CESifo WORKING PAPERS

8100
2020

February 2020

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
www.cesifo-group.org/wp

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CESifo *Working Paper No. 8100*

Marketplace Lending of SMEs

Abstract

Peer-to-business lending refers to online platforms facilitating loans from individuals to smalland medium-sized enterprises (SMEs). We conjecture that easy-to-understand risk ratings conveyed by the platform play a pronounced role in influencing the borrowing success of SMEs and that more sophisticated financial information and adverse selection are largely absent in these markets. We introduce a dataset of 414 SME marketplace loans and 8,236 online loan days to test these propositions. The data examined provide strong support for the importance of simple platform ratings in influencing investor behavior, while the effect of more detailed financial information is less pronounced.

JEL-Codes: G210, G240, G320.

Keywords: debt crowdfunding, entrepreneurial finance, digital platforms.

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INTRODUCTION

While banks often do not like to engage in start-up lending due to high failure rates, they are, nevertheless, the predominant form of entrepreneurial finance in both the U.K. (Cosh et al., 2009) and in the U.S. (Cole & Sokolnik, 2016; De Rassenfosse & Fischer, 2016; Tykvova, 2016). At the same time, there is a lack of equity investments for start-ups, as less than 0.2% of firms obtain financing from venture capitalists (Bertoni et al., 2011). Similarly, there is a dearth of finance available from angel lenders, factoring, trade customers, and suppliers, among other sources (Cosh et al., 2009). Therefore, it is not surprising that the online economy has brought with it the opportunity for crowdlending; that is, raising capital from many lenders who each contribute small amounts of capital through online portals (Belleflamme et al., 2013, 2014; Colombo et al., 2015). Massolution (2016) estimates that the crowdlending market raised $25 billion worldwide in 2015.

Peer-to-business lending of small- and medium-sized enterprises (SMEs) offers interesting opportunities to test theories about adverse selection in debt finance and lender sophistication. On the one hand, the costs of debt finance are high in crowdlending markets, as expected adverse selection costs associated with debt increase as interest rates rise (Stiglitz & Weiss, 1981). In fact, we might imagine that these adverse selection costs are so high that the market breaks down, because many loans fail to repay, and, consequently, no firms are funded in the first place. But at the same time, it is unclear whether or not individual lenders are sophisticated enough to understand these adverse selection risks. Also, it is unclear as to which signals lenders pay attention to in evaluating these risks. Do lenders respond to simple information provided by the platform, such as the platform risk ratings of the firm? Or, do lenders make use of more sophisticated financial information provided by the companies? Do individual crowdlending lenders pay attention to other investment opportunities, either on the same platform or other public debt investment

opportunities? Our central proposition is that in the presence of unsophisticated investors, information signals that are important in other types of debt markets are largely irrelevant in crowdlending markets, thereby rendering traditional adverse selection theory inapplicable in the context of peer-to-business lending. Given the newness of the corporate crowdlending market, there is scant theoretical or empirical work that examines the adverse selection costs of debt and the value of information disclosure in the context of individual lenders, who we would expect to be less sophisticated than banks or other types of professional lenders.

In this paper, we examine these questions using data from Zencap[1], the largest crowdlending platform for company loans in Germany. Zencap operates an online website that matches the capital needs of small- and medium-sized firms with retail investors willing to fund commercial loans. Technically, the loans are originated by a partner bank, which during a logical second pays out the loan to the borrower and at the same time sells the debt claim to crowd investors if the campaign was successful. Prior to a crowd lending campaign, Zencap evaluates the business risk of the borrower[2], sets the interest rate, and determines the general campaign characteristics, such as the period over which the loan can be funded.

We examine the period from March 2014 to November 2015[3], a period over which firms on the platform raised almost €14 million. Over this period, the median company seeking crowdlending had assets of €295,975, sought €60,000 in funds and typically raised €29,450 in the form of 3-year loans and at 657 basis points over prime. Comparing across firms, the data indicate that lenders respond to higher interest rates by bidding investment amounts without any apparent concern for adverse selection. The data further indicate that lenders pay much more attention to

[1] After Zencap merged with the British portal Funding Circle in late 2015, Funding Circle became the worldwide leading marketplace lender focusing on small business loans in the USA, the UK, Germany, Spain, and the Netherlands.
[2] How precisely Zencap evaluates credit risks is considered their business secrete.
[3] This is because after Zencap merged with Funding Circle in December 2015, the data are not comparable.

platform rankings of firm credit quality than they do with regard to financial variables such as net income, assets, and liabilities.

We also examine the daily data for each loan project. The typical funding period for a loan project lasts for a median of 20 days. The evidence shows strong support for the importance of simple platform ratings affecting investment decisions, while the effect of more sophisticated financial information is less robust and limited to capital structure and income variables. On the one hand, in the presence of more female lenders and lenders who have smart phones and subscribe to newsletters from the platform, there are significantly more daily investments. On the other hand, in the presence of parallel loan projects on the platform and higher returns to public debt outside of the platform, daily contributions are significantly lower. In a similar vein, parallel loan projects on the platform and higher returns to public debt outside of the platform are significantly related to shorter funding periods.

We provide several robustness checks on the data. Most notably, when we segregate the daily data by different types of firms according to their net income, age, revenues, and assets, we find differential factors that influence daily investment contributions. These patterns suggest further research topics as datasets on crowdlending become more developed over time and across other platforms and institutional contexts.

More generally, our paper contributes to the existing crowdlending literature in multiple ways. First, unlike most previous articles, we do not investigate the funding of individual loans but examining crowdlending of SMEs. The results in the previous literature might not apply to this kind of crowdlending, as the decision to fund a firm might be driven by a different rationale than funding private borrowers, who often want to refinance previous debt. Our focus is on the financial disclosures of companies, the ratings of the platform, and the impact of the interest rate set by the platform.

This paper is organized as follows. The next section discusses the related literature and develops our hypotheses. Thereafter, we describe the particular structure of the Zencap platform. After introducing the data and variables, we outline the methodology and provide multivariate analyses of the data, as well as several robustness checks. The concluding section discusses avenues for future research.

RELATED LITERATURE AND HYPOTHESES

Related Literature on Adverse Selection

In the adverse selection model of Stiglitz and Weiss (1981), banks cannot discriminate against risky borrowers, because they are imperfectly informed about the riskiness of the borrowers' projects. Because of the information asymmetry between lenders and borrowers, interest rates become inefficiently high, and borrowers with otherwise profitable projects that should receive funding leave the market. If borrowers do not have collateral, the problem is even more severe (Wette, 1983; Bester, 1985a). Consequently, individuals with poor endowments confront high interest rates and cannot realize their projects. Furthermore, verification of the project quality by outside parties might be too costly or practically impossible.

Research by Cho (1986) has shown that adverse selection disappears if borrowers offer equity and not debt. Using different assumptions, this finding has been refuted by Myers and Majluf (1984) and Greenwald et al. (1984) substantiating that adverse selection exists in equity markets as well. The theoretical debate temporarily culminated in the article by DeMeza and Webb (1987), who showed that both debt and equity markets can exhibit adverse selection. More precisely, in their model, lenders prefer equity over debt if *risk* is at the core of the information asymmetry. By contrast, if asymmetric information focuses on the *expected returns* of the firm, then lenders should

prefer debt over equity. Put differently, if firms have the same expected returns but differ in their riskiness, offers of debt finance will attract riskier firms—referred to as "nuts," to borrow from the language of Stiglitz and Weiss (1981). If firms have the same risk but differ in terms of their expected returns, offers of equity finance will attract lower than expected return firms—referred to as "lemons," to borrow the language of Ackerlof (1970).

Thus, according to DeMeza and Webb (1987), adverse selection can be mitigated, if borrowers offer the right financial instrument. Unfortunately, the DeMeza and Webb model does not offer any guidance about the financial instrument borrowers should offer if information asymmetry about risk *and* expected returns are equally pronounced. In peer-to-business lending, uncertainty is, however, most likely about both the risk and expected returns of the firm to be funded. In theory, engaging in peer-to-business lending does, therefore, not provide evidence *per se* that firms engaging in these activities are of low quality.

Finally, the incentive structure in peer-to-business lending is peculiar, because lenders constitute a group of individuals. This might lead to a better screening of borrowers, since more lenders jointly have larger capacities to investigate an investment target. For example, some of the lenders might be located geographically close to the borrower and can, thus, more cost efficiently conduct a due diligence. However, a large group of lenders might also suffer from more severe free-riding and collective action problems (Olson, 1965). This, in turn, can make the screening of borrowers even more difficult than it already is for traditional banks.

Related Literature on Crowdlending

To date, there has been a significant amount of work on donations and rewards-based crowdfunding (Agrawal et al., 2015; Colombo et al., 2015; Mollick & Nanda, 2016) and, to some extent, work on equity crowdfunding (Ahlers et al., 2015; Hornuf & Schwienbacher, 2018;

Vismara, 2016, 2017). In the realm of crowdlending, which is also referred to as peer-to-peer lending or marketplace lending, most of the work has focused on portals that allow lenders to fund the loans of private borrowers. However, almost nothing is known so far about crowdlending of SMEs.

In one of the first studies, Lin et al. (2013) investigate the funding process on Prosper and find that online friendship networks of borrowers signal credit quality to lenders. Furthermore, they find that these friendship networks increase the probability that a loan is funded, lower the interest rates being paid, and are correlated with lower default rates of the loan later on. In line with these finding, Iyer et al. (2016) also investigate data from Prosper and analyze the role soft factors play on loan performance in crowdlending. They find that lenders predict an individual's default probability with a 45% greater accuracy than the credit score of the borrower would suggest. However, lenders do not solely consider soft factors when funding a loan. Using Prosper data again, Herzenstein et al. (2011a) find that verifiable hard factors also play a role in funding decisions. Furthermore, they find that the identities of borrowers, who are considered to be more trustworthy or successful, are associated with a higher probability of funding success but a poorer loan performance.

Other studies have investigated the role of physical appearance, gender, age, and race in crowdlending. For example, Duarte et al. (2012), Pope and Sydnor (2011), and Ravina (2012) find that female borrowers have a higher probability of funding success and pay lower interest rates (Pope & Sydnor, 2011). Herzenstein et al. (2011a) find that female borrowers have lower default rates. However, Barasinska and Schäfer (2014) analyze data from the German platform Smava and find no evidence that female borrowers have better chances to obtain funding. Others have investigated the project description of proposed loans. Lin et al. (2013) find that an extensive loan description with shorter sentences has a positive effect on funding success. Dorfleitner et al. (2016)

investigate two German portals – Auxmoney and Smava – and find that spelling errors, text length, and keywords evoking positive emotions predict funding success on Auxmoney, while on Smava only specific keywords do. Moreover, the text length has an inversely u-shaped impact on funding success, with too short or too long texts decreasing the probability that a loan is funded.

Another strand of literature has investigated the impact of portal design. Crowdlending platforms run under one of two different mechanisms to match the funds of lenders with the capital needs of borrowers. Initially, many portals had implemented an auction, where borrowers set different interest rates that are selected in such a way that the loan is fully funded. Under the posted price mechanism, the portal determines the interest rate and provides a rating that applies for the respective loan. Wei and Lin (2017) show that there is a higher likelihood that a loan is funded under a posted price regime, while, under an auction mechanism, interest rates are relatively lower. Moreover, lenders generate a lower return under the posted price mechanism as loans are more likely to default.

Comparable with regular capital markets, crowdlending might be prone to herding behavior. Stakes are often small, and it might not be worthwhile for lenders to screen the borrower. Herzenstein et al. (2011b) demonstrate that strategic herding takes place in crowdlending. In particular, they reveal that a 1% increase in bids increases the probability of additional bids by 15%. However, this relationship holds only if the loan is not yet fully funded. Herding behavior decreases again when the loan is successfully funded. Moreover, they also find evidence that herding has a positive and significant effect on the later performance of the loan. Finally, Serrano-Cinca et al. (2015) investigate the performance of individual loans on Lending Club. They find that information like the debt level of a borrower is important for the accuracy with which the default of a loan is predicted, though the risk rating is most predictive of a default. Finally, Lin and

Viswanathan (2015) analyze whether or not there is a home bias in crowdlending. They show that such a bias is widespread, but this tendency cannot be explained by rational factors alone.

Our paper adds to the existing literature in the following way. Unlike most previous studies, we are not investigating peer-to-peer lending but crowdlending of SMEs. As a result, our results might substantially differ from previous findings on peer-to-peer lending and equity crowdfunding. While previous studies have investigated the loan description of individual borrowers (Dorfleitner et al., 2016), we analyze the financial disclosure of companies and the information generated by the platform.

Hypotheses

Our central hypotheses are grounded in adverse selection theory (Stiglitz and Weiss, 1981) and signaling theory (Milde & Riley, 1988; Ahlers et al., 2015). Adverse selection theory predicts that contractual offers affect the type of entrepreneurs and investors that will engage in a transaction. The normal setting of adverse selection in debt markets gives rise to situations where rising interest rates attract riskier entrepreneurs to the transaction (Stiglitz & Weiss, 1981). Naturally, in entrepreneurial settings that involve debt, there are significant information asymmetries at play, and disclosed information can mitigate the expected costs of adverse selection associated with higher interest rates (Cumming, 2006). However, the most pertinent signals, such as financial information from the entrepreneurial firm, may be less important than the promised returns and simple risk ratings, particularly if investors are less sophisticated. Traditional mechanisms of adverse selection may, therefore, not work in peer-to-business lending markets, and information signals to lower these costs may not work or may act in different ways.

