variable rather than altering the measures of project popularity, since the original measures are more natural and reflect the popularity of the project more directly. Between the project input and the funding output – the project popularity – there lies another important step: the pricing of the loan. The establishment of the interest rate differs per platform, as some platforms take full responsibility of setting the rate, whereas others provide a bandwidth based on the credit score, between which the company can determine the interest rate, and again other platforms give entrepreneurs complete freedom in choosing the interest rate. I do not expect the approach to matter for the key determinants, as the theory of supply and demand dictates that the loans are priced in such a way that the credit risk is properly reflected. These key determinants should consist of the credit-related project characteristics, as stated in the efficient loan pricing hypothesis. Feng et al. (2015) limit their scope to measuring funding success and incorporate the interest rate solely as an explanatory variable, however I also include it as a separate dependent variable. Eventually, the interest rate decides at which cost the entrepreneur is able to borrow the requested amount, and might therefore have important implications, not only for the entrepreneur itself but also for potential investors.

The objective of this paper is to provide some insight in the drivers of loan pricing and project popularity and detect any behavioural imperfections in the crowdfunding market. Based on previous literature, I expect credit quality to play an active role as a determinant of both loan pricing and project popularity. As a proxy for credit quality, I use the credit score that is assigned by the platform. This appears appropriate, based on the claims of Iyer et al. (2009). Working with credit scores is not an uncommon practice for crowdfunding platforms, although this often depends on the type of crowdfunding that is practiced: in donation or reward based funding less emphasis is placed on financial performance, whereas lending or equity based crowdfunding this should be a key aspect. To analyse the role of credit quality, Feng et al. (2015) scrutinize the impact of the PPDai credit score on funding success. In addition to the rating, I will also analyse the impact of a number of other factors. While constructing my hypotheses, I mentioned the expected influence of two project characteristics on the interest rate: the maturity and the purpose of the loan. I expect both variables to have a significant effect. A loan attribute that should not drive the interest rate but that presumably has some implications for the popularity of the project, is the targeted amount. Recall that controlling for this variable is necessary, since it is likely that both the completion time and the number of investors depend on the size of the project. Following Feng et al. (2015), I furthermore include a variable describing the industry in which the company is active, more or less conform the authors' inclusion of the borrower's occupation. Since I assume that better informing facilitates decision making, I choose to incorporate a measure that states whether or not historical financial information about the company, in the form of a financial statement, is available. Additionally, the age of the company might be a signal for its creditworthiness, as the literature has shown its relatedness to informational opacity. Besides, it is also a proxy for brand awareness, as older companies likely are more well-known with the public. For these reasons, I include a variable describing company age. Finally, I additionally include a proxy for the brand awareness of the platform as it might also have an effect on the popularity of a project. That is, more well-known platforms are expected to have a larger pool of potential investors. Together with the platform fixed effects, these variables will all be included as explanatory factors in the estimations of loan pricing and project popularity, in order to test the hypotheses and check for imperfect behaviour.

4.2 Data

I choose to focus my sample on projects that are published on Dutch platforms. Over 2015, the crowdfunding market in The Netherlands has grown with 128 million Euros, which is twice the amount of the previous year (Douw & Koren, 2016). According to the report, Dutch inhabitants invest an average amount of eight Euros in crowdfunding. Of the four different types, the lending form dominates, with a total amount of 91.1 million Euros over 2015 (Crowdfundmarkt, 2016). Looking at the total market size, the developments in 2015 transform The Netherlands into one of the world's leading countries in the field of crowdfunding. The country is placed third behind the United States and the United Kingdom, after controlling for population size. The advanced Dutch financial system, combined with the fierce growth in popularity of crowdfunding as a financing form, justifies the choice for the focus on Dutch projects for the empirical analysis.

I collect a list of all crowdfunding platforms active in The Netherlands through two sources: the crowdfunding platforms register[7] of the *Autoriteit Financiële Markten*, which is the Dutch

[7] This concerns a register of all crowdfunding platforms that received either a license or an exemption from the AFM. As the regulator notices, "when a company is not included in the register, it may mean that the company does not need a license or exemption, that the application is still under treatment with the AFM, or that the company is

financial regulator, and the overview of platforms by Douw & Koren, a Dutch crowdfunding consultant. Combining these sources generates a list of 114 platforms, which differ in objective and crowdfunding model. Since this study focuses on the lending type of crowdfunding, I disallow platforms that do not feature such projects. I further reduce the list by deleting platforms that function as an intermediary for other platforms, or solely display projects of another platform with which they co-act. Next, I remove the platforms that only allow for private loans or that are structured in a way that deviates substantially from their peers[8]. Finally, I exclude the platforms that have less than two closed project on their website. The rationale behind this, is that I include platform fixed effects, which will fully capture any project-specific influence if the platform's number of projects is limited to one. These scraping practices result in a dramatic decrease of the number of platforms in the sample. What remains is a clean overview of 18 crowdfunding platforms comprising a total of 777 projects, which serve as the basis for the empirical analysis.

The data collection is done manually, since no centralized record is being kept of all Dutch crowdfunding projects. To start, I draw the pricing of the loan, which is formed by the project's annual interest rate, directly from the platform's websites. Since this is a critical project feature, the interest rate is clearly stated with each proposition. Two projects from the sustainability-oriented platform Greencrowd, for which this is not disclosed, form the only exception to the rule. Next, I calculate the number of days that each project required to raise their targeted amount. Some platforms display this completion time for each of their projects, whereas other platforms only provide the dates on which investments have been made in the project, or choose to only present either the date on which the project was published, or the date on which the targeted amount was raised. For the latter group of projects, I collect the missing date from Crowdfundmarkt, which publishes information on a large number of Dutch crowdfunding projects, or from social media such as Facebook or Twitter. Most platforms allow entrepreneurs to only raise funds up to the targeted amount, and seal the project as soon as this amount is reached. Some platforms, however, allow overfunding, i.e. projects raising more money than the original target. For these cases, I calculate the completion time by dividing the total amount of days the project has been open for funding by the relative funding of that project. For example, if a project has been open for funding for thirty days and it collected twice the amount it set as a target on beforehand – denoting a relative funding of 200% – the total completion time is equal to fifteen days. I have information on this

committing an offense by undertaking activities without a license or exemption". Furthermore, the register also includes certain companies with activities similar to crowdfunding platforms, for which it is important to note that they are, in fact, not equal to crowdfunding platforms.

[8] ZonnepanelenDelen does not operate like a typical crowdfunding platform. This platform allows investors to acquire bonds with non-fixed interest rates (since returns are dependent on the amount of solar energy produced) and is, consequently, not comparable to other crowdfunding platforms.

measure for a total number of 681 observations. The other proxy of project popularity, the number of investors, is generally either given or deductible by counting the number of investments made. No more than a very small portion of the platforms does not provide this information, resulting in a total number of 756 observations for the variable.

Out of the eighteen platforms comprising my sample, fifteen operate a credit scoring system. In general, projects are placed in one of five categories, based on their repayment capacity. The credit score is displayed together with additional key information about the project, such as the targeted amount, interest rate and maturity. For a total number of four platforms, the number of credit grade categories differs from five, although this does not necessarily form a caveat. All4Funding, which had two closed projects on its website at the time of data collection, has adopted a risk classification system comprising five general categories and, on top of that, three separate categories for start-up companies. Both projects fall into one of the start-up categories. Given the fact that at a considerable amount of the other platforms, start-ups are automatically placed into the riskiest category, both projects receive the poorest rating in my dataset. Capital Circle, contributing with five projects to my sample, only employs three credit grade categories. Each of the five projects is assigned the rating 'B'. Since it is in the middle, I change the credit score of these projects to '3', being the middle of the five categories in my sample. Geldvoorelkaar has created a risk classification system that consists of six different categories. The lowest rating is reserved for convertible loans. Of the 183 closed projects that were published at the time of data collection, only two projects – naturally, both being convertible loans – received this rating. I choose to withdraw these projects from my dataset. Finally, Horeca Crowdfunding Nederland uses four categories. As the mean interest rate on this platform is relatively high, I choose to treat its projects as though none of them received the most favourable rating. To measure the credit score of each project in the sample, I construct a categorical variable that is equal to one for projects with the best rating, equal to two for projects with the second-best rating, and so on for the remaining three credit scores. Due to the three platforms in my sample that do not assign a credit score to their projects, the sample consists of a total number of 566 rated projects.

Credit-related loan characteristics, which are the maturity and the targeted amount, can be directly collected from the platform's websites, since this information is clearly stated with the loan proposal. Generally, loan purpose and industry are described in the project text, which has the goal to inform the public and persuade potential investors to participate in the project. The purpose of the loan varies from start-up to working capital, and from growth to a takeover. I create a categorical variable that comprises eight different categories, which are given in Table I. The industry variable that I create next, is also of a categorical nature, and is limited to the six bestrepresented industries in crowdfunding, according to the Dutch crowdfunding intermediator Crowdfundmarkt. The seventh category is destined for projects that are active in any industry other than these six. These industries can also be found in Table I. If there is any historical financial information regarding the company available, this is usually in the form of a document that is attached to the project. I create a binary variable that is equal to one if this information is provided, and zero otherwise. In a number of events, no information is given about the company itself, but financial accounts are available for the parent or holding company. For these cases, the variable also has a value of one. Concerning company age, I collect the month and year of incorporation for every company from CompanyInfo, the database of the Kamer van Koophandel[9]. Subsequently, I calculate the difference in years between the month in which the project was launched and the month in which the company was founded. I create another categorical variable, whereby I divide the age into six categories: companies less than one year old, between one and two years old, between two and three years old, between three and four years old, between four and five years old, and more than five years old. I expect that any dissimilarities in impact between companies older than five years are only marginal. Finally, I collect the media coverage of each platform by extracting the number of times a platform is mentioned in the Dutch media from the news articles database LexisNexis, whereby I start counting from the month in which the project was launched.