In entrepreneurial finance markets, generally, entrepreneurs typically have biased and unrealistic expectations about their expected returns (Astebro, 2002). The implication of these

biased entrepreneurial projections is important: entrepreneurs do not have superior information about expected returns relative to their investors. By contrast, entrepreneurs do have superior information and know more about risks often not fully disclosed to their investors (Cumming, 2006; Yung, 2009). For example, entrepreneurs know more than investors about how they might be enticed to quit the entrepreneurial endeavor and accept a job at a large company or risk changing countries and quitting the entrepreneurial endeavor altogether. Also, entrepreneurs know more than investors do about their personal tolerance for undertaking risky actions. Extant theory and empirical evidence in the context of venture capital is consistent with this view and consistent with the view that information asymmetry is more pronounced regarding risk than expected returns (Cumming, 2006, Yung, 2009). Therefore, venture capital investments are typically equity investments, as the adverse selection costs of debt are more pronounced (Cumming, 2006; Yung, 2009). Information asymmetry in venture capital is more pronounced regarding risk, whereby entrepreneurs know more about their own risk prospects than do their investors, while forming expectations about expected returns are equally difficult for both entrepreneurs and their investors, and, as such, offers of debt finance attract relatively riskier firms than offers of equity finance in venture capital.

Adverse selection in venture capital (Cumming, 2006; Yung, 2009) is likely very different than adverse selection in crowdfunding. The main difference is in terms of the sophistication of the investors and the role of the platform as an intermediary between investors and entrepreneurs in crowdlending. Individual investors are not as sophisticated as venture capitalists, and, as such, the role of equity as a mechanism to incentivize investors to gather information about the firm through due diligence and mitigate adverse selection costs in venture capital (Yung, 2009) is not as applicable for individual investors. Platforms purport to do due diligence on behalf of individual

investors and advertise their screening role by rating entrepreneurs. Therefore, predictions from adverse selection in venture capital do not necessarily apply in the case of crowdlending.

Prior evidence shows that in the case of publicly traded stocks, individual investors are less sophisticated than institutional lenders (Grinblatt & Keloharju, 2000; Barber & Odean, 2008). Lenders would ordinarily pay attention to financial information when making a company loan (e.g., Sufi, 2007). For example, the traditional debt financing literature (Bester, 1985b; Milde & Riley, 1988) suggests that loan size provides an effective signal of borrower quality, indicating that larger loans are selected by less risky projects. Furthermore, capital structure can signal the quality of a firm, because entrepreneurs eager to invest in their own firm provide a positive signal (Leland and Pyle, 1977).

Thus, detailed financial information that goes beyond what is captured by simple risk ratings might provide information about the quality of the loan, and this might entice lenders to finance a loan. This is also in line with previous finding in peer-to-peer lending, which indicate that lenders can predict the default probability of a loan and, thus, the desirability to invest in a loan with much greater accuracy than a simple risk score (Iyer et al., 2016).

Individual lenders on crowdlending platforms, by contrast, may have less ability to understand this information and, hence, focus more on the risk signals provided by the platform than the actual financial disclosures of the firm when deciding whether or not to invest. Analyzing data from Funding Circle, for example, Mohammadi and Shafi (2019) show in a cleverly designed analysis that institutional investors do much better than individual lenders in using the observable information on the platform website. They find that the crowd receives lower interest rates than intuitional investors, yet there is no difference in the failure rates of the loans these two groups finance. Similarly, Cumming et al. (2019) show that institutional investors are more sophisticated than individual investors with respect to contract terms in equity crowdfunding. Other studies on

peer-to-peer lending for consumer loans have shown that ratings predict loan defaults more accurately than, for example, the debt level of a borrower (Serrano-Cinca et al., 2015). Thus, unsophisticated lenders might use the risk ratings provided by the portal as a simple and effective heuristic to make an effective investment decision, even if more sophisticated information is available.

Hypothesis 1 (Risk Ratings and Quality Signals): *In a peer-to-business lending setting, lenders pay attention to easy-to-understand risk ratings from platforms more so than financial information concerning the firm.*

We note that the percentage of lenders who are family or friends in crowdlending may be high. If so, they are more likely to make investments without reference to financial statement indicators. At the same time, friends or family should not base their decision to crowdlend based on the ratings from the platform. Hence, if the presence of friends or family can explain an absent role of financial indicators, their presence should also not explain a positive role of platform ratings.

For many crowdlending platforms—including the one used in our empirical setting, as described further below, in the next section—nominal rates are set by the platform, insofar as the borrowing firm has little bargaining power to determine the interest rate as a formation of a contract between lenders and the borrowing firm. According to the platform used in our analyses here, for example, as a condition of participation on their platform, the platform sets the rate at its own discretion based on its own business model and investor needs, not merely the interests of the borrower. The borrowers generally have 21 days to obtain funding; however, they might be allowed to extent the funding period, if they cannot reach the funding goal within this period.

It is widely recognized that increases in interest rates are associated with greater adverse selection problems, in the sense that enticing lenders into financing a loan will become less likely (Stiglitz & Weiss, 1981; Ang, 2014). Adverse selection problems might be mitigated with firm age, because older and larger firms often have to disclose more information, making it easier for lenders to understand the credit risk. Lenders who are aware of the costs associated with higher interest rates would respond in turn by reducing their investment levels, if they felt that the higher rate was attracting excessively risky borrowers to go ahead. Put differently, lenders will build expectations about the return they can expect out of an investment by considering the risk of default.

However, there is strong empirical evidence that non-sophisticated lenders often have very low levels of financial literacy (Lusardi & Mitchell, 2007, 2008; Hilgert et al., 2003) and do not, for example, understand the relationship between bond prices and interest rates or the difference between bonds and stocks (van Rooij et al. (2011). Moreover, van Rooij et al. (2011) show that individuals with basic financial literacy tend to invest in riskier assets (such as peer-to-business loans) and often ask parents, friends, or acquaintances for financial advice. Given that peer-to-business loans are not brokered by financial advisors, and individual lenders are more likely to engage in them as a result of online or word-of-mouth marketing, we expect lenders in peer-to-business lending to be seduced by the promised interest rate.

Hypothesis 2 (Returns to Lenders): *In a peer-to-business lending setting, higher interest rates raise individual bid amounts and the total amount of capital raised due to higher returns to lenders.*

While higher interest rates may raise the total amount of capital on projects that go ahead, it is possible that higher interest rates reduce the number of projects that are financed. Diamond

(1991) provides evidence that borrowers may take up smaller loans to build up a reputation and obtain larger loans later on under better financing terms. In periods of high interest rates, borrowers with a low rating are less likely, due to the higher financing costs, to elect to borrow. There is also ample empirical evidence that a pre-existing relationship between firms and potential lenders affects the likelihood that firms later receive a loan (Petersen and Rajan, 1994), the interest rate paid (Berger and Udell, 1995), and the likelihood that loans can be sold on a secondary market (Drucker and Puri, 2009), making it attractive for a company to build up a relationship with lenders and to take up a loan if financially possible.

Many platforms—including the one used in our empirical setting, described in the next section—operate a mixed funding mechanism that has elements of a "Keep-it-All" mechanism (Cumming et al., 2019), because firms can make an offer to lenders to keep the funds even if the campaign was not fully funded. Hence, firms may decide whether to take up funds once the funding goal has been reached or the funding period has expired, even if the funding goal has not been reached. In case the borrower received a substantial amount of funding, i.e. almost reached the funding goal, the platform suggested to lenders and the borrower that the potential borrower could still take the funding, even though the campaign never reached the funding goal.[4] Given that the costs of financing decrease with lower interest rates, we would expect firms to be more likely to accept funds if the interest rates set by the platform are lower.

Hypothesis 3 (Costs of Funds): *In a peer-to-business lending setting, the higher the interest rates set by the platform, the lower the chance that firms will take funding.*

[4] According to the platform operators, lenders would usually consent to this proposal, because they intended to fund the loan in the first place.

We note that Hypothesis 3 is not trivially obvious, as higher interest rates may attract a larger pool of riskier borrowers who are unable to obtain financing elsewhere (Stiglitz and Weiss, 1981). Below, we conjecture the relationships that we believe might be present in the peer-to-business lending context and, thereafter, subject these propositions to empirical testing for the first time.

Finally, note that the variables pertaining to risk ratings, financial information, and interest rates are theoretically distinct. Financial information is complicated, and even in a developed country like Germany, only 66% of people were financially literate in 2015 (Klapper et al., 2015). Financial illiteracy amongst a third of the population implies that the financial statement information about a firm would not be well understood by a significant portion of the crowd; furthermore, it means that many crowdfunders would not understand that higher interest rates translate into material differences in payback probabilities. Further, because interest rates and risk ratings are set by the platform, potentially with a wide array of human discretion, there is no reason to expect crowdfunders would expect any degree of uniform signal or meaning across interest rates (returns to investors), detailed financial statement information (complicated information that is ignored), and simple platform risk rankings. In our empirical tests below, we consider these variables separately and together, as well as orthogonalize them to test these propositions.

STRUCTURE OF THE ZENCAP PLATFORM

Zencap operated a peer-to-business lending platform in Germany where borrowers are small- and medium-sized businesses. Lenders are private individuals. Zencap is based in Berlin, and its borrowers and lenders come from various parts of Germany. Lenders must register with the portal and provide some basic information, like their names and addresses. Creating an account is free of charge. Borrowers usually have 21 days to raise the capital needed (*funding period*), which can be

extended by the portal up to 61 days. Whether the funding period will be extended or not depends on an ad hoc decision made by Zencap and the potential borrower.[5] Zencap does not possess a banking license, so Wirecard bank ultimately extends an annuity loan between the borrower and the lenders in case the loan project is successfully funded on Zencap. Lenders can also use a portfolio builder tool that invests in any project that fulfills certain criteria like the risk rating, which the lender must actively define. A loan is successfully funded if lenders are willing to completely finance the requested amount. If the project is not completely financed or the borrower cancels it before the end of the funding period, pledges are returned to the lenders. Alternatively, the borrower can make an offer to the lenders to fund the project, even though the funding goal was not fully reached.

Each loan project entails a detailed description, where the business presents itself and indicates for what purpose the loan is going to be used. Unlike in private borrowers in peer-to-peer lending, the business also makes a recent profit and loss statement and balance sheet available to lenders online. Borrowers must extend a personal guarantee to have the project posted on the portal website. The principal amounts of loans on Zencap range from €10,000 to €250,000. Zencap assigns its own 5-level risk rating to borrowers (A+, A, B, C, C-) and determines the payable interest rate. Zencap earns a fee of 1 percentage point of loan repayments, which is charged on a monthly basis as long as the borrower is solvent. Loan periods on Zencap range between 6 and 60 months. Loans can be repaid anytime without an early repayment fee. When we collected the data at the end of 2015, only five loans had failed[6]. Thus, investigating loan failure does not yet yield

[5] The platform informed us that they have extended the funding period if they saw a realistic chance that funding could be successfully reached after the extended period. If, for example, the borrower had reached only 5% of the funding goal, then they would not have proposed to extend the funding period. However, if the borrower was close to the funding goal after 21 days, the funding period would have been extended. However, no strict thresholds have been set and the decision was made on a case by case basis.

[6] We observe three loans in default with a B rating, one with a C rating and one with a C- rating.

meaningful results. On Zencap, institutional bank lenders were not as active during the sample period as they are today on other crowdlending portals like Prosper or Lending Club.[7]

In order to have a loan project listed, borrowers need to fill out an online credit application and submit a recent profit and loss statement as well as the latest balance sheet. Together with the data analytics company *Schufa* (the German equivalent of FICO), the platform examines the loan application, which is free of charge for potential borrowers, within 48 hours. The Schufa scoring algorithm is based on logistic regressions and is regularly reviewed by universities (e.g., The Statistical Consulting Unit at the Department of Statistics at the Ludwig-Maximilian University in Munich) to ensure its quality.[8] While Schufa scoring most likely relies on hard factors, such as previous borrowing activities and defaults, the actual algorithm is considered a business secret of the company and unobserved by crowdlenders who only see the risk rating, partly based on the Schufa score, created by Zencap. While the risk rating might contain considerable information about the probability of default and, thus, whether lenders should invest their money in a loan, previous research (Lin et al. 2013; Iyer et al., 2016) indicates that crowdlending soft factors have a strong impact on loan performance and might drive funding decisions.

The platform also investigates the main accounts of the firm applying for the loan and makes an offer based on the available information. Ultimately, the loan is posted on the platform website, and lenders can then invest. The monthly installments are wired to lenders via the portal using an automatic debit transfer system. Platform fees are directly deducted from the monthly installments. Early repayment by the borrowers is free of charge and can always take place. While precise figures for Zencap are not available, it is clear that Zencap does not accept every loan application. For

[7] According to the CEO of one of the largest German peer-to-peer crowdlending platforms, it has been a decision by platform operators not to allow institutional investors to invest in loans during the sample period.
[8] See, e.g., https://www.schufa.de/en/about-us/data-scoring/scoring/transparent-scoring-methods/transparent_scoring_methods.jsp

example, German competitor Auxmoney has an acceptance rate of only 20%.[9] Thus, the platform might act as a gatekeeper and reduce the problem of adverse selection to some degree.

DATA AND METHOD

Data Source

The data were directly provided by the platform Zencap. They span the period from March 2014 to November 2015. Over this period, the 414 companies that used the Zencap platform raised €14 million in crowdlending. The median company asked for €60,000 and received €29,450, had €295,975 in assets, €44,100 net income, and had been incorporated for 10 years prior to seeking funding on the platform. The median funding period for a loan project lasted for 20 days, and the time range was 1-61 days for funding. On average, a firm received 57.5% of the requested funding, and the median success was 53.2%, with a minimum of 0.01% and a maximum of 100%. The median number of lenders for a loan project was 77, and the range was 4 to 301. Table 1 provides a complete list of variables, definitions, and summary statistics for all 414 companies in the dataset.[10]

[Table 1 About Here]

[9] See http://peersociallending.com/investing/peer-to-peer-lending-sites-16-of-the-worlds-best/.
[10] Some of the summary statistics reflect the unusual financial position of the borrowers in the dataset. For example, the odd firm has negative equity. Equity is the difference between assets and liabilities. It is possible for a firm at the founding stage to have liabilities exceeding assets.

Dependent Variables

In our empirical analysis, we use five different dependent variables that measure funding success and were previously used in researching Internet-based entrepreneurial finance (Mollick, 2014). These variables are the percentage of capital raised, relative to the project goal (*success*); the number of lenders in the loan project (*# lenders*); the total bid amount (*bid amount*); and a dummy variable equal to one, if the loan was successfully funded (*funded dummy*). Importantly, some borrowers were funded even though the campaign did not reach 100% of the funding goal (*success dummy*). The reason for such an outcome and thus the difference in the *funded dummy* and *success dummy* is twofold. First, some investors withdraw their investments right after the campaign so that the campaign ends with, for example, € 99.850 instead of € 100.000. In these cases, the platform would have still considered the funding to be successful, which is fully reflected in the *funded dummy*. Second, the borrower may have never reached the funding goal, but if lenders and borrowers consented, the latter could still take up the funding. In such a case, the platform would have made a suggestion that the campaign should be considered successful and the borrowers could decide whether to take up the funding or not. Furthermore, we include a variable that measures the time from the listing until the loan was funded (*listed to funded*). In a crowdfunding context, the number of lenders has recently been shown to positively influence market performance of the respective products (Stanko and Henard, 2017) and might thus serve as a proxy for the ultimate success of the firm.

Explanatory Variables

To investigate H1 and H2, we consider the yield on the debt issued by a firm through the peer-to-business lending minus the risk-free rate. For the risk-free rate, we use the daily yield of the current 10-year federal bond. The data was provided by Zencap and the German Central Bank.

To investigate whether lenders pay attention to easy-to-understand risk ratings that are created by the platform or whether they base their lending decisions on the more fine-grained financial information that is released by the firm, we consider several different variables. For the risk ratings, we consider the 5-level risk rating that is published by the platform and categorizes borrowers into risk classes A+, A, B, C, and C-.

In line with the theoretical literature on adverse selection, we consider the proposed principal amount of the loan (Bester, 1985b; Milde & Riley, 1988) and the current assets of the firm, the latter providing a measure of the financial substance of the firm. Moreover, as outlined above, capital structure might have an important impact on loan and firm performance (Leland and Pyle, 1977). We, therefore, included two measures of capital structure: current assets / current liabilities as well as liabilities / (liabilities and assets). Furthermore, as a measure of liquidity, we consider the net income of the firm. Borrowers also provided information about the reasons why the raised a loan through peer-to-business lending, including various financial motives, such as the firm wants to purchase assets, needs capital for an expansion, needs to pay tax liabilities, or simply needs further working capital.

Control Variables and Fixed Effects

Following prior research on crowdfunding and crowdlending, we included several control variables and fixed effects in our regression. First, in the cross-sectional specifications, we control for additional campaign specific characteristics. More precisely, we consider the funding period and the percentage of female lenders. Depending on the risk appetite of the lenders, the funding period of the campaign might reflect the risk of the borrower. If riskier firms are, for example, less appealing to lenders, the funding period might be longer or even extended in order to attract more funds. Moreover, the risk rating of some firms might appeal more to female lenders and

subsequently also attract additional male lender, which then makes funding success more likely. Both measures are clearly endogenous in our setting, not including them we clearly generate an omitted variable bias in our estimations.

Second, in line with Duarte et al. (2012), Pope and Sydnor (2011), and Ravina (2012), who find that female borrowers have lower default rates and, thus, a higher probability of funding success, we included a dummy variable indicating whether the borrower ultimately extending the personal guarantee was female. We further control for firm specific characteristics, such as the age of the firm at the time of funding, as well as industry fixed effects. Because younger firms and borrowers from certain industries might be inherently riskier, not including these two measures might generate an omitted variable bias in our estimations. Third, related research on equity crowdfunding has shown that investors consider stock markets and equity crowdfunding as substitutes (Hornuf & Neuenkirch, 2017), as there is evidence that a higher stock market volatility leads to larger premia being paid for crowd investments. We, therefore, control for the legal status of the borrower and the market conditions at the time of funding, which are measured by the Morgan Stanley Capital International (MSCI) returns for large and mid-cap firms on the German market. Finally, we included various dummy variables, including the day of the week, month of the year, and year dummies, which has become standard in the literature (Kuppuswamy & Bayus, 2018).

Cross-sectional regressions traditionally suffer from omitted variable bias. Even when considering the different control variables above, some unobserved heterogeneity across borrowers can always simultaneously affect the dependent variable and our variables of interest. For that reason, we also estimate various panel data models to control for this unobserved non-time varying heterogeneity. For the panel data estimations, we not only include campaign effects, which capture unobserved time-constant variations, such as contractual details or firm specific characteristics that

we did not explicitly model, but we also consider the campaign fixed effects that capture the dynamics of a crowd lending campaign and define campaign day dummy in line with Hornuf and Schwienbacher (2018), Kuppuswamy and Bayus (2018), and Vismara (2017).[11]

First, little is known about the responsiveness of investors to the marketing tools of crowdlending platforms, such as updates or newsletters. Individual lenders may likely be more responsive to the soft information released in newsletter updates relative to the financial information that is available online (Lin et al. 2013; Iyer et al., 2016). In related research on equity crowdfunding, Block et al. (2018) have shown that posting updates about business developments and cooperation projects of the firm increases the crowd's willingness to make an investment. Providing additional information about a firm in a newsletter might also help to overcome the problem of information overload. The Zencap newsletter is sent by the platform and may help to draw lenders' attention to the crowdlending portal and potential borrowers. The newsletter entails very brief information about the platform and borrowers that have been or will be listed on the website. Research on consumer behavior in the online economy has shown that information on the Internet is so plentiful that consumer attention becomes very limited (Wu & Huberman, 2007; Hodas & Lerman, 2013). While we do not observe the precise content of the newsletters, we consider whether lenders have subscribed to the newsletter and receive additional information a control variable, because subscribers to the newsletter could, for example, be more likely to commit more money and are less likely to read risk ratings.

Second, mobile phones do not only help foster the diffusion of knowledge (Asongu & Nwachukwu, 2016), they also enable investors to finance a loan project independent of their current

11 Note that we do not specify dummy variables for the first and the last days of the campaign as Hornuf and Schwienbacher (2018), Kuppuswamy and Bayus (2018), and Vismara (2017) have done in an equity crowdfunding setting, but for every day of the campaign. This is because the last days of a campaign often attract zero investments, the variables exhibit very little variance, and the campaign dummies for the last days of the campaign can statistically not be identified. For that reason, we decided to include dummies for every day of the campaign.

location. We, therefore, believe that lenders using smart phones invest more frequently in peer-to-business loans, because they have easier and constant access to crowdlending platforms and, thus, control for the usage of smart phones. Moreover, lenders who invest via the mobile phone could also have a different risk appetite, because using a mobile phone for investment purposes might involve the additional risk of less secure over the air mobile communication. Whether an investor uses a mobile phone or computer can change for every bid made.

Finally, lenders might not only consider the returns on the equity market but also the market environment of the debt market. We, therefore, included the yield on public debt, to again capture the effect of the risk-free rate.

Third, crowdfunding markets have pronounced concerns with information cascades, where lenders pay attention to the actions of other lenders (see Vismara, 2017, for evidence on information cascades in equity crowdfunding). We therefore included the lagged cumulative number of previous investments, and the lagged cumulative bid amount in the focal campaign, to capture the investment dynamics of the respective crowdlending campaign. This approach is consistent with the one adopted by earlier research on equity crowdfunding dynamics (Hornuf and Neuenkirch, 2017). Our conjecture that lenders pay attention to the actions of others is also consistent with evidence on competition in traditional banking markets (Dou et al., 2017) and recent research in reward-based crowdfunding, which indicate that projects that ultimately do not receive funding experience less backer support if more competing projects are around (Kuppuswamy & Bayus, 2018). We, therefore, included the number of parallel loan projects on the platform, to capture the severity of competition of loans seeking capital on Zencap.

Finally, for the panel data estimations, some of the variables previously included were collapsed as percentages of the respective variable per day. For example, we included the percentage of female lenders that participated on a given day.

Empirical Methods

We carry out two types of analyses on the data. First, we run cross-sectional regressions across each of the 414 firms that applied for funding. We consider logit analyses of whether or not the firm was funded and OLS regressions on the amount of funding, number of lenders, and time to funding (which is, after taking the natural logarithm, close to a normal distribution, confirmed by a Kolmogorov–Smirnov test). Further, for the percentage of funding with a bounded dependent variable, we use fractional response regressions (Cook et al., 2008). We considered whether or not different variables were overly correlated with one another and did not find any undue influence of any included or excluded variable in the regressions that materially affected the economic or statistical significance of the results. A correlation matrix is provided in Appendix A.

Second, we examine the dynamics of each day of the loan project. In line with previous research on reward-based (Kuppuswamy & Bayus, 2018) and equity crowdfunding (Block et al., 2018), we constructed a panel data set that aggregates the number and amount of individual investments in a particular campaign on a given day. The time dimension of the panel data set refers to the duration of the funding campaign in days, and the cross-sectional dimension is the peer-to-business lending campaign. This setting allows us to control more properly for unobserved non-time varying factors such as, the location of the borrower or the specific features of the loan contract. Figure 2 provides a histogram of the number of investments per investment day. In order to test for the robustness of the estimation techniques, we estimate random effects, fixed effects, and negative binomial panel data models.

[Figures 1 and 2 About Here]

EMPIRICAL RESULTS

Empirical Results

Cross Sectional Regressions

Table 2 presents regressions of the cross-sectional differences across the 414 peer-to-business lending projects. The data indicate that a 1-standard deviation increase in net income is reflected in a 3.5%-4.8% higher percentage funded (Models 1a and 1b). Larger assets reduce the time to funding in Model 5, but this effect is significant only at the 10% level, and the economic effect of a 1-standard deviation increase in assets from the mean is to lower the time to funding by 2.1%. A 1-standard deviation increase in current assets / current liabilities decreases the probability of success by 4.4%-5.8% (Models 1a and 1b), which contrasts with Hypothesis 1. In a similar vein, a 1-standard deviation increase in principal amount from the mean is reflected in a 22.0% lower percentage funded (Model 1), a 16.4% decrease in the number of lenders (Model 3), a 26.8% decrease in the amount bid (Model 4), and a 21.1% increase in the days to funding. Liabilities / (liabilities + equity) increase the percent funded in Model 1b, but the other financial variables are not significant in any of the models. By contrast, the variables for the risk rating provided by the platform are statistically significant and economically large. The risk ratings of the borrower increase the percent funded (Model 1) by the following amounts: Risk A+ raises the percent funded by 64.7%, Risk A by 52.5%, Risk B by 30.3%, and Risk C by 19.2% (each relative to Risk C-). The risk rating raises the number of lenders by 63.1 for Risk A+ and 42.3 for Risk A, each relative to Risks B, C, and C-. Further, the risk rating of the borrower increases the bid amount (Model 4) by €48,013 for Risk A+; €38,755 for Risk A; €22,568 for Risk B; and €14,516 for Risk C (each relative to Risk C-). The risk rating of the borrower reduces time to funded by 21.9 days for Risk A+, 18.0 days for Risk A, 11.2 days for Risk B, and 6.9 days for Risk C (each relative to Risk C-).

Note that the differences in the coefficients on these ratings in Table 2 are pronounced, ranging typically from 20-70% different than the coefficient on the next rating level from one rating to the next, and over a 300% change in the coefficient from the bottom-to-the-top rating in some cases (the sole exceptions in Table 2 are the ratings coefficients in Model 2 and in Model 1b for A and A+). These coefficient estimates are statistically different from one another (in terms of their confidence intervals) insofar as the coefficient for A+ is significantly larger than that for both B and C at the 5% level, and A is significantly larger than that for C. However, the confidence intervals around the ratings that are immediately proximate to one another are not statistically different; that is, the coefficient on A+ is not statistically different than that for A, and A is not statistically different from B, and B is not statistically different from C. The difference from one category to the next is, therefore, highly suggestive with the magnitude of the estimates, but it is not conclusive. Below, therefore, we carry out some additional tests (see Table 6 and accompanying text). Overall, the data in Table 2 are supportive of Hypothesis 1, that easy-to-understand risk ratings have a strong impact on funding decisions, while borrows also consider some of the more substantive signals that are provided by borrowers. The only caveat is that the data in Table 2 enable conclusive assessment of the differences between risk ratings two or more away (e.g., A+ to B, or A to C) and do not enable conclusive assessment of risk ratings proximate to one another (e.g., A+ to A, or A to B).

Interest rates are set by the platform. Risk ratings are set by the platform. These variables may or may not be related to financial conditions of the borrower. Financial conditions are a product of the firm activities. Interest rates are set by employees of the platform using various things these employees may or may not deem to be relevant to interest rates. Risk ratings are similarly set by employees of the platform, and they may or may not view the factors that should affect interest rates as the same or different than the factors that affect risk ratings. But as we see

below in Table 3, risk ratings are in fact scantly related to the financial characteristics of the borrower. An ordinal variable for risk ratings of the borrower artificially imposes a structure on the distance between ratings (and with a linear structure A+, A, B, C translates into 4, 3, 2, 1), so the banking literature normally does not use such a specification and instead uses dummy variables for different risk ratings (for recent work, see Cumming, Lopez-de-Silanes, McCahery, and Schwienbacher, 2019, and references therein to prior work). In Table 2, we considered alternative specifications (available on request) using an ordinal variable for the risk ratings, as well as an orthogonalized ordinal variable between ordinal risk ratings and the interest rate. The specifications without orthogonalization have the exact same inference as Model 1a in Table 2 whereby the interest rate and ordinal risk ratings are positive and significant at the 1% level. In the other specification with orthogonalization, the interest rate variable is statistically significant in Model 1a, and the orthogonalized variable for ordinal risk ratings is positive and statistically significant at the 1% level.