4.3 Model design

The set-up of my empirical analysis is clear-cut: I test the impact of a specified set of project characteristics on the interest rate and the two measures of project popularity. In the regressions, I make sure to control for a number of attributes, to uncover any behavioural imperfections. The regressions of loan pricing can be written as:

$$Interest\ rate_i = \beta_0 + \sum_{k=1}^{N} x_i^k \beta^k + \sum_{m=1}^{M} y_i^m \varphi^m + \varepsilon_i, \qquad (1)$$

Where $Interest\ rate_i$ is the annual rate that investors receive over the loan, x_i^k denotes the k^{th} explanatory characteristic of project i, β^k is the corresponding regression coefficient, y_i^m denotes the m^{th} control variable with respect to project i, and φ^m is the corresponding regression coefficient.

[9] The Kamer van Koophandel is the Dutch Chamber of Commerce, and manages the Commercial Register in which all Dutch companies and legal entities are registered with their current data.

Here, the explanatory characteristics are credit score, maturity, and loan purpose. The control variables are targeted amount, industry, historical financial data, company age, and platform media coverage. The regressions of the two measures of project popularity are analogous and can be written as:

$$Project\ popularity_i = \beta_0 + \sum_{k=1}^{N} x_i^k \beta^k + \sum_{m=1}^{M} y_i^m \varphi^m + \varepsilon_i, \tag{2}$$

where $Project\ popularity_i$ is either the completion time or the number of investors. In these regressions, the explanatory variables are credit score, interest rate, maturity, and targeted amount, whereas the control variables are loan purpose, industry, historical financial data, company age, and platform media coverage.

Given that each of the three dependent variables is of a continuous nature, I apply an ordinary least squares (OLS) model for the estimation of the regressions. I use robust standard errors to control for heteroskedasticity in my sample. Figure I illustrates the one-on-one coalition between credit score and the three dependent variables in the analysis. The charts indicate that the relationship between credit score and interest rate is linear. In contrast, the connection between credit score and completion time might be non-monotonous. For the number of investors, the effect appears less outspoken. Figure II exhibits the direct relationship between interest rate and both completion time and the number of investors. The relationship between interest rate and completion time and that between interest rate and the number of investors appear almost mirrored. In both cases, some non-monotony seems to be present. In order to further address these nonlinearity concerns, I treat the credit score mainly as a categorical variable in the regressions, and I additionally create a categorical variable that divides the interest rate into three categories: low, medium, and high. The regression estimates will show whether these nonlinearity concerns are grounded.

5. Results

The descriptive statistics for all the key characteristics in the dataset are reported in Table III. Probably, a few alterations should be made regarding some variables. The number of investors and especially completion time are rather skewed, given the relatively large difference between the mean and the median value of the two variables. I choose to log transform a total of four variables, which are completion time, the number of investors, targeted amount, and platform media coverage. This decision is based on the observation that the minimum and maximum value, which are not reported, are particularly far apart. Not doing this would give too much weight to the extreme values in the sample. Regarding platform media coverage, I need to make an additional adaption, since some observations have a value equal to zero. I therefore do not take the log of the original values, but instead log transform the value *plus one*. Assuming that the sample accurately represents the Dutch crowdfunding market[10], I can distillate an image of the typical characteristics of a project, based on the median – and in some cases mean – values in my sample. The loan has a targeted amount of 68,000 Euros with an interest rate of 7% and a maturity of 4 years, receives the middle credit score three and an average external rating of 2. The company is active in hospitality (assuming that none of the 'other' industries have a larger share) and requires the loan for start-up capital. No historical financial data are available, the company is less than one year old, and the project is published by a platform that has been covered 90 times in the Dutch media. Of course the exact combination of these values will likely not be observed, since the characteristics impact each other.

Although the analysis of this paper will be performed at the project level, I wish to carry out a few straightforward tests in order to highlight certain dissimilarities between platforms. I identify the six largest platforms in the sample, based on the number of closed projects that are published on their websites. These are Collin Crowdfund, Crowdaboutnow, Geldvoorelkaar.nl, Horeca Crowdfunding Nederland, Kapitaal Op Maat and Oneplanetcrowd. Table IX, which is included in Appendix B, provides the platform-level descriptive statistics for some key characteristics. The platforms differ on a number of topics: Two out of the six largest platforms, Crowdaboutnow and Oneplanetcrowd, do not assign a rating to their projects, and for the latter platform, information on the variable completion time is also unavailable. Furthermore, Collin Crowdfund and Geldvoorelkaar.nl are the only platforms to publish external ratings, alongside their self-established credit score. Content-wise, the platforms without a credit scoring system appear to have considerably lower interest rates than their rating peers. A relationship seems to exist, as the correlation between the interest rate and a dummy indicating that the project received a credit score, is equal to 0.590. This indicates that rated projects are likely to be priced higher, which can perhaps be ascribed to the platform focus: the ones that are more investment oriented likely choose to attract investors with relatively high expected returns, whereas for the audience of platforms that focus less on this aspect, other factors might be more relevant. On a different note, the popularity of projects seems to deviate substantially from platform to platform. On average, projects of Collin Crowdfund and Geldvoorelkaar.nl have a notably lower completion time than

[10] This should be the case, since according to each of the platforms, no particular distinction is made in the process of removing projects from their website. Therefore, it is safe to assume that the sample I analyse is representative for the Dutch (lending-based model) crowdfunding market.

the ones of Crowdaboutnow and a considerably higher number of investors than projects of Crowdaboutnow and Oneplanetcrowd. On both measures, the other two platforms, which are Horeca Crowdfunding Nederland and Kapitaal Op Maat, are in between. Finally, I would like to highlight the different distributions of the platforms with regard to the five credit score categories. Some platforms automatically assign the worst rating to start-up companies, which they consider as particularly risky. Of the large platforms, Geldvoorelkaar.nl is the only one to apply this principle. Both Collin Crowdfund and Kapitaal Op Maat do not allocate this rating to any of their projects. The reason for this could be twofold: either they have declined each project that would receive this rating, or they just do not have come across such a project yet. The main takeaway from the platform-level descriptive statistics, is that each platform has unique characteristics that attract different projects and investors.

In order to illustrate these characteristics, Figure III shows the median values of the four largest platforms on a limited number of variables: interest rate, completion time, number of investors, and targeted amount. Additionally, the 25th and 75th percentile values are displayed. On top of the information that has been discussed above, the graphs provide some general insights in the between-platform dissimilarities. For each of the four variables, I use a t-test to verify the statistical significance of the difference between the means of the highest and lowest scoring platform. Also these results are reported in Table IX. All of the test statistics are highly significant, which justifies the forming of some statements regarding the roles of each platform. Out of the four platforms, Geldvoorelkaar.nl seems to be more appropriate for higher priced loans and has projects that attract more investors, vis-à-vis Crowdaboutnow, which distributes lower interest rates and has projects that draw a lower number of investors. Furthermore, Collin Crowdfund publishes faster completing projects and focuses on larger projects, versus Crowdaboutnow, which has projects that require more time to complete funding and target lower amounts. On each of the four project characteristics, Kapitaal Op Maat appears to act more or less in the middle of the market. The differences signal that the type of capital seekers and capital providers might deviate from platform to platform, and that the market is characterized by heterogeneity.

Returning to the analysis on the project level, the pairwise correlations that are displayed in Table IV provide some more insight in the interactions within the sample. The two measures of project popularity, completion time and the number of investors, do not appear to be highly correlated. A probable explanation of this observation is that the two variables measure different aspects of the popularity of a project. The positive coefficient might be largely ascribable to the possible mediating effect of the size of the project: larger projects likely require more completion time and attract a higher number of investors. The positive correlation of the interest rate with both measures, which claims that loans that are priced higher, attract more investors, but also require more time to raise their targeted amount, indicates that investors are more cautious towards riskier projects. That is, on average they seem more hesitant to invest and provide lower amounts when the credit risk increases. With regard to the explanatory variables, the correlation matrix shows both some expected and some unexpected results. Obviously, the correlation between credit score and interest rate is rather high, indicating that the pricing of the loan is indeed actively driven by the assessment of the credit quality. That the correlation is not perfect, signals that the interest is also subject to other factors. Furthermore, the likely dependence of completion time and the number of investors on the project's targeted amount is endorsed by the coefficients. The correlation between the number of investors and project size is particularly high, suggesting that due to limited funds of investors, larger projects mechanically draw more investors. What is surprising, finally, is the relatively high correlation of platform media coverage with the two measures of project popularity. Since perfect behaviour of investors suggests that the popularity of a project should not depend on the media coverage of the platform, these coefficients are a tentative indication of imperfect behaviour. The actual analysis will have to provide a more comprehensive understanding of the effective interactions and the key determinants of loan pricing and project popularity. The next section discusses the results of this analysis.

5.1 Determinants of loan pricing and project popularity

Table V reports the results from linear regression of the interest rate onto the earlier specified explanatory variables and controls. Consistent with the literature and my expectations, the interest rate and the credit score are positively related. That the rating is the most salient driver of the interest rate is implied by the fact that the R^2 increases only marginally as the additional explanatory variables and controls are added in column (2) and (3), respectively. Assuming that the credit score succeeds in reflecting credit quality, the interest rate fulfils its main role: expressing credit risk. Compared to projects with the most favourable rating, the ones that receive the worst credit score pay, on average, an over two percentage point higher interest rate. Somewhat unanticipated is that I find no indication for a maturity risk premium. Investors should require a compensation for the increased probability of a rise in the market interest rate, while their capital is tied up in the project until its maturity. Since the variation in the loan period is fairly low – 80% of the projects have a maturity between three and five years – this might not be necessary. Furthermore, as foreseen, loan purpose seems to matter for the pricing of the loan: projects that have the objective of collecting start-up capital deal with significantly higher rates than their peers whose purpose relates to growth, property and renovation, a takeover, or miscellaneous. The influence of loan purpose is to be fully attributed to the perceived riskiness of projects in this first category, and it still holds when I control for company age. The latter variable itself does not have a considerable impact, which is consistent with the idea that any credit-related signals are captured by the credit score. What is interesting, is that the targeted amount appears to have a positive and significant impact on the interest rate of the project, which means that entrepreneurs wishing to borrow a relatively large amount should be willing to pay a higher interest rate to investors. One might argue that a larger loan results in higher loan expenses, which increases the repayment uncertainty. As it is the main objective of the credit score to portray this risk, the targeted amount should have no separate effect on the interest rate of the project. Therefore, the found significant coefficient forms evidence for a behavioural imperfection, which calls for the rejection of the efficient loan pricing hypothesis. As predicted, the additional controls do not have a considerable impact on the pricing of the loan.

The question remains whether investors do display fully efficient behaviour. The results from linear regression of the two measures of project popularity are documented in Table VI. In Panel A, the dependent variable is the project's completion time. The interest rate is added as an explanatory variable. The outcomes indicate that three out of the four loan characteristics significantly impact the completion time. That the interest rate does not have a notable influence, does not mean that investors are indifferent to its value. What this finding indicates, is that the loans are fairly priced, assuming that the ratings adequately reflect the credit quality. Since the credit score and the interest rate move together, the effect of the latter is captured by the former. Therefore, the significant influence of the credit score can be considered natural. The fact that the the difference with the best credit score keeps growing up to and including the second-worst rating, implies that investors generally have a preference for less risky projects, as these on average require less time to raise their targeted amount. Hence, there seems to be some form of risk aversion among investors. This is not an indication of imperfect behaviour, since investors in general do not have access to unlimited funds. In order to check if the interest rate perhaps does have an additional influence that does not appear immediately due to nonlinearity, I include a categorical variable that can take three values: low, medium, and high. I use the 30^{th} and 70^{th} percentile values as cut points, which are respectively 6% and 8%. The coefficients show no signs of any notable non-monotone relationship, which leads me to conclude that no additional behaviour is triggered by the interest rate other than objectifying credit risk. On the other two credit-related measures, the results are rather straightforward: Investors prefer projects with a relatively low maturity and a relatively low targeted amount. The coefficients indicate that a one-year increase in the maturity of the project leads to a 12.7% increase in its completion time, and a 10% rise in the targeted amount of the project results in a 6.2% longer time to complete. As I explained, the latter relationship is intuitive: when two projects receive equal average investments but differ in size, then the larger project requires more time to raise its targeted amount than the smaller project. This likely explains the high significance of the coefficient. The reason that investors favour projects with a shorter duration might be that, according to my earlier results on loan pricing, these projects' lower riskiness is not translated into a lower interest rate. As a result, investors make the correction themselves by adjusting their demand. Of the control variables, two yield surprising results: both company age and platform media coverage appear to have a significant influence on the popularity of the project. In essence, these two variables can be seen as drivers of brand awareness, since I assume that any credit-related information signalled by company age is captured by the credit score. It is likely that older companies are more well-known with the public, since they have had more time to build up a reputation. Likewise, it might help for projects to be published on a platform that has been covered in the media a large number of times. Both variables seem to be negatively related to completion time, although the significance of company age does not apply to all of the age groups: projects of companies with an age between three and four years and between four and five years do not have a significantly lower completion time than projects of companies less than one year old. Still, brand awareness appears to matter for the popularity of the project. This finding suggests that investors make some type of quality inference from the age of the company and the media coverage of its platform, which implies that investors make limited efforts to delve into the market. The question is whether these factors display the same conduct towards the second aspect of project popularity.

The number of investors shows to depend on slightly less variables. Panel B of Table VI displays the regression results. The only loan characteristic that exhibits a strong impact is the project's targeted amount. Its highly significant coefficient implies that a 10% increase in project size results in an approximate 7.2% rise in the number of investors. That the targeted amount is an important driver of this number also shows through the R^2 of the regression: approximately 86% of the variation in the number of investors is explained by the variables in the model. This value drops to a mere 37% when the targeted amount is excluded from the analysis. Also the effect of the interest rate is somewhat significant, however both statistically and economically this is only marginal. What the positive coefficient indicates, is that investors approach riskier projects with more caution: investing happens at a lower speed, whereas the provided average amounts are also lower. Similar to the regressions I performed on completion time, I include a categorical variable in order to test for nonlinearity in the impact of the interest rate. Despite the visual indication provided by Figure III, I find no statistical evidence. The remaining two loan characteristics, credit score and maturity, do not seem to have a considerable impact on the number of investors attracted by the project. In contrast, there is one other element that drives the behaviour of investors: the media coverage of the platform. To be specific, an increase of 10% in the media coverage of the platform that publishes the project is estimated to result in a rise of 2.5% in the number of investors, ceteris paribus. Given the consistency of the variable's impact, it can be concluded that an increase in the media coverage of the platform publishing the project, is associated with a rise in the popularity of the project. Taking its two proxies into account, a possible interpretation of the result is that projects published on a platform which name is mentioned in the media relatively often, attract a different type of investors. This group consists of relatively small investors that make fast decisions. Projects on less covered platforms draw more institutional-type investors that provide larger amounts and require more decision time. The effect is explainable, since small, private investors are likely to have limited time and resources to extensively familiarize themselves with the crowdfunding market. As I stated, they might therefore wrongfully infer media coverage as a signal of quality. This type of behaviour should not be observable, since higher media coverage of the platform is no guarantee for better projects.

Based on the presented results, I can reject both the efficient loan pricing and the efficient investment hypothesis, as I find evidence for the salience of two behavioural imperfections. First of all, the pricing of the loan is affected by its targeted amount. This is surprising, since loan size should not separately affect the interest rate that investors receive on the project. Second, project popularity is partially driven by the media coverage of the platform. This finding suggests that investors might make a quality inference, that is either conscious or unconscious. What can be concluded, is that the market displays imperfect behaviour, that might prevent it from operating optimally.

5.2 Credit quality

The previous passage has illustrated that behaviour in the crowdfunding market can be considered imperfect. One of the only factors separately influencing both loan pricing and project popularity, is the project's credit score. As this measure has the objective of evaluating the quality of a company's credit, it is used as a tool in determining the interest on a loan and making investment decisions. Given the seemingly important role of credit risk, this aspect will be analysed more extensively in this section.

5.2.1 Informativeness of the credit score

Regarding the project's credit score and its external ratings, one might have some endogeneity concerns, i.e. one might suspect that their effect on loan pricing and project popularity is driven by information that is already available to investors. If this is the case, then the credit scores have no particular informative power. To test if this indeed happens, I employ a two-stage estimation model. In the first stage of this model, two auxiliary regressions are estimated. Dependent variables of these regressions are the credit score and the average of the external ratings, respectively. All of the explanatory variables in my previous regressions – maturity, targeted amount, loan purpose, industry, historical financial data, company age, and platform media coverage – will also function as explanatory variables in these estimations. The regressions can be written as:

$$Credit\ score_i = \alpha_0 + \sum_{k=1}^{N} x_i^k \beta^k + \varepsilon_i, \qquad (3)$$

where $Credit\ score_i$ is either the platform's own credit score, or the average of the external ratings. The results of the two auxiliary regressions are reported concisely in Panel A of Table VII.

In the second stage, I regress the interest rate and the two measures of project popularity, completion time and the number of investors, onto the predicted values of the credit score and the external ratings and a set of control variables. Furthermore, I include variables that capture the residuals – the difference between the predicted and the actual values of the scores. These regressions can be written as:

$$Interest\ rate_i = \beta_0 + \beta_1 \widehat{CS}_i + \beta_2 D_{CS,i} + \beta_3 \widehat{ER}_i + \beta_4 D_{ER,i} + \sum_{m=1}^{M} x_i^m \varphi^m + v_i \qquad (4)$$

and

$$Project\ popularity_i = \beta_0 + \beta_1 \widehat{CS}_i + \beta_2 D_{CS,i} + \beta_3 \widehat{ER}_i + \beta_4 D_{ER,i} + \sum_{m=1}^{M} x_i^m \varphi^m + v_i, \qquad (5)$$

where $\widehat{CS}_i$ is the predicted credit score, $D_{CS,i}$ is the difference between the predicted and the actual credit score, $\widehat{ER}_i$ is the predicted average of the external ratings, and $D_{ER,i}$ is the difference between the predicted and the actual average of the external ratings. The identification conditions dictate that, in this stage, a number of regressors should be excluded that is equal to at least the number of endogenous variables in the estimation. Since the predicted score and the 'difference' variable can together be seen as one endogenous variable, I need to eliminate a minimum of two instruments from the second-stage regressions. These should be variables that do influence credit quality, but that do not have a considerable impact on loan pricing and project popularity, respectively. In the case of the former, deciding which factors should to exclude should be unequivocal, since I expect that most credit-related information is captured by the credit score. Recall from the previous results with regard to loan pricing, that most of the controls indeed do not have any notable direct impact.

One of these controls is the industry in which the company is active. Some industries are considered riskier than others for reasons such as increased competition or sensitivity of demand. For example, due to often high competition, changing market conditions and dependency on the economic climate, an industry such as retail might be considered rather volatile, whereas health can be considered a relatively stable business environment. Platforms and independent rating agencies can choose to build an industry-based risk factor into the rating that they assign to the project. The estimates of the auxiliary regressions confirm this, as companies active in services and retail on average receive lower credit scores from the platform than firms in other industries, and external rating agencies appear to disadvantage hospitality companies. Taking this into account, the only observable impact of the company's industry on the interest rate on the loan is expected to be through the credit score, which justifies the choice for excluding this variable. For the second removable object, I select company age, which is another control that does not seem to affect loan pricing other than in an indirect manner. Younger companies are seen as relatively opaque and therefore riskier than their older peers. Newly founded companies, for example, often are not able to present historical figures that indicate their financial strength, but can only raise forecasts they have yet to live up to. As a result, one would expect that these firms receive lower ratings than their older peers. The actual impact of company age shows to be minimal, however. Likely, its effect is captured by loan purpose, which seems particularly important for the credit score.