The data further indicate that a 1-standard deviation change in the risk-free nominal yield is reflected in a 21.1% higher percentage funded (Model 1), consistent with Hypothesis 2. Figures 3 and 4 confirm the positive relationship graphically and show that there are no apparent non-linearities in the relationship. The relation between interest rates and percentage funded is quite stable over the entire range of interest rates in the data. Further consistent with Hypothesis 2, Models 3, 4, and 5 show that a 1-standard deviation change in the risk-free nominal yield is reflected in a 17.1% higher the number of lenders, a 22.9% higher bid amount, and a 15.5% lower time from being listed to being funded, respectively (and relative to the average values of each of these dependent variables).

[Table 2 and Figures 3 and 4 About Here]

At the time we obtained the data, only five loans were in default. This fact implies that until the end of the observation period most lenders had not experienced a loan default and might have had difficulties building expectations of how promised returns differed from the expected returns of any given loan proposal. This evidence further explains how investors behaved in a way consistent with Hypothesis 2.

Consistent with Hypothesis 3, Model 2 shows that a 1-standard deviation change in the risk-free nominal yield is reflected in a 6.4% lower likelihood that firms will take funding. Most loan projects are funded, except for 11% that are not (Table 1). At higher interest rates, some companies do not take up the funding offers.

Some of the control variables are significant as well. The data in Table 2 indicate that a 1-standard deviation change in the percent of female lenders is associated with a 4.0% increase in the percentage funded (Model 1), although this effect is not robust to the other specifications. Female borrowers likewise have no significant effects on the likelihood of being funded in these models, which contrasts with the results for crowdlending of personal loans (Duarte et al., 2012; Pope & Sydnor, 2011; Ravina, 2012). A 1-standard deviation increase in the number of employees from the mean is reflected in a 23.6% lower percentage funded (Model 1), a 25.9% higher number of lenders (Model 3), a 20.2% higher amount bid (Model 4), and a 25.9% increase in the days to funding. A 1-standard deviation higher loan duration from the mean is reflected in a 2.4% higher percentage funded (Model 1), a 2.2% higher number of lenders (Model 3), and a 2.5% higher amount bid (Model 4).

Finally, note that we considered other variables in these cross-sectional regressions, such as the use of mobile devices. These other variables were statistically insignificant, and their

inclusion/exclusion did not affect the other variables. Hence, for reasons of succinctness, we do not include them in the cross-sectional regressions in Tables 2 and 3.

Table 3 presents ordered logit estimates of the risk rankings. There is only one model in Table 3, which is an ordered logit model, where the dependent variable is the ordinal risk ranking. The additional columns are the marginal effects for each ranking – because in an ordered logit model the marginal effects are not necessarily equal across rankings as the model does not impose a linear structure on the distance from one ranking to the next. The data indicate that the most important—in terms of both statistical significance and the magnitude of the effect—factors influencing platform risk rating are the number of employees and female participation. Both effects are statistically significant at the 1% level, and the size of the average marginal effects is very large for each of the risk rating categories. By contrast, the other variables are either statistically insignificant or marginally significant at the 10% level but with small average marginal effects. For example, net income is positive and significant at the 10% level, but the average marginal effects are not materially different from zero.

[Table 3 About Here]

We acknowledge that one concern in Table 3 is that the percentage of female lenders is endogenous to the platform rankings, at least insofar as rankings matter more to men than women. We include the variable here as female participation may be anticipated in advance of the project campaign, since some types of projects are naturally more appealing to women than men, and vice versa. Dropping this variable does not materially affect the other coefficients on the variables reported in Table 3. However, prior evidence on gender in investment and due diligence ranges widely from showing that females show no significant difference in due diligence and risk

assessment than males (Sila e99t al., 2016) to showing that females are more careful in respect of due diligence (Cumming et al., 2015). Based on this prior work that shows women are at least no worse at due diligence, we do not reckon that it is plausible that women are more likely to be swayed by simple rankings than men. Instead, it appears that borrowers who are expected to attract a female gender interest are more likely to receive a higher platform ranking. Further research that enables a causal design setting with other datasets is clearly warranted. To conduct a more causal analysis that considers unobserved non-time varying factors, we now move to the panel data estimations.

Overall, Table 3 indicates that the risk rating figure does not fully summarize the financial information of the borrower. In fact, the correlation matrix in Appendix A shows that ratings and financial information are statistically uncorrelated. None of the ratings and none of the financial information show any statistical correlation at the 5% level of significance or even at the 10% level of significance. Hence, there is no issue with the econometric identification being blurred as between ratings and firm financial information.

Panel Data Estimates

Table 4 provides an analysis of daily data within each loan project. The data used are the same as in Tables 2 and 3, except they are converted from cross-sectional to investment days in a panel data structure, whereby each loan project day is a unit of observation, and we used firm fixed effects. Firm-specific variables that do not change by day cannot be included as variables in the regression specifications; nevertheless, in the next subsection, below, we consider subsets of the data by firm-specific characteristics to, again, test some of the hypotheses outlined above. We include campaign fixed effects, as well as fixed effects by campaign day, and show robustness to using random effects.

[Table 4 About Here]

The dependent variable in Table 4 is depicted graphically in Figure 2. The investments per day are depicted as a function of female participation, newsletter subscriptions, the use of mobile phones, MSCI returns, the nominal yield, the yield on public debt, the number of parallel loan projects, the number of prior investments in the project, and the dollar value of prior investments in the project. Three variables in Table 4 may be considered to be endogenous: female participation, newsletter subscribers, and mobile users. We considered as a possible instrument the median levels in prior deals in the same category for similar types of firms. With that instrument, these variables tended to be statistically insignificant, and the other variables were unaffected. Without these variables included, we found similar results for the other exogenous variables, as reported in Table 4, and, hence we simply report the results with these three variables without the use of instruments, as these variables are not central to our analyses.

The data in Table 4 indicate that the number of investments per day increases by 1.4% with a 1-standard deviation increase in female participation (although this effect is not statistically robust across different specifications), 8.3% with a 1-standard deviation increase in newsletter subscriptions, 2.7% with a 1-standard deviation increase in the use of mobile phones, 12.2% with a 1-standard deviation increase in nominal yield, -14.7% with a 1-standard deviation increase in the yield on public debt, -25.1% with a 1-standard deviation increase in the number of parallel loan projects, -21.0% with a 1-standard deviation increase in the number of prior investment in this project, and 14.9% with a 1-standard deviation increase in the dollar value of prior investments in this project. Unlike in German equity crowdfunding (Hornuf and Neuenkirch, 2017), MSCI returns

are unrelated to investments per day in Table 4. These findings are quite robust to the different model specifications in Table 4.

Because some investors may use the portfolio builder tool that has been provided by Zencap, they may not make lending decisions based on the specific information that is provided on the website. However, the portfolio builder tool also requires specifications, for example, with regard to the risk rating in which investors wish to invest. Thus, for this variable the use of the portfolio builder tool only leads to a delayed investment decision that has already been made when entering the information in the portfolio builder tool. To address the issue of whether the portfolio builder tool has an impact on our results more thoroughly, we ran specifications removing the first day of the campaign when investments based on the portfolio builder tool was executed.[12] We observe the results as the same, though even stronger than what we previously report. We report these results in Appendix B as Models 7a and 7b.

Panel Data Estimates with Subsets of the Data by Firm Characteristics

To test Hypothesis 1 more thoroughly in the panel data setting, Tables 5 and 6 present regressions analogous to those in Table 4, with subsets of the data by financial data (net income, revenue, and assets); firm age (in Table 5); and by risk class (in Table 6). These variables are not explanatory variables in the models in Tables 4-6, because they do not vary over time, and, hence, cannot be included in a panel regression with firm fixed effects. In order to test for the impact of the time constant explanatory variables and to investigate our hypotheses in the panel data setting,

[12] If investors base their decisions on the portfolio builder tool, they do not make any active decision once a new loan becomes available. That is, once a new loan is online, the portfolio builder tool will immediately invest in the loan, if the loan falls under the general specification investors have made beforehand (e.g. "invest in all loans by female founder"). Thus, dropping the first day of a campaign excludes all investments based on the portfolio builder tool. Dropping the first day of a campaign also drops investments made by investors not using the tool, but such an exclusion weakens our results, which would lead us to underestimate our coefficients.

we conduct median splits and run separate regressions for the variables of interested. Furthermore, because the nominal yield and the risk class are correlated, we estimate separate regressions for each risk class and test for the effect of the explanatory variables within a given risk class.

[Tables 5 and 6 About Here]

The regression results indicate that for larger net income firms, there is a marginally greater impact on investments / day for female participation and mobile phones in Table 5. The impact on the numbers of investments per day is comparable for high and low income firms for newsletter subscribers (Models 15 versus 16), but newsletter subscriptions have a more pronounced impact on the amounts invested (Model 23 versus 24). For smaller net income firms, there is a greater impact on investments / day for yields on public debt, the number of parallel loan projects, the cumulative investments, and the cumulative bid amount, and the nominal yield is positively related to investments per day, as expected.

Segregating the data by firm age, the results in Table 5 indicate that for young firms, there is a greater impact on investments / day when there are more newsletter subscribers and mobile phone users, as well as more prior projects and larger prior bid amounts (Models 17 and 18). For older firms, there is a greater impact on investments / day when there is more female participation, higher yields on public debt, and more parallel loan projects on the platform (Models 17 and 18). However, for amounts invested (Models 25 and 26), there is a greater impact of female investors, mobile users, nominal yields, and yields on public debt.

Segregating the data by revenue, the results in Table 6, Models 19 and 20, indicate that for high revenue firms, there is a greater impact on investments / day (Models 19 and 20) and amounts of investment / day (Models 27 and 28) for female participation, newsletter subscribers, and mobile

phone users. For low revenue firms, there is a greater impact on investments / day when there are higher MSCI returns, higher yields on public debt, a greater number of parallel loan projects (consistent with younger firms), and greater levels of cumulative prior investments and cumulative prior investment amounts (Models 19 and 20). However, amounts of investment / day (Models 27 and 28) for low revenue firms are more dependent on yields on public debt, the number of parallel projects, cumulative prior investments, and bid amounts.

Segregating the data by assets, the results in Table 5 indicate that for high assets firms, there is a greater impact on investments / day for mobile users, higher numbers of cumulative prior investments, and cumulative prior investment amounts (Models 21 and 22). For low assets firms, there is a greater impact on investments / day associated with female participation, newsletter subscribers, higher yields on public debt, and greater numbers of parallel loan projects (Models 21 and 22). Investment amounts per day (Models 29 and 30) for low asset firms depend more on female participation, newsletters, mobile users, yields on public debt, and the number of parallel projects.

Segregating the data by risk category, the results in Table 6 indicate that the marginal impact of female participation is insignificant for Risk Class A+ and A (Models 31, 32, 36, 37) and statistically significant and increasing in the marginal effects for Risk Classes B and C and C- (Models 33-35, 38 and 39). Newsletter subscriptions have the smallest economic significance for Risk Class A+; the largest for Risk Class C, minus the numbers of investments / day (Models 31-35); the smallest economic significance for Risk Class A+; and largest for Risk Class C for amounts invested / day (Models 36-40). Mobile phone usage has the smallest economic significance for Risk Class C- (Model 35, and statistically insignificant in Model 40) and the largest economic significance for Risk Class A+ in Model 31 for the number of investments / day and Model 36 for amounts invested / day. MSCI returns are statistically significant for investment amounts / day for

Risk Class A+ and statistically insignificant for all other regressions in Table 6, except for Model 35 for Risk Class C-, where they are positive and significant. Nominal yields are similarly insignificant except for Model 34, where they are marginally significant at the 10% level. Yields on public debt have a negative and significant effect on the number of investments / day and investment amounts / day in each regression (with the exceptions of Models 32, 33, 35, and 40) and have the largest economic significance for the lower risk class ratings. Similarly, the number of parallel investments has a negative and significant effect on the number of investments / day and investment amounts / day (with the exception of Models 31, 36, and 40) and tend to have larger economic significance for lower risk class ratings. Finally, as shown in Tables 4 and 5, Table 6 indicates that the cumulative number of investments negatively affects the number of investments per day and positively affects the amount of investment / day, while cumulative investment amounts positively affect the number of investments per day and negatively affect the investment amounts per day; both effects tend to be bigger for the lower risk class ratings.

Overall, the data are consistent with the view that the economic impact of factors that affect investment amounts per day and numbers of investments per day depend on the particular project characteristic. Generally, the factors increase in importance for firms that are deemed to be riskier, as per the broad risk rating categories provided by the platform, which is in line with Hypothesis 1. As with Table 2, we assessed the statistical significance of the difference between coefficient estimates.[13] Only with a few exceptions, these differences in Table 6 are large and statistically significant. To highlight one exception, in Table 6, Model 31 and Model 32, for risk ratings A+ and A, respectively, there is a statistically significant difference in the magnitude of the estimate for mobile phone usage (0.5446 versus 0.1804) but not for newsletters (0.3808 versus 0.3537).

[13] For the standard formula, see for example http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.458.9930&rep=rep1&type=pdf

With the larger number of daily observations in the different categories, the tests of differences from A+ to A, A to B, etc., tend to show greater significance in the difference between coefficient estimates relative to the cross-sectional regressions reported above. Moreover, we find many differences in Table 6 in terms of statistically significant factors in one regression category versus another.

The results are similar for the subsets of data segregated by the financial variables of the borrowing firms. In line with our earlier findings from the cross-sectional setting, these latter patterns are less clear-cut, as discussed above. The likely explanation is that investors are more systematically responsive to easy-to-understand risk ratings than they are to signals provided by financial variables.

Arguably, some of the categories in Tables 4-6 are too heterogeneous. It is possible to restrict the subsamples further by grouping variables or by using propensity score matching. However, in doing so, the number of groups and variation in subsets of the data reduces commensurately with the number of subsets of categories, and the patterns are again less clear-cut. As such, we focused on the reported broader categories to present the information that is most salient in the data.

DISCUSSION AND CONCLUSION

In this paper, we examined the nascent and growing market for peer-to-business loans, where individuals are lending to SME companies through online marketplaces like Zencap. We conjectured that lenders in these marketplaces would pay scant attention to financial statement information and, instead, rely on signals from the platform to infer investment quality due to a lack of sophistication. Also, we conjectured that lenders would have scant apparent concern over issues of adverse selection.

In particular, we examined data from the largest crowdlending platform for company loans in Germany in 2014 and 2015. Firms on the platform typically ask for €60,000 in funds and raise €29,450 in the form of 3-year loans at 657 basis points over prime and do so in a period of 21 days. Higher interest rates set by the platform do not appear to discourage lenders with respect to higher adverse selection costs and attract more lenders at all rates, up to 1500 basis points over the risk-free rate. Financial variables, such as net income and the capital structure, are weak indicators of funding success, unlike platform risk ratings, which are extremely significant and robust predictors of success. Daily contributions are positively impacted by the participation of female lenders, as is the use of newsletters and smart phones. In line with earlier finding for reward-based and equity crowdfunding (Hornuf & Schwienbacher, 2018; Kuppuswamy & Bayus, 2018; Vismara, 2017), borrowing firms are particularly subject to competition from competing loan campaigns, which reduce daily contributions and are, therefore, related to longer funding periods. In general, firms with lower risk rating scores by the platform are more sensitive to factors that affect daily contribution amounts and the number of contributions per day.

Despite the richness and novelty of the dataset, our paper also has clear limitations. Little is known about the motivation of lenders to engage in these markets. While some lenders may be curious early adopters and simply want to try out new financing technologies, others might be serious investors looking for opportunities to earn a return in a low interest rate environment. Moreover, the observation period of our sample is rather short. Our results might fundamentally change once debt markets move into an environment with higher prime interest rates. In such a scenario, crowdlending borrowers might have greater difficulties in repaying their loans, and lenders might not be in the position to realize positive returns.

We have noted that only five loans were in default during the observation period in this dataset. However, we do not know how many loans have been successfully repaid by the end of

the dataset and how many borrowers have repaid late. Moreover, we do not know if borrowers will default in the future, and nor do we know other measures of success or failure in the long term of the borrowing companies. Future research is warranted on the long-term impact of peer-to-business lending on entrepreneurial growth.

As more data become available, future research could assess other dimensions of loan quality, lender returns, and SME performance. Moreover, platform differences and international differences in crowdlending for SMEs could be examined to better understand the role of legal and cultural factors affecting online lending, similar to recent international studies of traditional banking markets (Levine et al., 2017) and reward-based crowdfunding (Giudici et. al., 2018).

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Figure 1. Histogram for Time Listed to Time Funded

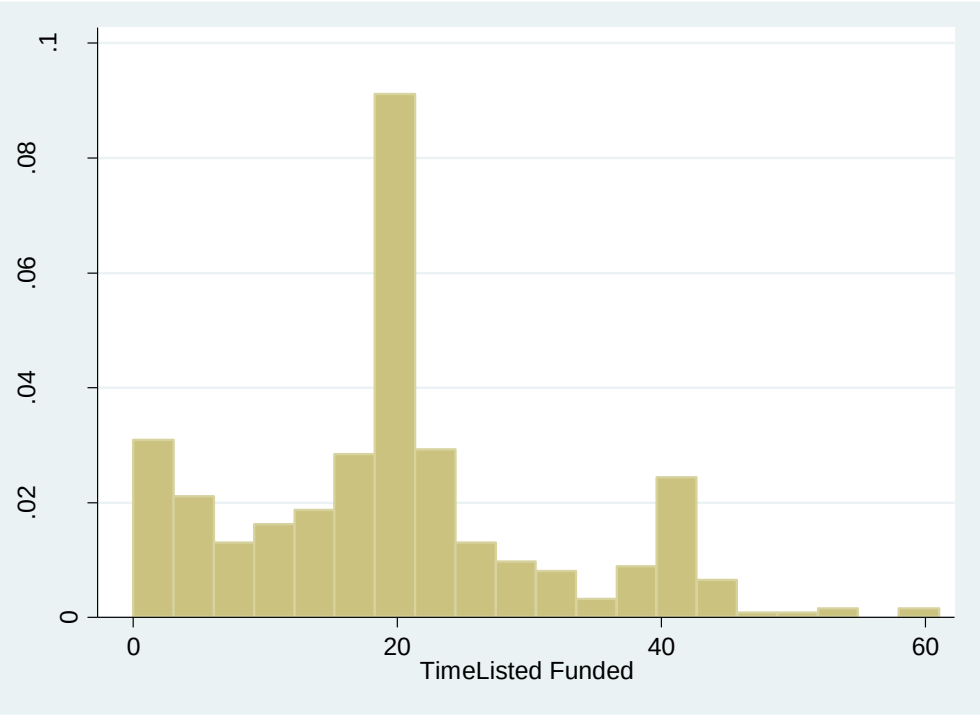


Figure 2. Histogram of Investments per Investment Day

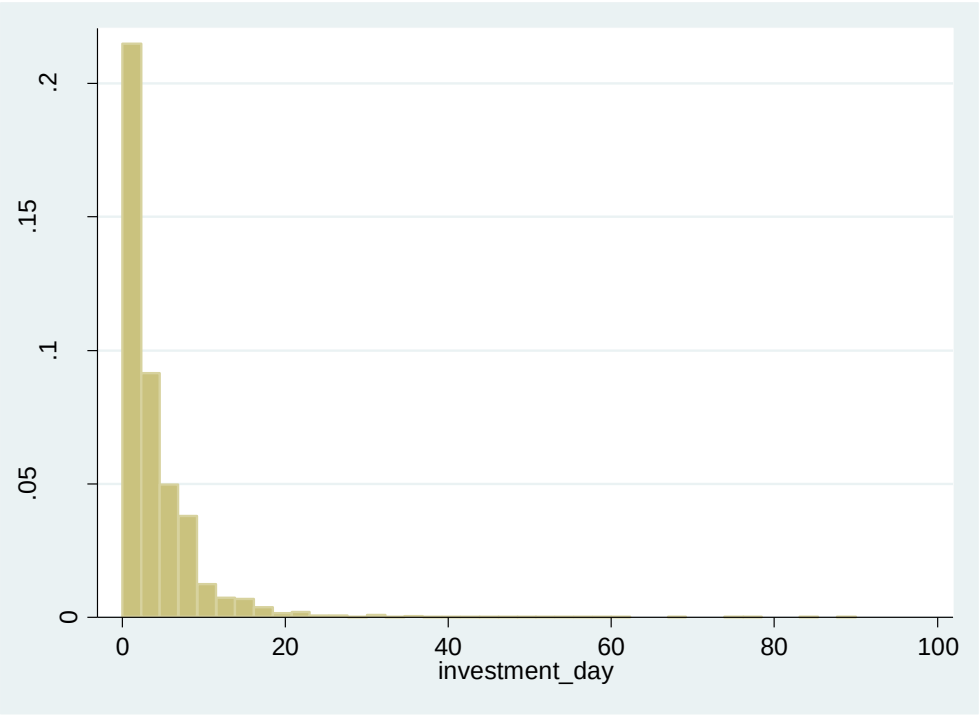
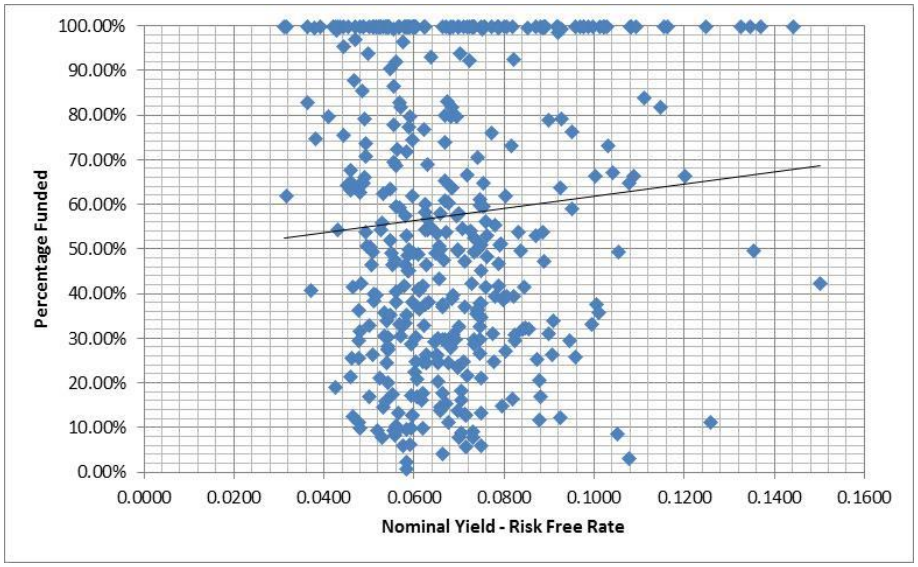
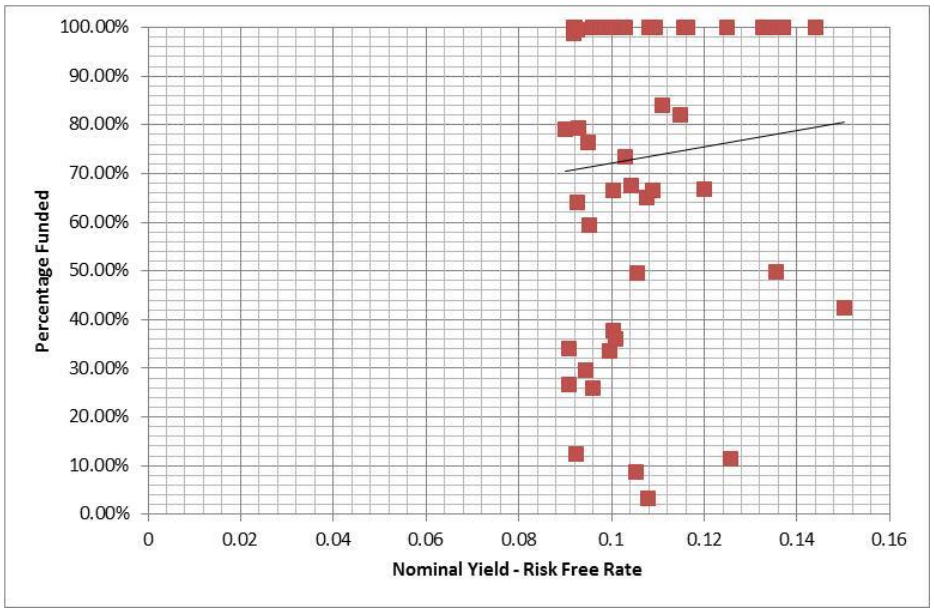


Figure 3. Scatter Plot of Nominal Interest – Risk-Free Rate and Percentage Funded (for Full Sample)



Pearson correlation = 0.082

Figure 4. Scatter Plot of Nominal Interest – Risk-Free Rate and Percentage Funded (for Subsample Risk-Free Nominal Yield Rate >0.09)



Pearson correlation = 0.081

Table 1. Summary Statistics

This table defines and provides summary statistics for the all of the variables by platform in the dataset.

Variable	Definition	Observations	Mean	Median	Std. Dev.	Min	Max
Dependent Variables							
Success (% of Capital Raised)	The percentage of capital raised relative to the loan project goal.	414	0.58	0.532	0.32	0.01	1
Success Dummy	A dummy = 1 if Success =1, 0 otherwise.	414	0.23	0	0.42	0	1
# Lenders	The number of lenders in the loan project.	414	84.70	77	47.28	4	302
Bid Amount	The total amount bid by lenders.	414	33,680.68	29,450.00	22,297.93	400.00	124,800.00
Funded Dummy	Dummy equal to 1 if the loan was funded, 0 otherwise.	414	0.89	1	0.31	0	1
Time Listed to Funded	The number of days from being listed on the platform to the end of the loan project.	414	20.12	20	11.85	0	61
Investment Characteristics							
Risk-Free Nominal Yield	The yield on debt issued by the firm minus the risk-free rate.	414	0.0685	0.0657	0.0190	0.0313	0.1502
Percent Female Lenders	The percentage of lenders that were female that financed the loan.	414	0.07	0.0714	0.03	0	0.2363636
Principal Amount	The total amount of debt raised.	414	72,183.57	60,000.00	46,889.03	10,000.00	250,000.00
Loan Duration (Months)	The number of months that the loan is outstanding.	414	34.01	36	13.80	6	60
Firm Characteristics							
Number of Employees	The number of employees at the firm at the time of crowdlending.	414	17.55	10	28.51	1	300
Female Borrower	A dummy variable equal to one if the CEO of the firm is female.	414	0.16	0	0.37	0	1
Assets	The assets of the firm at the time of crowdlending.	414	808,571.20	295,975.00	1,409,318.00	9,000.00	14,600,000.00
Current Assets/Current Liabilities	The current assets divided by the current liabilities of the firm at the time of crowdlending.	414	2.87	1.297928	14.10	0	256.2
Liabilities	The total liabilities of the firm at the time of crowdlending.	414	808,609.80	295,975.00	1,409,146.00	9,000.00	14,600,000.00
Equity	The total shareholders' equity of the firm at the time of crowdlending.	414	160,649.70	49,241.67	519,186.70	-1,214,900.00	7,492,967.00
Net Income	The net income of the firm at the time of crowdlending.	414	66,744.35	44,100.00	101,940.60	-346,300.00	1,112,533.00
Age	The number of years the Firm Has been in Business until the Time of	414	13.86	10.00	17.21	1	231

Table 1 (Continued)