Next, I need to determine which two variables will be excluded from the regressions of project popularity. More or less the same reasoning applies here: any credit quality signals derivable from the different characteristics should be entirely captured by the credit score, and therefore no direct influence should be observable of these characteristics on the popularity of the project. As a first measure, I recommend loan purpose, which gives some indication of the project's riskiness. It should be noted that the loan purpose probably does not affect the external ratings, as I assume that they do not specifically take this into account when establishing a credit score. Still, it is possible that loan purpose captures certain risk-related project characteristics. Indeed, companies wishing to collect start-up capital receive a lower credit score than their peers that have another purpose. Moreover, the variable already showed not to be a direct determinant of project popularity. For the second variable that is to be removed from the second-stage regression of project popularity, I push forward industry, which is the same variable I also exclude from the interest rate estimation. The argumentation is similar: industry-related risk might play a role with regard to the credit quality of the project, but the popularity of the project should not depend on the industry of the company in any other way than through the interest rate. One might argue that personal preferences of investors play a role, however I choose to neglect this, since I assume that these preferences are widely dispersed across investors.

Estimation results of the second stage regressions are reported in Panel B of Table VII. Most importantly, these indicate that the project's credit scores – both the one constructed by the platform and the ones issued by independent rating agencies – are informative. More specifically, the scores are considered to be value adding instruments that help in setting interest rates and making investment decisions. This is illustrated by the significant coefficients on the 'difference' variables in the regressions of the interest rate and completion time, which show that yet unobserved information is translated into credit quality. With respect to this unobserved information, one can think of hard data, such as the company's financials, but also of various soft attributes like the character of the entrepreneur or the strategy of the company. It is likely that the significant impact of the predicted credit score on loan pricing is driven by loan purpose, as this is one of the key determinants of both the interest rate and the credit score. Since the number of investors is not significantly influenced by the credit scores, neither the predicted score nor its residual has any notable impact.

5.2.2 Individual impact of external ratings

The previous section revealed that, in addition to the platform's credit score, the ratings issued by independent agencies have a considerable impact on both the project's interest rate and its popularity. I have no information, however, on the individual influence of these ratings. In my sample, I identify four different external ratings: the Graydon score[11], the Dun & Bradstreet score[12], the Creditsafe score[13], and the BKR score[14]. With a total number of three, Geldvoorelkaar.nl is the only platform that publishes more than one of these ratings. I wish to directly compare the individual impact of these three measures on loan pricing and project popularity, and test whether

[11] The Graydon score indicates the probability of default within one year, of which the calculation is based on financial accounts, payment behaviour, company characteristics and unusual information.

[12] The Dun & Bradstreet score is based on a number of factors that are expected to have the most impact on risk assessment and company defaults in that particular country.

[13] The Creditsafe score is an indication of a company's creditworthiness, which is calculated on the basis of a number of company characteristics and financial information.

[14] The BKR score measures the average default risk of the entrepreneur in private, and does not relate to the company itself.

the informative power of the platform's credit score is robust to the external ratings. Therefore, I analyse a subsample that comprises solely projects of Geldvoorelkaar.nl. The results from regressions of the project's interest rate, completion time, and number of investors are reported in Table VIII. Both company ratings, the Graydon score and the Creditsafe score, significantly impact the interest rate. Similar to the role of the platform score, a worsening of any of these ratings results in an increase in the interest rate of the project, ceteris paribus. In contrast, it appears that for investors, the external ratings have no clear added value compared to the platform's credit score. The project's completion time is not dependent on any of these ratings, whereas the number of investors is only slightly influenced by the BKR score of the entrepreneur: the result of a one-unit amelioration of the score is a 4.8% rise in the number of investors, ceteris paribus. This does not mean that the ratings almost are not considered at all. What it indicates is that their impact does not significantly differ from that of the platform's credit score. The main takeaway is that the latter measure shows to be more informative than the external ratings, which verifies its robustness. This provides confirmation of the notion that the credit score adds value and functions as a guidance tool for the participants in the market.

5.3 Personal characteristics of the entrepreneur

So far, this paper has identified two salient behavioural imperfections, and has shown the informativeness of the credit score. The identification of one remarkably influential soft factor – platform media coverage – evokes the question whether other soft characteristics can play an important role in determining interest rates and the popularity of projects. Studies of traditional credit markets have found evidence for different types of discrimination, mainly based on race (e.g., Cavalluzzo and Cavalluzzo, 1998; Bostic and Lampani, 1999; Cavalluzzo et al., 2002; Blanchflower et al., 2003) and gender (e.g., Marlow and Patton, 2005; Coleman and Robb, 2008; Muravyev et al., 2009; Bellucci et al., 2010). I choose to focus on the type of discrimination that should be most easily identifiable taking into account the availability of data, which is the one based on gender. Interestingly, most of the research finds increased credit constraints for females vis-à-vis their male peers or no difference at all, which contrasts with the results found by a number of studies on peer-to-peer lending (Pope and Sydnor, 2011; Duarte et al., 2012; Ravina, 2012) that indicate discrimination against males. In a perfect market, the entrepreneur's gender should not have any impact on his or her access to finance. Applied to the current study, no difference with regard to the project's interest rate and its popularity should be observable between projects of male and female entrepreneurs. In order to also scrutinize the role of personal characteristics of the entrepreneur more generally, I explore the effect of the presence of a photo displaying the entrepreneur. This might matter: Pope and Sydnor (2011) find signals of a negative market response to projects that do not feature a photo. To measure the effect, I include a dummy that is equal to one if the project features at least one photo of the entrepreneur, and zero otherwise. For analysing the impact of gender, I create a categorical variable that comprises four groups: projects of solely male entrepreneurs, projects of solely female entrepreneurs, projects of both male and female entrepreneurs, and projects of entrepreneurs whose gender is not specified. The regression results are reported in Table X, which is included in Appendix B. Panel A of the table displays the estimation of the project's interest rate. No direct effect is found of the presence of a photo of the entrepreneur on the interest rate on the loan. This is not surprising, given that the rate is determined before the project is published. Regarding gender, I find the slightest indication for discrimination against males: on average, the interest rates on projects of female entrepreneurs are lower than the rates on projects of their male peers, which is in line with the peer-to-peer lending literature. The significance of this difference is only minimal, however, hence the question is to what extent any generalizable inferences can be drawn from this finding. In Panel B, the regression estimations are reported for project popularity. The results demonstrate that investors do not notably respond to the presence of the entrepreneur's photo. Furthermore, I find no evidence for discrimination between projects of male and female entrepreneurs. What I do detect, is that single-gender projects are less popular among investors than projects of entrepreneurs of both genders, in terms of their completion time. I can think of two explanations for this phenomenon. On the one hand, having both genders on board is a form of diversification. As investors might have a preference for entrepreneurs of their own gender, both-gender projects should be able to count on the sympathy of all investors. On the other hand, the result might be driven by the fact that both-gender projects are always lead by more than one entrepreneur, whereas same-gender projects might often belong to a single entrepreneur. The latter group might be perceived as riskier by investors. Most importantly, the findings indicate that no considerable discrimination appears to exist between the two genders.

Even though I find no direct evidence for increased financial constraints of either males or females, they might still exist, since the effects of gender may vary for different values of certain loan characteristics. Specifically, the level of implied credit risk possibly determines to what extent the entrepreneur's gender drives access to credit. Therefore, I follow Barasinka and Schäfer (2010) and include interactions of the variable 'Male' – which is a dummy variable that is equal to one if the project is lead by only male entrepreneurs and zero otherwise – with the set of dummy variables indicating the credit score and the interest rate of the project. The results of the complemented regressions are reported in Table XI, which is part of Appendix B. No gender discrimination seems to exist in terms of loan pricing, since none of the interaction terms hold significant coefficients. The signals of discrimination against males that were found in the regression without interaction terms, have disappeared. In the meantime, the coefficients indicate that investors are influenced by gender: projects that receive any other than the most favourable rating, on average have a lower completion time when they are lead by female entrepreneurs versus when the entrepreneurs are male, compared to projects with the highest credit score. I do not find the same results when I replace the 'Male' variable with the female dummy; instead, the interaction terms do not have any significant impact (I do not report these results). What these findings suggest, is that investors have a preference against projects of male entrepreneurs. The results are not consistent, however, which means there is no ground to state that gender-based discrimination is a persistent issue in crowdfunding. Still, these signals are a hint that behaviour in the market might not be fully efficient, adding to this paper's earlier indications.

5.4 Robustness checks

The sample of this study comprises a total of 18 platforms. The number of closed projects on their websites – at time of data collection – varies from 2 to 183. It is possible that the results are driven by certain characteristics of small platforms. To examine the robustness of my findings, I analyse a subsample that is limited to projects of the six largest platforms. Recall that two of these six platforms do not assign credit scores. Since I included the credit score as an explanatory variable in all of the regressions, due to its proven impact, this paper's analysis has disregarded the projects of those platforms. Therefore, they are effectively not part of the scrutinized sample. This means that, in practice, I analyse a subsample comprising projects of the four largest platforms that make use of credit scores: Collin Crowdfund, Geldvoorelkaar.nl, Horeca Crowdfunding Nederland, and Kapitaal Op Maat. The regressions of the interest rate, completion time, and the number of investors are reported in Table XII, which is included in Appendix B. The estimates show that all of the main results are robust to the impact of small platforms. The most discernable change regards to the number of investors, and signifies the increased significance of the impact of the project's credit score and the interest rate. Furthermore, the two most pronounced implied behavioural imperfections, the impact of the size of the loan on its interest rate and the effect of the media coverage of the platform on the popularity of the project, did not lose ground in terms of significance. Hence, any suspicions about the contamination of this paper's results by attributes of small platforms turn out to be unfounded.

6. Conclusion

Crowdfunding is a financing form that has been gaining in popularity at a remarkable speed over the past few years. Due to a considerable amount of information asymmetry and an often low participation threshold for investors, imperfect behaviour might be observed. The objective of this paper is to analyse whether this is the case, so that a statement can be made about the efficiency of the crowdfunding market. I construct two null hypotheses, which I refer to as the efficient loan pricing hypothesis and the efficient investment hypothesis. According to these hypotheses, the demeanour of all market participants can be considered fully rational. By analysing a sample comprising projects of the notable Dutch platforms with a lending-based model, I find evidence against these hypotheses. To be specific, two particular anomalies become apparent: First of all, in order to borrow a larger amount, the entrepreneur should be willing to pay investors a higher interest rate. Second, the more media attention that the platform receives, the more popular the project becomes. These findings signal deficiencies in the behaviour of the main market participants. One of the project characteristics that shows to play a considerable role in determining interest rates and driving decisions of investors is the credit score that the project receives from the platform. I test for its endogeneity and find that this measure of credit quality is informative, i.e. that its effect is driven by yet unobserved information. The impact of the credit score holds when I control for the effect of external ratings. Finally, I analyse the role of personal characteristics of the entrepreneur. I find some indication for gender-based discrimination, however the results are inconsistent and therefore lack sufficiency as a basis for any meaningful implications. What can be concluded from these results, is that the crowdfunding market can not be considered fully efficient, as some behavioural imperfections appear to be persistent. Possibly, this is due to the stage of development in which the market finds itself, however no considerable changes might be observable as long as the problems arising from information asymmetry are not alleviated and less sophisticated investors keep access to the market.

Until now, no research has focused on detecting imperfect behaviour in the crowdfunding market. Most of the literature analyses which factors play an important role with regard to the decision making of investors, entrepreneurs, and platforms in order to gain an understanding of the interactions in the market. The method of this paper goes one step further: it distillates impactful characteristics and judges whether their influence is grounded, using basic economic theory. Therefore, it contributes to the body of knowledge revolving around crowdfunding and peer-to-peer lending by providing insight in observed deviations from efficient behaviour, based on empirical analysis.

The findings of this paper have several important implications for all of the participants in the market. First of all, entrepreneurs should seriously consider the cost of debt. That is, if they desire to borrow a larger amount, they should be prepared to pay a higher interest rate to investors. An informed choice should therefore be made, as the entrepreneur ideally should target an amount that does not largely exceed the necessary quantity. Second, for platforms that aim for speedy investments and low completion times of their projects, the message appears simple: seeking publicity is beneficial. Boosting the media coverage will help platforms draw more small investors that make rapid decisions. Third, the average investor can be regarded as risk averse, due to limited funds. Whereas their use of the credit score as an instrument to infer credit quality can be viewed as rational, a deliberate trade-off between all of the loan characteristics should be made. In contrast, investors should neglect factors such as the media coverage of the platform, as this expectedly does not have any consequences for the quality of the project.

There might be some alternative explanations for the two most salient behavioural imperfections found by this paper. Regarding the positive association between the size of the loan and the interest rate, one might argue that investors regard entrepreneurs with larger loan requests as overconfident. As a result, they might exert influence on the demand side by requiring a higher interest rate. Since the completion time and the number of investors straightforwardly increase as projects become larger, it is hard to distinguish any other effects. The overconfidence interpretation can, however, neither be seen as an indicator of efficient behaviour, as the demeanour of investors would be based on suspicion instead of proof. With respect to the role played by the platform media coverage in determining the popularity of projects, it is possible that behaviour is driven by cautiousness rather than by a quality inference. Being more familiar with a certain platform, as the investor has read or heard more about it, might make the investor more trusting towards that particular platform, as opposed to other platforms. Furthermore, one might argue that the effect is not driven by an active evaluation, but that instead investors choose the platform that first comes up in their minds. Also both of these explanations advocate that the positive association between platform media coverage and project popularity can be considered a signal for imperfect behaviour.

Since the objective of my research is to perform a general assessment of behavioural imperfections in the crowdfunding market, there are some limitations. This is a cross-sectional study that ignores developments over time, considering the inaccessibility of these data and the fact that such an analysis goes beyond the scope of this paper. Perhaps, deviations from inefficient behaviour might only be of a temporary nature. It would be interesting to scrutinize whether certain imperfections persist, or that they disappear as the market matures. Furthermore, the sample is limited to platforms in one country. Likely, noteworthy dissimilarities between countries exist, due to distinctive financial systems and investor characteristics. Earlier, I mentioned the comparison of peer-to-peer lending markets in the United States and China by Chen and Han (2012), which shows that investors in the two countries rely on different types of information. A comparison between platforms in multiple countries might therefore yield even more generalizable results regarding the behaviour in the market. A third limitation is that only a bounded number of characteristics is analysed. Although I identify the fundamental determinants with respect to the loan and the entrepreneur, including more controls increases the probability of finding additional signals of imperfect behaviour. For example, I have found a cautious signal of gender-based discrimination by investors. Being only one personal characteristic of the entrepreneur, exploring the effects of more personal characteristics of the entrepreneur would perhaps yield further results suggesting behavioural imperfections.

Besides the mentioned potential avenues for future research, I propose two additional directions, based on the two behavioural imperfections that are found in this paper. According to my results, larger loans are associated with higher interest rates. Therefore, it would be interesting to test whether these loans can actually be considered riskier, i.e. whether the probability of default increases as the amount rises, perhaps due to overconfidence. This would justify the observed relationship. Next, the found impact of platform media coverage on project popularity calls for a more in-depth analysis of the influence of the media on behaviour in crowdfunding. One can think of testing the effect of project media coverage instead of that of the platform, to see if this has a similar impact on the popularity of the project. Additionally, as social media become increasingly powerful as tools for communication tool, it would be interesting to analyse the effect of these channels. All together, much is yet to learn about the properties of crowdfunding as a financing form and the determinants of behaviour in the market.

Appendix A

Table I – Variable definitions

Variable	Definition
Relative completion time	The time in days a project needs to complete, divided by the total targeted amount of the project in thousands of Euros
Average investment	The average investment a project receives in Euros, divided by the total targeted amount of the project in Euros
Interest rate	The nominal interest rate investors receive over the loan, in % p.a.
Credit score	Categorical variable with five values showing the credit score of the project, where 5 portrays the highest risk and 1 denotes the lowest risk
External ratings	The total sum of the scaled external ratings, including the Graydon score, the Dun & Bradstreet score, the Creditsafe score and the BKR score, divided by the number of external ratings published by the platform
Maturity	The total period of the loan, after which investors are repaid the initial amount
Targeted amount	The total amount in Euros that the company wishes to collect, which is expressed on beforehand
Loan purpose	Categorical variable with eight values showing the purpose of the loan: inventories, growth, property & renovation, solar panels & sustainability, start-up, takeover, working capital, or other
Industry	Categorical variable with seven values showing the industry in which the company is active: hospitality, services, retail, energy & sustainability, health, IT, or other
Historical financial data	Dummy variable that is equal to 1 when any type of past financial data is available, such as a balance or a profit & loss statement
Company age	Categorical variable with six values showing the age of the company at time of starting the crowdfunding campaign, measured in years: less than one year old, between one and two years old, between two and three years old, between three and four years old, between four and five years old and more than five years old. This is calculated by taking the difference between the month in which the project was launched and the month in which the company was founded
Platform age	Categorical variable with six values showing the age of the platform at time of starting the crowdfunding campaign, measured in years: less than one year old, between one and two years old, between two and three years old, between three and four years old, between four and five years old and more than five years old. This is calculated by taking the difference between the month in which the project was launched and the month in which the platform was founded
Platform media coverage	The number of times the platform was mentioned in the Dutch media at time of project launch

This table displays the variables that are included in this research, and provides a detailed description of each variable. The data gathering process is further explained in the Data section.

Table II – Crowdfunding platforms

Platform	Focus	Closed projects on website	Interest rate	Completion time	Number of investors
All4Funding	General	2	Yes	No	No
AygoDutch	General	6	Yes	No	Yes
Capital Circle	General	5	Yes	Yes	No
Collin Crowdfund	General	151	Yes	Yes	Yes
Crowdaboutnow	General	161	Yes	Yes	Yes
Crowdpartners	General	4	Yes	No	No
Duurzaam Investeren	Sustainability	14	Yes	Yes	Yes
Funding Circle	General	5	Yes	No	No
Geldrond	General	3	Yes	No	No
Geldvoorelkaar.nl	General	183	Yes	Yes	Yes
Greencrowd	Sustainability	22	Yes	No	Yes
Horeca Crowdfunding Nederland	Hospitality	33	Yes	Yes	Yes
Investormatch	General	8	Yes	No	Yes
Kapitaal Op Maat	General	129	Yes	Yes	Yes
NLInvesteert	General	4	Yes	Yes	Yes
Oneplanetcrowd	Sustainability	36	Yes	No	Yes
Regiofund	General	2	Yes	Yes	No
The Dutch Deal	General	9	Yes	No	Yes

This table provides a list of the platforms that are included in the sample, and states their focus and the number of closed projects on their website at time of data collection. Furthermore, it indicates whether data are available on the three dependent variables, which are interest rate, completion time and the number of investors.