Variable	Definition	Observations	Mean	Median	Std. Dev.	Min	Max
Legal Entity Status of Borrower							
PLC (AG)	Dummy=1 for AG companies.	414	0.02	0	0.13	0	1
Registered Cooperative (eG)	Dummy=1 for eG companies.	414	0.00	0	0.07	0	1
Registered Merchant (eK)	Dummy=1 for eK companies.	414	0.04	0	0.20	0	1
Freelancer	Dummy=1 for Freelancer companies.	414	0.03	0	0.17	0	1
LLC (GmbH)	Dummy=1 for GmbH companies.	414	0.56	1	0.50	0	1
LP with LLC as GP (GmbH & Co KG)	Dummy=1 for GmbH and Co KG companies.	414	0.09	0	0.29	0	1
LP (KG)	Dummy=1 for KG companies.	414	0.01	0	0.11	0	1
Non-Registered Merchant (neK)	Dummy=1 for neK companies.	414	0.08	0	0.27	0	1
General Partnership (OHG)	Dummy=1 for OHG companies.	414	0.01	0	0.11	0	1
Other	Dummy=1 for other companies.	414	0.13	0	0.34	0	1
small LLC (UG)	Dummy=1 for UG companies.	414	0.01	0	0.12	0	1
Reason for Raising External Capital							
Asset Purchase	Dummy=1 if the company indicated the reason for crowdlending was to purchase assets.	414	0.12	0	0.32	0	1
Expansion / Growth Capital	Dummy=1 if the company indicated the reason for crowdlending was for expansion/growth capital.	414	0.46	0	0.50	0	1
Other	Dummy=1 if the company indicated the reason for crowdlending was for reasons other than the choices listed here.	414	0.08	0	0.27	0	1
Tax Liability	Dummy=1 if the company indicated the reason for crowdlending was to pay for tax liabilities.	414	0.02	0	0.14	0	1
Working Capital	Dummy=1 if the company indicated the reason for crowdlending was for working capital.	414	0.32	0	0.47	0	1

Table 1 (Continued)

Variable	Definition	Observations	Mean	Median	Std. Dev.	Min	Max
Risk Rating of Borrower							
Risk A+	Highest platform rating of borrower.	414	0.05	0	0.22	0	1
Risk A	2nd highest platform rating of borrower	414	0.21	0	0.41	0	1
Risk B	3rd highest platform rating of borrower	414	0.47	0	0.50	0	1
Risk C	4th highest platform rating of borrower	414	0.23	0	0.42	0	1
Rick C-	Lowest platform rating of borrower	414	0.04	0	0.18	0	1
Market Conditions							
MSCI	MSCI returns in the month of initiating crowdlending	414	-0.0002	-0.0001	0.0045	-0.0218	0.0182
Industry Dummy Variables							
Accommodation and food service activities	Dummy variables equal to 1 for the respective industries.	414	0.03	0	0.17	0	1
Agriculture, forestry and fishing		414	0.02	0	0.13	0	1
Arts, entertainment and recreation		414	0.00	0	0.05	0	1
Construction		414	0.09	0	0.28	0	1
Electricity, gas, steam and air conditioning supply		414	0.00	0	0.05	0	1
Financial and insurance activities		414	0.03	0	0.17	0	1
Human health and social work activities		414	0.06	0	0.24	0	1
Information and communication		414	0.07	0	0.26	0	1
Manufacturing		414	0.11	0	0.32	0	1
Other		414	0.08	0	0.28	0	1
Other services activities		414	0.19	0	0.39	0	1
Professional, scientific and technical activities		414	0.04	0	0.19	0	1
Real estate activities		414	0.00	0	0.00	0	0
Rental and leasing activities		414	0.02	0	0.14	0	1
Transporting and storage		414	0.04	0	0.19	0	1
Wholesale and retail trade, repair of motor vehicles and motorcycles		414	0.21	0	0.41	0	1

Table 2. Cross-Sectional Analysis of Loan Projects

This table provides OLS (Models 1, 2-6) and Logit (Model 2) estimates of success indicators. Variables are defined in Table 1. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Model 1a: Success (% of Capital Raised) OLS		Model 1b: Success (% of Capital Raised) Percentage Model		Model 2: Funded=1	
	Coefficient	t-statistic	Marginal Effect	t-statistic	Marginal Effect	t-statistic
Investment Characteristics						
ln (Risk-Free Nominal Yield)	6.4524	4.79***	9.4543	4.56***	-3.4283	-2.14**
Percent Female Lenders	0.7868	2.42**	0.7464	1.61	0.1651	0.38
ln (Number of Employees)	-0.2849	-13.81***	-0.3912	-15.88***	-0.0285	-1.04
ln (Principal Amount)	-0.2547	-10.28***	-0.3995	-9.14***	0.0107	0.36
ln (Loan Duration [Months])	0.0407	3.09***	0.0493	3.11***	0.0023	0.13
Firm Characteristics						
Female Borrower	-0.0476	-1.65*	-0.0546	-1.47	-0.0377	-0.81
ln (Assets)	-0.0035	-0.28	-0.0096	-0.69	0.0222	1.4
Current Assets/Current Liabilities	-0.0018	-2.43**	-0.0024	-4.92***	0.0008	0.22
Liabilities / (Liabilities + Equity)	-0.0025	-0.44	-0.0030	-0.65	-0.0069	-0.42
Net Income (in thousand EUR)	0.0020	1.73*	0.0028	2.10**	0.0005	0.26
Ln (Age)	0.0069	0.46	0.0197	1.05	-0.0130	-0.74
Industry Dummies?	Yes		Yes		Yes	
Legal Status of Borrower						
PLC (AG)	0.0697	0.41	-0.1700	-0.89	0.0509	1.18
Registered Cooperative (eG)			-0.2532	-1.37		
Registered Merchant (eK)	0.0864	0.55	-0.1202	-0.84	0.0632	2.13**
Freelancer	0.1688	1.06	-0.0965	-0.64		
LLC (GmbH)	0.1062	0.71	-0.0911	-0.71	0.1481	1.17
LP with LLC as GP (GmbH & Co KG)	0.1452	0.95	-0.0189	-0.14	0.0449	0.91
LP (KG)	0.0927	0.53	-0.1330	-0.7		
Non-Registered Merchant (neK)	0.1346	0.88	-0.0915	-0.62	0.0447	0.97
General Partnership (OHG)	0.1272	0.72	-0.0656	-0.35	-0.0015	-0.01
Other	0.0236	0.16	-0.2071	-1.5	0.0811	2.48**
small LLC (UG)	0.2482	1.43				
Reason for Raising External Capital						
Asset Purchase	0.0178	0.21	0.0621	1.75*	0.0029	0.07
Expansion / Growth Capital	-0.0319	-0.39	0.0154	0.53	0.0429	1.42
Other	0.0095	0.11	0.0537	0.95	0.0299	0.9
Tax Liability	0.0000		0.1076	1.32	-0.1735	-0.65
Working Capital	-0.0277	-0.34				

	Model 1a: Success (% of Capital Raised) OLS		Model 1b: Success (% of Capital Raised) Percentage Model		Model 2: Funded=1	
	Coefficient	t-statistic	Marginal Effect	t-statistic	Marginal Effect	t-statistic
Risk Rating of Borrower						
Risk A+	0.6470	4.86***	0.4083	20.13***	-0.3848	-0.65
Risk A	0.5246	4.44***	0.4842	7.60***	-0.2377	-0.64
Risk B	0.3030	2.99***	0.3973	3.24***	-0.1069	-0.7
Risk C	0.1918	2.40**	0.2022	2.19**	-0.0901	-0.59
Market Conditions and Listing Day Dummies						
MSCI	2.7494	1.01	3.1217	0.71	6.2448	1.75*
Monday	0.0228	0.18	-0.0082	-0.08	0.0851	2.12**
Tuesday	0.0179	0.14	-0.0209	-0.22	0.0970	1.62
Wednesday	0.0586	0.46	0.0571	0.65	0.0935	1.39
Thursday	0.0545	0.43	0.0357	0.39	0.0914	1.38
Friday	0.0113	0.09	-0.0121	-0.13	0.0877	1.1
Saturday	-0.0015	-0.01	-0.0470	-0.35		
February	-0.1021	-1.94*	-0.1525	-2.61***	-0.0259	-0.27
March	-0.1077	-2.14**	-0.1544	-2.58**	-0.0312	-0.31
April	0.0149	0.27	0.0168	0.29	-0.0178	-0.15
May	0.1697	2.78***	0.1768	3.6	0.0265	0.4
June	-0.0130	-0.26	-0.0152	-0.27	-0.0816	-0.67
July	0.0724	1.36	0.0770	1.36	-0.0596	-0.48
August	0.1978	3.60***	0.1944	3.89***	-0.0770	-0.57
September	0.1904	3.02***	0.2008	3.43***	-0.2011	-0.89
October	0.2171	3.88***	0.2464	5.91***	-0.1959	-1.05
November	-0.0435	-0.76	-0.0473	-0.63	-0.1567	-0.88
December	-0.0718	-1.05	-0.1100	-1.05	-0.1057	-0.59
Year 2015	0.1244	3.84***	0.1603	3.19***	0.0016	0.04
Constant	3.3884	9.09***	19.1551	12.69***	4.5460	0.94
Model Dianostics						
Number of Observations	414		414		414	
F-Statistic (LR for Logit)	11.42***		879.05***		46.49	
Adjusted R2 (Pseudo R2 for Logit)	0.6118		0.238		0.1753	

Table 2. (Continued)	Model 3: # Lenders		Model 4: Bid Amount		Model 5: Time Listed to Funded	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Investment Characteristics						
ln (Risk-Free Nominal Yield)	535.1274	2.38**	405664.5	3.64***	-163.9199	-2.92***
Percent Female Lenders	59.3331	1.09	30311.5	1.13	4.417013	0.33
ln (Number of Employees)	31.3750	9.11***	14167.14	8.31***	10.87714	13.18***
ln (Principal Amount)	-27.70	-6.69***	-18100.0	-8.83***	8.49	8.34***
ln (Loan Duration [Months])	5.4461	2.48**	2424.267	2.23**	-0.1090	-0.21
Firm Characteristics						
Female Borrower	-6.7145	-1.39	-2960.227	-1.24	0.5808	0.5
ln (Assets)	-2.95	-1.42	-753.0	-0.73	-0.9450	-1.9
Current Assets/Current Liabilities	-0.0037	-0.03	-14.7986	-0.24	0.0071147	0.24
Liabilities / (Liabilities + Equity)	0.104	0.11	-83.30	-0.18	-0.0212	-0.1
Net Income (in thousand EUR)	-0.0825	-0.43	0.00126	0.13	-0.0398	-0.86
Ln (Age)	2.22	0.9	982.00	0.8	-0.0718	-0.12
Industry Dummies?	Yes		Yes		Yes	
Legal Status of Borrower						
PLC (AG)	-16.4222	-0.58	-7181.247	-0.51	2.2518	0.44
Registered Cooperative (eG)					-1.5443	-0.22
Registered Merchant (eK)	-5.9024	-0.23	-1014.12	-0.08	-3.4691	-0.82
Freelancer	9.5748	0.36	5168.872	0.39	0.8475	0.19
LLC (GmbH)	-2.2599	-0.09	-488.4714	-0.04	0.4081	0.11
LP with LLC as GP (GmbH & Co KG)	13.8323	0.54	5493.943	0.43	1.6655	0.42
LP (KG)	8.8544	0.3	-750.2392	-0.05	-1.3689	-0.26
Non-Registered Merchant (neK)	5.5376	0.22	1599.116	0.13	0.8378	0.21
General Partnership (OHG)	-6.4123	-0.22	-2868.142	-0.2		
Other	-12.9414	-0.51	-6081.802	-0.49	1.0952	0.28
small LLC (UG)	12.8128	0.44	7268.043	0.51	-2.3809	-0.47
Reason for Raising External Capital						
Asset Purchase	7.9549	0.55	6861.137	0.96	-4.9695	-1.45
Expansion / Growth Capital	4.7795	0.35	2215.185	0.33	-2.7200	-0.84
Other	9.1815	0.62	4785.518	0.66	-2.8623	-0.82
Working Capital	5.8397	0.42	2374.805	0.35	-2.7991	-0.86

Table 2. (Continued)	Model 3: # Lenders		Model 4: Bid Amount		Model 5: Time Listed to Funded	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Risk Rating of Borrower						
Risk A+	63.12549	2.84***	48013.21	4.37***	-21.94273	-4.02***
Risk A	42.32645	2.14**	38754.99	3.97***	-18.0141	-3.69***
Risk B	20.48998	1.21	22567.89	2.70***	-11.27453	-2.70***
Risk C	14.16269	1.06	14516.97	2.20**	-6.924293	-2.09**
Market Conditions and Listing Day Dummies						
MSCI	109.2159	0.24	176837.9	0.79	-46.26263	-0.43
Monday	9.170248	0.42	2973.15	0.28	-1.634961	-0.32
Tuesday	9.309099	0.44	4219.475	0.4	-0.9483157	-0.19
Wednesday	16.37547	0.78	8079.63	0.77	-1.525525	-0.3
Thursday	15.40683	0.73	7620.288	0.73	-1.259752	-0.25
Friday	7.696055	0.37	3178.368	0.31	-0.2395501	-0.05
Saturday	10.30806	0.42	3161.361	0.26	-2.948249	-0.5
February	-12.65179	-1.44	-3358.824	-0.77	1.676674	0.8
March	-14.78843	-1.76*	-5095.29	-1.23	2.472851	1.23
April	12.00051	1.32	3962.196	0.88	-3.077823	-1.43
May	32.76345	3.22***	13097.34	2.60***	-1.858624	-0.77
June	2.930852	0.35	1950.18	0.48	-0.435628	-0.22
July	13.9001	1.56	7529.54	1.71*	-1.371218	-0.65
August	40.2425	4.39***	16166.8	3.56***	-5.262486	-2.41**
September	38.10073	3.62***	16822.46	3.23***	-12.10887	-4.71***
October	47.46552	5.09***	18039.22	3.91***	-13.19683	-5.86***
November	26.81853	2.83***	2658.207	0.57	-8.612705	-3.80***
December	16.25169	1.42	-2260.479	-0.4	-10.90055	-4.01***
Year 2015	51.90517	9.60***	9884.771	3.70***	-9.616746	-7.31***
Constant	-295.4943	-4.75***	-147383.4	-4.79***	-87.5885	-6.14***
Model Dianostics						
Number of Observations	414		414		414	
F-Statistic (LR for Logit)	8.05***		6.92***		9.53***	
Adjusted R2 (Pseudo R2 for Logit)	0.5214		0.4725		0.5699	

Table 3. Cross-Sectional Analysis of Loan Risk Rankings

This table provides an ordered logit analysis of project risk rankings. Variables are defined in Table 1. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Coefficient	t-statistic	Marginal Effect Risk C -	Marginal Effect Risk C	Marginal Effect Risk B	Marginal Effect Risk A	Marginal Effect Risk A+
Investment Characteristics							
Percent Female Lenders	13.0604	4.16***	-0.2953	-2.0630	0.2497	1.7386	0.3700
ln (Number of Employees)	1.0099	5.16***	-0.0228	-0.1595	0.0193	0.1344	0.0286
ln (Principal Amount)	0.3708	1.63	-0.0084	-0.0586	0.0071	0.0494	0.0105
ln (Loan Duration [Months])	-0.0099	-0.08	0.0002	0.0016	-0.0002	-0.0013	-0.0003
Firm Characteristics							
Female Borrower	0.3004	1.07	-0.0062	-0.0451	-0.0002	0.0421	0.0094
ln (Assets)	-0.1768	-1.48	0.0040	0.0279	-0.0034	-0.0235	-0.0050
Current Assets/Current Liabilities	0.0102	1.51	-0.0002	-0.0016	0.0002	0.0014	0.0003
Liabilities / (Liabilities + Equity)	-0.0197	-0.39	0.0004	0.0031	-0.0004	-0.0026	-0.0006
Net Income	1.9658	1.73*	-0.0444	-0.3105	0.0376	0.2617	0.0557
Ln (Age)	0.0832	0.59	-0.0019	-0.0131	0.0016	0.0111	0.0024
Industry Dummies?	Yes						
Legal Status of Borrower							
AG (PLC)	0.8185	0.74	-0.0130	-0.1044	-0.0445	0.1276	0.0342
Registered Merchant (eK)	2.5542	1.32	-0.0216	-0.1934	-0.3479	0.3153	0.2475
Freelancer	0.1436	0.15	-0.0031	-0.0220	0.0009	0.0198	0.0043
LLC (GmbH)	1.7443	1.67*	-0.0200	-0.1719	-0.1936	0.2728	0.1127
LP with LLC as GP (GmbH & Co KG)	0.8480	1.01	-0.0207	-0.1362	0.0243	0.1093	0.0234
LP (KG)	0.9018	1.01	-0.0148	-0.1169	-0.0443	0.1390	0.0369
Non-Registered Merchant (neK)	1.9668	1.66	-0.0203	-0.1780	-0.2422	0.2957	0.1449
General Partnership (OHG)	1.0763	1.19	-0.0165	-0.1328	-0.0677	0.1690	0.0480
Other	1.5532	1.3	-0.0185	-0.1588	-0.1640	0.2476	0.0937
small LLC (UG)	1.2859	1.49	-0.0195	-0.1564	-0.0846	0.2010	0.0595
Reason for Raising External Capital							
Asset Purchase	-0.0322	-0.09	0.0007	0.0051	-0.0007	-0.0043	-0.0009
Expansion / Growth Capital	-0.1211	-0.51	0.0028	0.0192	-0.0024	-0.0161	-0.0034
Other	-0.1149	-0.29	0.0027	0.0186	-0.0033	-0.0149	-0.0031
Tax Liability	-0.3981	-0.48	0.0109	0.0680	-0.0219	-0.0476	-0.0095

	Coefficient	t-statistic	Marginal Effect Risk C -	Marginal Effect Risk C	Marginal Effect Risk B	Marginal Effect Risk A	Marginal Effect Risk A+
Market Conditions and Listing Day Dummies							
MSCI	-10.9738	-0.41	0.2481	1.7334	-0.2098	-1.4608	-0.3109
Monday	-0.0816	-0.26	0.0019	0.0131	-0.0021	-0.0107	-0.0022
Wednesday	-0.0137	-0.05	0.0003	0.0022	-0.0003	-0.0018	-0.0004
Saturday	0.1725	0.22	-0.0036	-0.0262	0.0005	0.0239	0.0053
February	-0.7155	-1.44	0.0219	0.1261	-0.0523	-0.0802	-0.0155
March	0.0609	0.13	-0.0013	-0.0095	0.0009	0.0082	0.0018
April	-0.0285	-0.05	0.0007	0.0045	-0.0006	-0.0038	-0.0008
May	0.3070	0.52	-0.0061	-0.0453	-0.0022	0.0437	0.0099
June	-0.3831	-0.79	0.0100	0.0642	-0.0174	-0.0472	-0.0095
July	-0.2799	-0.55	0.0071	0.0465	-0.0114	-0.0350	-0.0071
August	0.2396	0.45	-0.0050	-0.0361	0.0002	0.0334	0.0074
September	-0.8846	-1.49	0.0297	0.1592	-0.0775	-0.0936	-0.0177
October	0.0614	0.12	-0.0014	-0.0096	0.0009	0.0083	0.0018
November	-0.4817	-1	0.0132	0.0822	-0.0262	-0.0577	-0.0115
December	0.1633	0.28	-0.0034	-0.0249	0.0008	0.0226	0.0050
Ordered Logit Cutoffs							
Cut 1	8.1678						
Cut 2	10.7385						
Cut 3	13.2817						
Cut 4	15.4150						
Model Dianostics							
Number of Observations	414						
LR Statistic	112.88***						
Pseudo R2	0.1065						

Table 4. Analysis of Daily Data

This table provides panel data estimates of daily investment amounts. Variables are defined in Table 1. Variables excluded where the model would not otherwise converge. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Model 7 (Panel, Random Effects): Number of Investment / Day		Model 8 (Panel, Fixed Effects): Number of Investment / Day		Model 9 (Negative Binomial, Random Effects): Number of Investment / Day		Model 10 (Negative Binomial, Fixed Effects): Number of Investment / Day		Model 11 (Random Effects): Amount Investment / Day		Model 12 (Fixed Effects): Amount Investment / Day		Model 13 (Negative Binomial, Random Effects): Amount Investment / Day		Model 14 (Negative Binomial, Fixed Effects): Amount Investment / Day	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Female Percentage Day	0.3168	1.50	0.2681	1.29	0.1777	3.72***	0.1684	3.51***	102.2442	0.72	69.1967	0.49	0.3802	7.19***	0.3806	7.13***
Newsletter Percentage Day	1.0487	9.52***	1.0520	9.73***	0.4461	17.32***	0.4466	17.31***	545.8970	7.39***	546.2713	7.47***	0.9852	33.65***	1.0057	34.07***
Mobile Percentage Day	0.5697	3.12***	0.5532	3.08***	0.2378	5.84***	0.2340	5.74***	168.5426	1.38	159.2029	1.31	0.4942	10.83***	0.5013	10.88***
MSCI Return	1.2049	0.43	1.9422	0.70	-0.3114	-0.46	-0.1068	-0.16	-280.2590	-0.15	59.7532	0.03	-0.7155	-0.82	-0.6812	-0.77
Nominal Yield	29.0155	2.09**			1.3743	1.00	1.5365	0.66	-737.1427	-0.08			-3.0604	-3.77***	-3.3208	-3.55***
Yield on Public Debt	-2.3015	-4.14***	-0.8681	-1.32	-0.4907	-5.70***	-0.2408	-2.04***	-944.1086	-2.57**	-1282.9860	-2.89***				
Number of Parallel Loan Projects	-0.1250	-12.46***	-0.1187	-11.39***	-0.0235	-11.45***	-0.0252	-10.79***	-55.7298	-8.33***	-47.8659	-6.79***	-0.0043	-2.78***	-0.0034	-2.01**
Cumulative Lag Number of Investments	-0.0240	-4.90***	-0.0346	-6.89***	0.0009	0.98	-0.0022	-2.30**	31.5618	9.65***	33.7672	9.96***	0.0143	17.79***	0.0154	17.76***
Cumulative Lag Bid Amount (in thousand EUR)	0.0404	3.83***	0.0372	3.47***	0.0054	2.84***	0.0060	2.86***	-59.50	-8.45***	-75.60	-10.45***	-0.0061	-3.06***	-0.0125	-5.91***
Constant	11.3242	10.08***	10.5242	24.99***	2.5843	20.00***	2.4986	12.99***	4799.5500	6.65***	3713.6190	13.04***	-0.2048	-2.59***	-0.2614	-2.99***
Campaign Day Dummy	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	8236		8236		8236		8236		8236		8236		8236		8236	
Number of Groups	414		414		414		414		414		414		414		414	
Within R2	0.0400		0.0402						0.0374		0.0380					
Between R2	0.0878		0.0797						0.0006		0.0017					
Overall R2	0.0310		0.0364						0.0256		0.0136					

Table 5. Daily Data Segregated into Subsets by Financial Characteristics of Loan Project

This table provides panel data estimates of the number of investments per day (Models 15-22) and investment amounts (Models 23-30). Variables are defined in Table 1. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Model 15 (Negative Binomial, Fixed Effects): Number of Investment / Day, Net Income > 44,066		Model 16 (Negative Binomial, Fixed Effects): Number of Investment / Day, Net Income < 44,066		Model 17 (Negative Binomial, Fixed Effects): Number of Investment / Day, Found Year < 2002		Model 18 (Negative Binomial, Fixed Effects): Number of Investment / Day, Found Year > 2001		Model 19 (Negative Binomial, Fixed Effects): Number of Investment / Day, Revenue > 947,333		Model 20 (Negative Binomial, Fixed Effects): Number of Investment / Day, Revenue < 947,333		Model 21 (Negative Binomial, Fixed Effects): Number of Investment / Day, Assets > 888,777		Model 22 (Negative Binomial, Fixed Effects): Number of Investment / Day, Assets < 888,777	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Female Percentage Day	0.1723	2.50***	0.1600	2.38**	0.1766	2.94***	0.1706	2.15**	0.1890	2.81***	0.1620	2.35**	0.0746	0.84	0.2088	3.65***
Newsletter Percentage Day	0.4436	12.01***	0.4437	12.27***	0.4366	13.57***	0.4603	10.60***	0.4846	13.20***	0.4238	11.66***	0.3942	7.86***	0.4697	15.55***
Mobile Percentage Day	0.2529	4.34***	0.2051	3.55***	0.2123	4.18***	0.2866	4.16***	0.2934	5.05***	0.1657	2.89***	0.2751	3.52***	0.2042	4.24***
MSCI Return	-0.0833	-0.09	-0.0330	-0.03	-0.5584	-0.66	1.0644	0.97	-2.0030	-2.09**	1.9353	2.07**	-2.2777	-1.89*	1.0211	1.26
Nominal Yield	-5.2517	-1.47	6.0982	1.76*	2.6870	0.99	-2.2355	-0.45	2.9619	0.80	0.3140	0.10	1.5653	0.32	2.1081	0.76
Yield on Public Debt	-0.0128	-0.08	-0.5022	-2.93***	-0.4811	-3.16***	0.3487	1.75*	-0.0167	-0.11	-0.5529	-2.97***	0.1637	0.76	-0.4389	-3.06***
Number of Parallel Loan Projects	-0.0238	-7.26***	-0.0285	-8.54***	-0.0265	-8.78***	-0.0250	-6.52***	-0.0217	-6.73***	-0.0315	-9.18***	-0.0264	-6.08***	-0.0270	-9.68***
Cumulative Lag Number of Investments	-0.0024	-2.04**	-0.0035	-1.95*	-0.0004	-0.37	-0.0055	-3.50***	-0.0006	-0.53	-0.0063	-3.85***	-0.0043	-2.24**	-0.0020	-1.73*
Cumulative Lag Bid Amount (in thousand EUR)	0.0063	2.55***	0.0129	3.00***	0.0004	0.14	0.0152	4.74***	0.0039	1.48	0.0130	3.78***	0.0099	2.78***	0.0053	1.94*
Constant	2.9116	10.37***	2.2781	7.67***	2.5462	11.15***	2.5975	6.63***	2.2323	7.62***	2.9278	10.94***	2.5500	6.60***	2.5552	11.03***
Campaign Day Dummy	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	4116		4120		5328		2908		4160		4076		2286		5950	
Number of Groups	198		216		255		159		172		242		100		314	

Table 5. (Continued)	Model 23 (Negative Binomial, Fixed Effects): Amount Investment / Day, Net Income > 44,066		Model 24 (Negative Binomial, Fixed Effects): Amount Investment / Day, Net Income < 44,066		Model 25 (Negative Binomial, Fixed Effects): Amount Investment / Day, Found Year < 2002		Model 26 (Negative Binomial, Fixed Effects): Amount Investment / Day, Found Year > 2001		Model 27 (Negative Binomial, Fixed Effects): Amount Investment / Day, Revenue > 947,333		Model 28 (Negative Binomial, Fixed Effects): Amount Investment / Day, Revenue < 947,333		Model 29 (Negative Binomial, Fixed Effects): Amount Investment / Day, Assets > 888,777		Model 30 (Negative Binomial, Fixed Effects): Amount Investment / Day, Assets < 888,777	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Female Percentage Day	0.4004	5.25***	0.2866	3.77***	0.3174	4.73***	0.5017	5.63***	0.4677	6.28***	0.3264	4.22***	0.2667	2.71***	0.4283	6.67***
Newsletter Percentage Day	1.0212	24.06***	0.9672	23.48***	1.0410	28.33***	0.9209	18.35***	1.0620	25.29***	0.9465	22.70***	0.9654	16.91***	1.0206	29.36***
Mobile Percentage Day	0.5055	7.50***	0.4516	6.96***	0.4484	7.87***	0.5270	6.56***	0.5519	8.36***	0.4241	6.54***	0.4213	4.65***	0.4866	8.94***
MSCI Return	-0.0430	-0.03	-1.5789	-1.26	-0.5247	-0.48	-0.7965	-0.53	-2.1658	-1.74*	0.8533	0.68	-2.9030	-1.85*	0.6275	0.59
Nominal Yield	-7.7064	-4.93***	-1.0488	-0.86	-1.7628	-1.60	-8.4921	-4.58***	-3.0704	-2.15**	-2.9241	-2.23**	-6.4977	-3.32***	-2.7309	-2.47**
Yield on Public Debt	-0.2368	-2.71***	-0.5367	-5.90***	-0.3101	-3.85***	-0.4411	-4.38***	-0.2554	-2.95***	-0.5053	-5.45***	-0.1071	-0.92	-0.5118	-6.75***
Number of Parallel Loan Projects	-0.0048	-1.74*	-0.0152	-5.35***	-0.0096	-3.75***	-0.0090	-2.86***	-0.0054	-1.96**	-0.0130	-4.51***	-0.0055	-1.53	-0.0139	-5.70***
Cumulative Lag Number of Investments	0.0127	11.20***	0.0183	10.75***	0.0154	13.18***	0.0144	9.43***	0.0137	12.32***	0.0150	8.94***	0.0203	11.44***	0.0128	10.84***
Cumulative Lag Bid Amount (in thousand EUR)	-0.0080	-3.09***	-0.0120	-2.72***	-0.0156	-5.45***	-0.0055	-1.66*	-0.0100	-3.77***	-0.0101	-2.55**	-0.0186	-5.24***	-0.0100	-3.31***
Constant	0.3250	2.19**	0.0111	0.08	-0.1171	-0.95	0.5948	3.18***	-0.0706	-0.48	0.1932	1.34	0.2271	1.14	0.1429	1.17
Campaign Day Dummy	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Number of observations	4116		4120		5328		2908		4160		4076		2286		5950	
Number of Groups	198		216		255		159		172		242		100		314	

Table 6. Daily Data Segregated into Subsets by Risk Rating of Loan Project

This table provides panel data estimates of the number of investments per day (Models 31-35) and investment amounts (Models 36-40). Variables are defined in Table 1. *, **, *** significant at the 10%, 5%, and 1% levels, respectively.