Table III – Descriptive statistics

Panel A: Explanatory variables

	Mean	Median	Std. Dev.	10th percentile	90th percentile
Interest rate	6.83%	7.00%	1.75%	4.40%	8.50%
Completion time	22	3	31	1	73
Number of investors	106	77	98	29	212
Credit score					
1	0.08	0	0.27	0	0
2	0.20	0	0.40	0	1
3	0.33	0	0.47	0	1
4	0.18	0	0.39	0	0
5	0.22	0	0.41	0	0
Targeted amount	110,385	68,000	131,844	16,000	250,000
Maturity	4.32	4	1.72	3	5

Panel B: Controls

	Mean	Std. Dev.
Loan purpose		
Inventories	0.04	0.19
Growth	0.16	0.37
Property & renovation	0.06	0.24
Energy &	0.06	0.24
sustainability	0.29	0.45
Start-up		
Takeover	0.05	0.22
Working capital	0.24	0.43
Other	0.10	0.30
Historical financial data	0.16	0.36
External ratings	2.11	0.69
Platform media coverage	110	98

	Mean	Std. Dev.
Industry		
Hospitality	0.24	0.42
Services	0.09	0.29
Retail	0.14	0.35
Energy & sustainability	0.08	0.27
Health	0.09	0.29
IT	0.02	0.15
Other	0.34	0.47
Company age		
Less than 1 year	0.46	0.50
1 to 2 years	0.11	0.32
2 to 3 years	0.07	0.25
3 to 4 years	0.06	0.24
4 to 5 years	0.05	0.21
More than 5 years	0.25	0.43

The total sample includes 777 observations. Not all variables hold this number of observations, since variables such as completion time, average investment and credit score are not available for each project. This table displays the mean, median, standard deviation, 10th percentile and 90th percentile value for each variable included in this research.

Table IV – Correlation matrix

	Interest rate	Completion time	Number of investors	Credit score	Maturity	Targeted amount	Historical financial data	Company age	Platform media coverage
Interest rate	1.000								
Completion time	0.082	1.000							
Number of investors	0.071	0.038	1.000						
Credit score	0.656	-0.003	0.063	1.000					
Maturity	-0.062	0.047	0.112	-0.034	1.000				
Targeted amount	-0.006	0.098	0.752	-0.130	0.046	1.000			
Historical financial data	-0.121	0.066	0.139	-0.066	0.006	-0.053	1.000		
Company age	-0.029	-0.011	0.127	-0.088	-0.056	0.152	0.111	1.000	
Platform media coverage	0.054	-0.257	0.274	0.375	0.178	-0.040	-0.048	0.012	1.000

This table presents pairwise correlations for a total number of 500 observations (due to the exclusion of projects without a credit score and projects for which the interest rate, completion time or number of investors is unknown) between interest rate, completion time, number of investors, credit score, maturity, targeted amount, availability of past financial data, company age, and platform media coverage. Table I provides a detailed description of each variable.

Table V – Determinants of loan pricing

	(1)	(2)	(3)
Credit score			
1 (reference category)			
2	0.803***	0.730***	0.713***
	(3.49)	(3.18)	(3.00)
3	1.390***	1.306***	1.325***
	(6.85)	(6.45)	(6.27)
4	1.823***	1.728***	1.726***
	(8.79)	(8.21)	(8.03)
5	2.445***	2.200***	2.200***
	(10.79)	(9.39)	(8.97)
Maturity		-0.020	-0.017
		(-0.51)	(-0.44)
Loan purpose			
Start-up (reference category)			
Inventories		-0.117	-0.215
		(-0.94)	(-1.38)
Growth		-0.114	-0.272**
		(-1.08)	(-2.26)
Property & renovation		-0.237	-0.387**
		(-1.47)	(-2.34)
Energy & sustainability		-0.589	-0.534
		(-1.14)	(-1.12)
Takeover		-0.066	-0.240**
		(-0.59)	(-1.99)
Working capital		-0.035	-0.167
		(-0.40)	(-1.59)
Other		-0.459***	-0.533***
		(-3.93)	(-4.31)
Targeted amount (log)			0.144***
			(3.57)
Industry dummies	No	No	Yes
Historical financial data	No	No	Yes
Company age dummies	No	No	Yes
Platform media coverage	No	No	Yes
Platform fixed effects	Yes	Yes	Yes
N	564	564	564
R^2	0.645	0.658	0.676

This table presents the results from linear regressions of the dependent variable interest rate onto various project characteristics and fixed effects. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table VI – Determinants of project popularity

Panel A: Completion time

	(1)	(2)	(3)	(4)
Credit score				
1 (reference category)				
2	0.244	0.204	0.185	0.226
	(1.13)	(0.91)	(0.85)	(0.98)
3	0.332*	0.379*	0.448**	0.467*
	(1.68)	(1.75)	(2.03)	(1.96)
4	0.636***	0.776***	0.787***	0.745***
	(2.63)	(2.94)	(3.07)	(2.79)
5	0.551***	0.673**	0.737***	0.686**
	(2.90)	(2.63)	(2.80)	(2.54)
Interest rate		-0.046	-0.056	
		(-0.60)	(-0.83)	
Interest rate				
Low (reference category)				
Medium				-0.283
				(-1.29)
High				-0.189
				(-0.77)
Maturity		0.107**	0.120***	0.117**
		(2.25)	(2.64)	(2.54)
Targeted amount (log)		0.516***	0.632***	0.639***
		(8.88)	(9.96)	(10.06)
Platform media coverage (log)			-0.687***	-0.686***
			(-8.08)	(-8.15)
Company age				
Less than 1 year (reference category)				
1 to 2 years			-0.387**	-0.392**
			(-2.19)	(-2.20)
2 to 3 years			-0.434**	-0.443**
			(-2.00)	(-2.04)
3 to 4 years			-0.255	-0.241
			(-1.03)	(-0.97)
4 to 5 years			-0.209	-0.190
			(-0.81)	(-0.74)
More than 5 years			-0.338**	-0.337***
			(-2.74)	(-2.73)
Loan purpose dummies	No	No	Yes	Yes
Industry dummies	No	No	Yes	Yes
Historical financial data	No	No	Yes	Yes
Platform fixed effects	Yes	Yes	Yes	Yes
N	507	507	507	507
R^2	0.224	0.333	0.463	0.464

Table VI – Determinants of project popularity (cont'd)

Panel B: Number of investors				
	(1)	(2)	(3)	(4)
Credit score				
1 (reference category)				
2	0.211	0.002	0.011	0.028
	(1.32)	(0.03)	(0.15)	(0.34)
3	0.313**	0.116	0.069	0.105
	(2.04)	(1.38)	(0.89)	(1.25)
4	0.248	0.111	0.089	0.124
	(1.55)	(1.13)	(0.99)	(1.37)
5	0.168	-0.002	-0.029	0.020
	(0.94)	(-0.02)	(-0.28)	(0.19)
Interest rate		0.050*	0.054*	
		(1.71)	(1.86)	
Interest rate				
Low (reference category)				
Medium				0.031
				(0.31)
High				0.096
				(0.83)
Maturity		-0.009	-0.012	-0.013
		(-0.60)	(-0.77)	(-0.86)
Targeted amount (log)		0.743***	0.729***	0.736***
		(40.68)	(38.10)	(39.73)
Platform media coverage (log)			0.255***	0.258***
			(8.60)	(8.58)
Loan purpose dummies	No	No	Yes	Yes
Industry dummies	No	No	Yes	Yes
Historical financial data	No	No	Yes	Yes
Company age dummies	No	No	Yes	Yes
Platform fixed effects	Yes	Yes	Yes	Yes
N	545	543	543	543
R^2	0.179	0.807	0.857	0.856

This table presents the results from linear regressions of the dependent variables completion time and number of investors, respectively, onto various project characteristics and fixed effects. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table VII – Two-stage regressions

Panel A: First-stage regressions

	Credit score	External ratings
Maturity	-0.058 (-1.33)	-0.009 (-0.22)
Targeted amount (log)	0.046 (0.70)	-0.002 (-0.05)
Controls	Yes	Yes
N	564	348
R^2	0.361	0.235

Panel B: Second-stage regressions

	Interest rate		Completion time		Number of investors	
	(1)	(2)	(3)	(4)	(5)	(6)
Pred. credit score	0.531*** (2.76)	0.416*** (2.69)	0.187 (1.40)	-0.042 (-0.26)	-0.006 (-0.14)	-0.018 (-0.31)
Diff. credit score	0.526*** (12.55)	0.417*** (8.41)	0.222*** (3.98)	0.155*** (3.08)	0.006 (0.28)	-0.009 (-0.52)
Pred. external ratings		-0.311 (-0.93)		0.391 (0.97)		-0.044 (-0.31)
Diff. external ratings		0.230*** (4.17)		0.311*** (3.81)		0.029 (1.26)
Industry fixed effects	No	No	No	No	No	No
Company age fixed effects	Yes	No	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	564	348	507	331	543	345
R^2	0.669	0.577	0.452	0.401	0.852	0.889

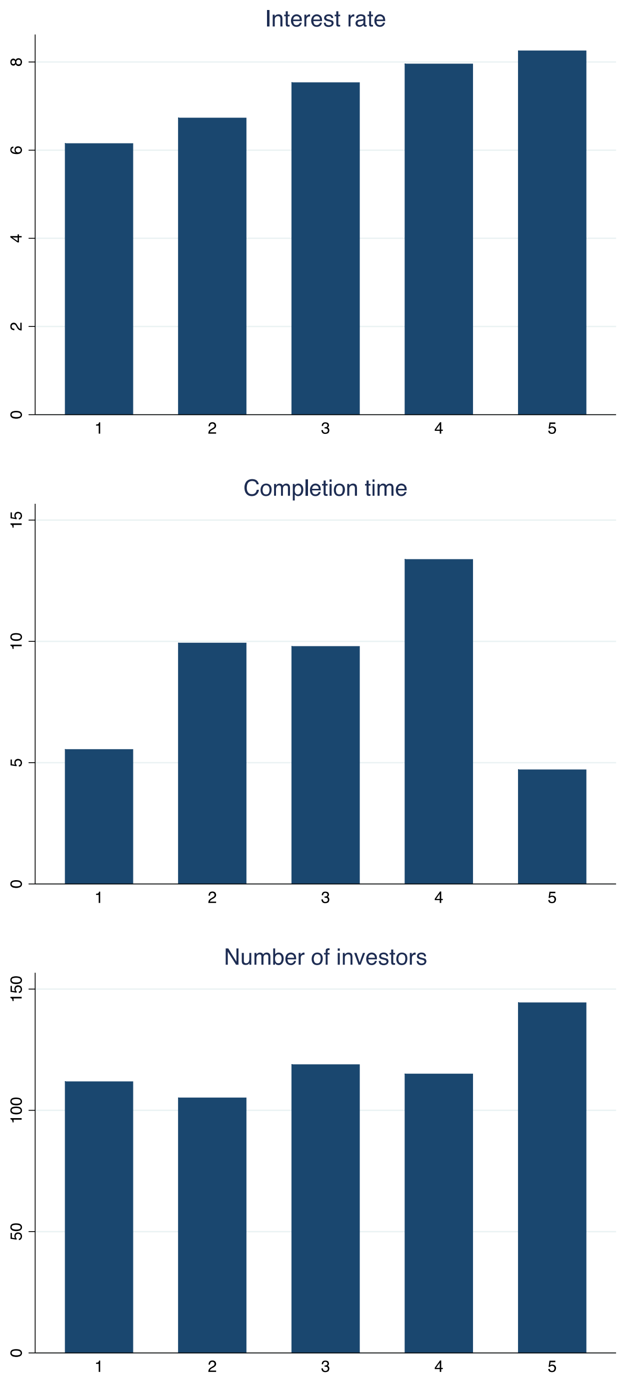
This table presents the results from the two-stage regressions of the three main dependent variables, which are the interest rate, completion time, and the number of investors, onto the credit score and external ratings, and various project characteristics and fixed effects. Panel A reports the results from linear regression of the credit score and the external ratings onto various project-specific and platform-specific variables. In the left column the dependent variable is the platform's credit score, whereas in the right column the dependent variable is the average of the external ratings, which are the Graydon score, the Dun & Bradstreet score, the Creditsafe score, and the BKR score. Panel B reports the results from linear regression of the interest rate, completion time, and the number of investors onto the predicted values of the credit score and the external ratings, the differences between the actual and the predicted values, and a number of project characteristics and fixed effects. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table VIII – External ratings

	Interest rate	Completion time	Number of investors
Graydon	0.185**	-0.059	0.002
	(2.01)	(-0.44)	(0.07)
Creditsafe	0.089**	0.065	0.021
	(1.84)	(1.28)	(1.28)
BKR	0.037	-0.075	0.047*
	(0.44)	(-0.67)	(1.77)
Credit score	0.442***	0.192***	-0.003
	(6.54)	(3.02)	(-0.12)
Controls	Yes	Yes	Yes
N	183	183	183
Adj. R^2	0.675	0.417	0.921

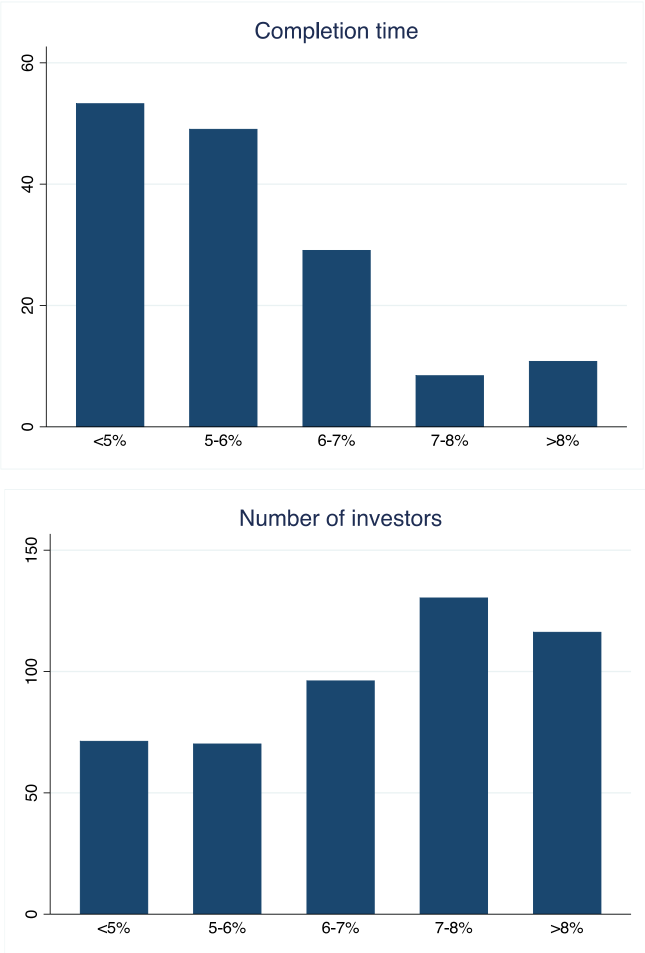
This table presents the results from linear regression of the three dependent variables interest rate, completion time, and number of investors onto three different external ratings and various project characteristics and fixed effects. The sample consists of only projects of the platform Geldvoorelkaar.nl, which is the only Dutch platform that publishes more than one external rating: The Graydon score, the Creditscafe score, and the BKR score. Controls include maturity, targeted amount, loan purpose, industry, historical financial data, company age, and platform media coverage. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure I – Interest rate, completion time, number of investors by credit score



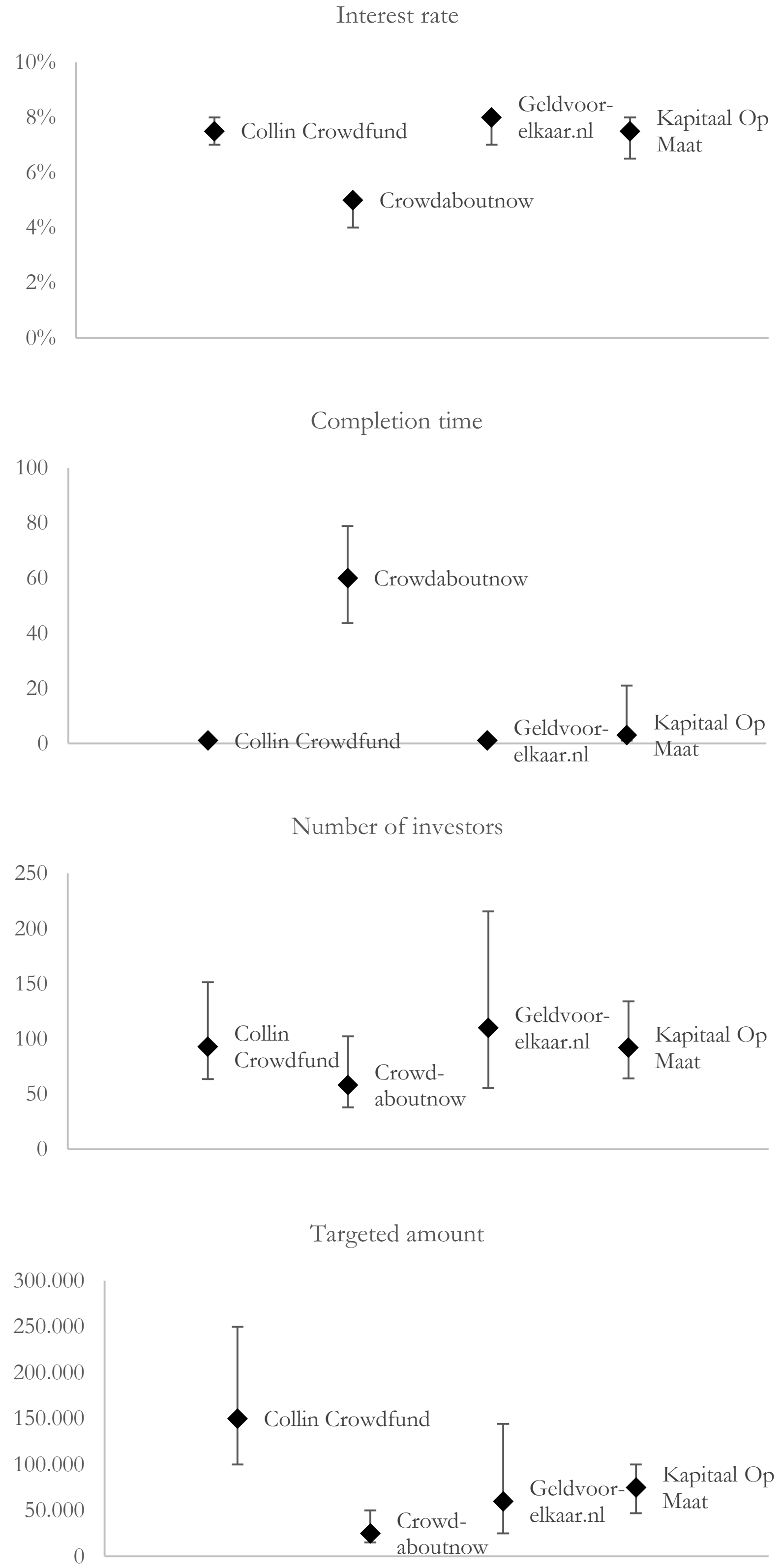
This figure illustrates, respectively, the mean interest rate, the mean completion time, and the mean number of investors within each credit category. Projects are classified on a scale from one to five, where one denotes the highest credit quality and five portrays the lowest credit quality.

Figure II – Completion time and number of investors by interest rate category



This figure illustrates, respectively, the mean completion time and the mean number of investors within each interest rate category. Projects are classified on a scale consisting of five categories, which are below five percent, between five and six percent, between six and seven percent, between seven and eight percent, and above eight percent.

Figure III – Comparison of four largest platforms



For the variables interest rate, targeted amount, completion time, number of investors, and targeted amount, this figure displays the median values, together with the 25th and 75th percentile values for the four largest platforms based on the number of closed projects on their website.

Appendix B

Table IX – Descriptive statistics: platform level

	Collin Crowdfund			Crowdaboutnow			Geldvoorelkaar.nl		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Interest rate	7.55%	7.50%	0.56%	4.94%	5.00%	1.96%	7.57%	8.00%	1.17%
Completion time	3.7	1.0	6.5	60.2	59.7	24.3	4.2	1.0	8.5
Number of investors	116	93	69	66	51	58	162	110	151
Credit score									
1	0.01	0	0.08	-	-	-	0.11	0	0.32
2	0.25	0	0.43	-	-	-	0.09	0	0.29
3	0.42	0	0.50	-	-	-	0.15	0	0.36
4	0.32	0	0.47	-	-	-	0.04	0	0.21
5	0.00	0	0.00	-	-	-	0.60	1	0.49
Targeted amount	183,858	150,000	130,935	44,277	25,000	62,232	109,203	60,000	134,520
	Horeca Crowdfunding Nederland			Kapitaal Op Maat			Oneplanetcrowd		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Interest rate	8.30%	8.00%	0.61%	7.20%	7.50%	0.82%	5.88%	5.75%	1.36%
Completion time	15.5	5.0	18.5	17.3	3.0	26.6	-	-	-
Number of investors	79	78	34	106	92	58	65	50	40

Credit score									
1	0.00	0	0.00	0.11	0	0.31	-	-	-
2	0.27	0	0.45	0.19	0	0.39	-	-	-
3	0.30	0	0.47	0.47	0	0.50	-	-	-
4	0.33	0	0.48	0.24	0	0.43	-	-	-
5	0.09	0	0.29	0.00	0	0.00	-	-	-
Targeted amount	121,788	95,000	72,603	83,705	75,000	55,311	72,278	50,000	62,101

	Highest	Lowest	Diff.	(*t*-stat)
Interest rate	Geldvoorelkaar.nl	Crowdaboutnow	2.63%	(14.88)
Completion time	Crowdaboutnow	Collin Crowdfund	56.5	(28.42)
Number of investors	Geldvoorelkaar.nl	Crowdaboutnow	96	(5.86)
Targeted amount	Collin Crowdfund	Crowdaboutnow	139,581	(11.90)

The six largest Dutch crowdfunding platforms are identified, based on the number of closed projects that are displayed on their website. For these platforms, this table shows the mean, median and standard deviation for the three dependent variables, which are the interest rate, completion time and the number of investors, and the explanatory variables credit score and targeted amount. Furthermore, between-platform comparisons on the three dependent variables and the explanatory variable targeted amount are provided. For each of these four variables, Figure I shows the mean, together with the 25th and 75th percentile value, for the four largest Dutch crowdfunding platforms. Based on the number of closed projects on their website, these platforms are Collin Crowdfund, Crowdaboutnow, Geldvoorelkaar.nl, and Kapitaal Op Maat. This table displays the highest scoring platform on each of the four variables on the left, whereas the lowest scoring platform on each of the four variables is shown on the right. A *t*-test is used to determine the statistical significance of the difference between the highest and lowest scoring platform. The *t*-statistics are in parentheses.

Table X – Entrepreneur characteristics

Panel A: interest rate

Picture	0.083
	(0.83)
Gender	
Male (reference category)	
Female	-0.136*
	(-1.67)
Both	0.095
	(1.27)
Not specified	0.175
	(1.01)
Controls	Yes
N	564
Adj. R^2	0.678

Panel B: project popularity

	Completion time	Number of investors
Picture	-0.026	0.027
	(-0.18)	(0.57)
Gender		
Male (reference category)		
Female	-0.206	-0.010
	(-1.40)	(-0.20)
Both	-0.290**	0.017
	(-2.43)	(0.54)
Not specified	0.161	0.005
	(0.84)	(0.08)
Controls	Yes	Yes
N	507	543
Adj. R^2	0.471	0.858

This table presents the results from linear regressions of the three main dependent variables, which are the interest rate, completion time, and the number of investors, respectively, onto a dummy variable indicating whether or not a picture of the entrepreneur(s) is shown, a variable indicating the gender of the entrepreneur(s) (if specified), and various project characteristics and fixed effects. In Panel A, the dependent variable is the interest rate, whereas in Panel B, the dependent variables are the two measures of project popularity, which are completion time and the number of investors. In panel A, controls include maturity, targeted amount, loan purpose, industry, historical financial data, company age, and platform media coverage. In panel B, controls also include interest rate. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table XI – Entrepreneur characteristics (with interactions)

Panel A: interest rate

Picture	0.080
	(0.78)
Gender	
Male (reference category)	
Female	-0.259
	(-1.39)
Both	-0.029
	(-0.15)
Not specified	0.066
	(0.27)
Credit score	
1 (reference category)	
2	0.705**
	(2.45)
3	1.332***
	(5.47)
4	1.782***
	(7.17)
5	2.306***
	(8.11)
Male * credit score = 2	-0.066
	(-0.27)
Male * credit score = 3	-0.090
	(-0.45)
Male * credit score = 4	-0.152
	(-0.71)
Male * credit score = 5	-0.234
	(-1.15)
Controls	Yes
N	564
Adj. R^2	0.679

Panel B: project popularity

	Completion time	Number of investors
Picture	-0.018	0.031
	(-0.12)	(0.64)
Gender		
Male (reference category)		
Female	0.508*	0.145
	(1.94)	(1.07)
Both	0.434*	0.176
	(1.86)	(1.37)
Not specified	0.681***	0.152
	(2.63)	(1.09)

Credit score		
1 (reference category)		
2	-0.278	0.041
	(-1.20)	(0.40)
3	-0.140	0.048
	(-0.56)	(0.42)
4	0.068	0.072
	(0.24)	(0.54)
5	0.370	-0.056
	(1.20)	(-0.36)
Male * credit score = 2	1.285***	-0.055
	(3.56)	(-0.46)
Male * credit score = 3	1.431***	0.033
	(3.59)	(0.26)
Male * credit score = 4	1.683***	0.010
	(3.76)	(0.07)
Male * credit score = 5	1.068**	0.038
	(2.48)	(0.26)
Interest rate	-0.017	0.047
	(-0.25)	(1.33)
Male * interest rate	-0.074	0.020
	(-1.35)	(0.80)
Controls	Yes	Yes
N	507	543
Adj. R^2	0.492	0.859

This table presents the results from linear regressions of the three main dependent variables, which are the interest rate, completion time, and the number of investors, respectively, onto a dummy variable indicating whether or not a picture of the entrepreneur(s) is shown, a variable indicating the gender of the entrepreneur(s) (if specified), some interaction terms of the dummy indicating the entrepreneur(s) is/are male and the different credit score dummies, and various project characteristics and fixed effects. In Panel A, the dependent variable is interest rate, whereas in Panel B, the dependent variables are the two measures of project popularity, which are completion time and the number of investors. Controls include maturity, targeted amount, loan purpose, industry, historical financial data, company age, and platform media coverage. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table XII – Robustness checks

Panel A: interest rate	
Credit score	
1 (reference category)	
2	0.666***
	(3.41)
3	1.272***
	(7.41)
4	1.721***
	(9.76)
5	2.066***
	(9.68)
Maturity	0.016
	(0.46)
Targeted amount (log)	0.121***
	(3.08)
Loan purpose	
Start-up (reference category)	
Inventories	-0.246
	(-1.63)
Growth	-0.340***
	(-2.84)
Property & renovation	-0.336**
	(-2.18)
Energy & sustainability	-0.630
	(-1.29)
Takeover	-0.247**
	(-2.05)
Working capital	-0.227**
	(-2.31)
Other	-0.572***
	(-4.78)
Controls	Yes
N	496
Adj. R^2	0.585

Panel B: project popularity		
	Completion time	Number of investors
Credit score		
1 (reference category)		
2	0.171	0.019
	(0.78)	(0.32)
3	0.450**	0.099*
	(2.04)	(1.67)
4	0.862***	0.106
	(3.43)	(1.54)
5	0.793***	-0.024
	(3.06)	(-0.29)
Interest rate	-0.078	0.049**
	(-1.17)	(2.56)

Maturity	0.101**	-0.011
	(2.33)	(-0.84)
Targeted amount (log)	0.661***	0.765***
	(10.94)	(47.38)
Company age		
Less than 1 year (reference category)		
1 to 2 years	-0.432**	-0.010
	(-2.49)	(-0.24)
2 to 3 years	-0.445**	-0.002
	(-2.08)	(-0.04)
3 to 4 years	-0.255	0.014
	(-1.01)	(0.26)
4 to 5 years	-0.194	-0.084
	(-0.76)	(-1.24)
More than 5 years	-0.332***	-0.047
	(-2.71)	(-1.60)
Platform media coverage (log)	-0.703***	0.276***
	(-8.20)	(10.06)
Controls	Yes	Yes
N	496	496
Adj. R^2	0.458	0.874

This table presents the results from linear regressions of the three main dependent variables, which are the interest rate, completion time, and the number of investors, respectively, onto various project characteristics and fixed effects. The sample that is used, is limited to projects of the six largest platforms, based on the number of closed projects on their website. These platforms are Collin Crowdfund, Crowdaboutnow, Geldvoorelkaar.nl, Horeca Crowdfunding Nederland, Kapitaal Op Maat, and Oneplanetcrowd. Since the credit score is included as a variable, projects of Crowdaboutnow and Oneplanetcrowd are not taken into account. In Panel A, the controls include industry, historical financial data, company age, and platform media coverage, whereas in Panel B, the controls include loan purpose, industry, and historical financial data. T-statistics based on robust standard errors are reported in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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