	Model 31 (Negative Binomial, Fixed Effects): Number of Investment / Day, Risk Class A+		Model 32 (Negative Binomial, Fixed Effects): Number of Investment / Day, Risk Class A		Model 33 (Negative Binomial, Fixed Effects): Number of Investment / Day, Risk Class B		Model 34 (Negative Binomial, Fixed Effects): Number of Investment / Day, Risk Class C		Model 35 (Negative Binomial, Fixed Effects): Number of Investment / Day, Risk Class C-	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Female Percentage Day	-0.0425	-0.21	0.0125	0.13	0.2523	3.63***	0.2213	1.96**	1.0767	2.09**
Newsletter Percentage Day	0.3808	3.25***	0.3537	6.39***	0.4089	10.98***	0.6686	12.02***	0.7282	3.35***
Mobile Percentage Day	0.5446	3.01***	0.1804	2.08**	0.2166	3.69***	0.2607	2.89***	-0.0740	-0.26
MSCI Return	-1.1894	-0.50	1.4771	1.15	0.0257	0.03	-2.4086	-1.61	8.5230	2.31**
Nominal Yield	-3.8255	-0.08	-17.1443	-1.12	5.9385	0.79	17.1581	1.87*	-36.5549	0.00
Yield on Public Debt	-1.6700	-2.69***	-0.4325	-1.70	0.0531	0.32	-1.3015	-4.38***	-2.5868	-1.42
Number of Parallel Loan Projects	-0.0079	-0.66	-0.0209	-4.10***	-0.0335	-10.38***	-0.0215	-3.94***	0.0833	3.10***
Cumulative Lag Number of Investments	-0.0031	-0.81	-0.0027	-1.45	-0.0007	-0.46	-0.0048	-2.14**	-0.0212	-3.23***
Cumulative Lag Bid Amount (in thousand EUR)	0.0043	0.62	0.0068	1.95*	0.0039	1.01	0.0059	1.05	0.0421	2.01**
Constant	4.3349	1.60	3.9216	4.24***	2.0835	3.82***	1.6391	2.00**	21.8412	0.01
Campaign Day Dummy	Yes		Yes		Yes		Yes		Yes	
Number of observations	415		1712		4101		8236		148	
Number of Groups	20		82		185		274		13	

Table 6. (Continued)	Model 36 (Negative Binomial, Fixed Effects): Amount Investment / Day, Risk Class A+		Model 37 (Negative Binomial, Fixed Effects): Amount Investment / Day, Risk Class A		Model 38 (Negative Binomial, Fixed Effects): Amount Investment / Day, Risk Class B		Model 39 (Negative Binomial, Fixed Effects): Amount Investment / Day, Risk Class C		Model 40 (Negative Binomial, Fixed Effects): Amount Investment / Day, Risk Class C-	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Female Percentage Day	0.3285	1.40	0.1659	1.54	0.4666	6.03***	0.4070	3.22***	1.1516	1.45
Newsletter Percentage Day	0.7863	5.53***	0.8501	12.92***	0.9728	23.08***	1.2602	19.52***	0.9880	3.09***
Mobile Percentage Day	0.6967	3.15***	0.4387	4.38***	0.4319	6.46***	0.5725	5.67***	-0.1172	-0.32
MSCI Return	4.4611	1.34	2.6933	1.50	-2.2275	-1.77*	-1.2610	-0.61	8.5429	1.52
Nominal Yield	24.6136	1.60	5.2372	0.81	1.1013	0.36	-0.3008	-0.10	7.7177	0.59
Yield on Public Debt	-0.8657	-2.31**	-0.2943	-2.02**	-0.2865	-3.24***	-0.8015	-5.53***	-0.4392	-0.55
Number of Parallel Loan Projects	0.0059	0.64	-0.0106	-2.19**	-0.0165	-5.84***	-0.0098	-2.28**	0.0260	1.49
Cumulative Lag Number of Investments	0.0077	1.57	0.0125	6.51***	0.0170	11.69***	0.0153	6.35***	0.0189	1.93*
Cumulative Lag Bid Amount (in thousand EUR)	-0.0071	-0.77	-0.0071	-1.89*	-0.0162	-4.41***	-0.0199	-2.97***	-0.0023	-0.07
Constant	-0.7705	-0.77	-0.2820	-0.64	-0.1846	-0.79	-0.0584	-0.18	-0.7704	-0.49
Campaign Day Dummy	Yes		Yes		Yes		Yes		Yes	
Number of observations	415		1712		4101		8236		148	
Number of Groups	20		82		185		274		13	

Appendix A: Correlation Matrix

This table presents correlations across the 414 campaigns. Correlations greater than 0.09, 0.10, and 0.13 in absolute value are statistically significant at the 10%, 5%, and 1% levels, respectively.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
	Dependent Variables																									
1	Success (% of Capital Raised)	1.00																								
2	# Lenders	0.23	1.00																							
3	Bid Amount	0.34	0.87	1.00																						
4	Funded Dummy	-0.13	-0.09	-0.05	1.00																					
5	Time Listed to Funded	-0.61	0.14	0.03	0.02	1.00																				
	Investment Characteristics																									
6	Risk-Free Nominal Yield	0.12	-0.10	-0.19	-0.10	-0.12	1.00																			
7	Percent Female Lenders	0.07	0.13	0.15	0.00	-0.01	-0.20	1.00																		
8	Ln (Principal Amount)	-0.58	0.51	0.50	0.09	0.58	-0.26	0.09	1.00																	
9	Ln (Loan Duration [Months])	-0.40	0.02	-0.09	-0.03	0.38	0.06	-0.10	0.28	1.00																
	Firm Characteristics																									
10	Ln (Number of Employees)	-0.09	0.14	0.23	0.09	0.21	-0.07	0.01	0.31	0.11	1.00															
11	Female Borrower	0.07	-0.10	-0.11	-0.04	-0.11	0.02	0.04	-0.16	-0.06	-0.08	1.00														
12	Ln (Assets)	-0.21	0.26	0.34	0.17	0.21	-0.11	0.08	0.53	0.00	0.49	-0.13	1.00													
13	Current Assets/Current Liabilities	-0.10	-0.03	-0.04	0.02	0.00	-0.09	0.01	-0.01	-0.01	-0.09	-0.02	-0.02	1.00												
14	Liabilities / (Liabilities + Equity)	0.01	-0.02	-0.03	-0.01	-0.04	0.05	-0.06	-0.05	0.01	0.00	-0.01	0.03	0.04	1.00											
15	Net Income	-0.09	0.18	0.20	0.05	0.06	-0.19	-0.07	0.30	0.02	0.10	-0.03	0.25	0.13	0.01	1.00										
16	Ln (Age)	-0.01	0.13	0.13	0.04	0.02	-0.06	0.03	0.12	0.09	0.09	-0.1	0.38	-0.10	0.00	0.13	1.00									
	Reason for Raising External Capital																									
17	Asset Purchase	0.04	0.01	0.06	-0.08	-0.05	0.01	-0.03	0.01	0.11	0.08	-0.04	0.04	0.02	-0.02	0.11	0.02	1.00								
18	Expansion / Growth Capital	-0.12	0.05	0.00	0.10	0.09	0.00	0.00	0.10	0.11	0.06	-0.12	-0.03	0.05	0.05	0.00	0.01	-0.35	1.00							
19	Other	0.03	-0.04	-0.02	-0.02	-0.01	0.03	-0.06	-0.06	-0.03	-0.06	0.08	-0.05	-0.03	-0.01	-0.05	0.01	-0.11	-0.26	1.00						
20	Tax Liability	0.10	-0.02	-0.04	-0.03	-0.07	-0.02	-0.07	-0.11	-0.07	-0.08	0.05	-0.08	-0.01	-0.01	0.04	0.09	-0.05	-0.12	-0.04	1.00					
21	Working Capital	0.05	-0.03	-0.01	-0.03	-0.04	-0.02	0.07	-0.05	-0.15	-0.07	0.09	0.06	-0.05	-0.03	-0.07	-0.05	-0.26	-0.64	-0.20	-0.09	1.00				
	Risk Rating of Borrower																									
22	Risk A+	0.05	0.10	0.12	0.03	-0.02	-0.30	0.06	0.04	0.07	0.02	0.06	-0.01	0.04	-0.02	0.03	0.09	-0.02	0.02	-0.02	0.06	-0.01	1.00			
23	Risk A	0.01	0.19	0.28	0.02	0.01	-0.45	0.23	0.23	0.05	0.07	0.01	0.11	0.04	-0.04	0.13	0.02	0.05	-0.03	-0.05	-0.07	0.05	-0.12	1.00		
24	Risk B	-0.20	-0.14	-0.17	0.00	0.11	-0.13	-0.10	0.03	0.05	-0.03	-0.04	-0.01	0.01	0.02	0.03	-0.05	0.00	0.03	0.05	0.02	-0.07	-0.22	-0.50	1.00	
25	Risk C	0.13	-0.03	-0.09	-0.02	-0.05	0.50	-0.10	-0.18	-0.09	-0.02	-0.02	-0.07	-0.05	0.02	-0.13	0.04	-0.05	0.00	0.01	0.02	0.02	-0.12	-0.27	-0.52	1.00
	Market Conditions																									
26	MSCI	0.00	-0.06	-0.03	0.03	-0.07	0.08	0.04	-0.03	-0.09	0.01	0.01	0.06	0.01	0.04	0.06	0.05	0.08	-0.10	-0.05	0.02	0.07	0.06	-0.03	-0.04	0.00

Appendix B.

The alternative Model 7 without the variables Female Percentage Day, Newsletter Percentage Day, and Mobile Percentage Day in Table 4 (Model 7a). Likewise, we considered removing the first day of the campaign, which only strengthens the results. That alternative Model 7 (Model 7b).

	Model 7a (Panel, Random Effects): Number of Investment / Day, Excluding Select RHS Variables		Model 7b (Panel, Random Effects): Number of Investment / Day, Excluding Select RHS Variables and First Day of Campaign	
	Coefficient	t-statistic	Coefficient	t-statistic
MSCI Return	1.2156	0.43	-1.4255	-0.54
Nominal Yield	29.2590	2.11**	16.2187	2.04***
Yield on Public Debt	-2.4245	-4.34***	-3.1237	-7.35***
Number of Parallel Loan Projects	-0.1269	-12.56***	-0.1149	-12.91***
Cumulative Lag Number of Investments	-0.0243	-4.93***	0.0119	-2.66***
Cumulative Lag Bid Amount. (in thousand EUR)	0.0420	3.96***	0.00003	3.38***
Constant	11.84217	10.53***	4.4586	1.53
Campaign Day Dummy	Yes		No	
Number of observations	8236		7822	
Number of Groups	414		414	
Within R2	0.1667		0.0200	
Between R2	0.2945		0.1991	
Overall R2	0.0848		0.0725	

Appendix C

This Table provides summary statistics for the daily data used in Tables 4-6.

Variable Name	Definition	Observations	Mean	Median	Stdev	Min	Max
Number of Investment / Day	The number of investments per day.	8,650	4.05	3.00	5.50	0.00	90.00
Amount Investment / Day	The amounts in Euros invested per day	8,650	1612.00	600.00	2979.00	0.00	86100.00
Female Percentage Day	The percentage of female investors per day	8,650	0.06	0.00	0.16	0.00	1.00
Newsletter Percentage Day	The percentage of investors per day that subscribed to the platform newsletter	8,650	0.30	0.25	0.32	0.00	1.00
Mobile Percentage Day	The percentage of investors per day that used mobile phones	8,650	0.09	0.00	0.19	0.00	1.00
MSCI Return	MSCI returns on the investment day	8,650	0.00	0.00	0.01	-0.04	0.04
Nominal Yield	The nominal risk-free yield in Germany	8,650	0.07	0.07	0.02	0.04	0.16
Yield on Public Debt	The yield on publicly issued debt in Germany	8,650	0.54	0.54	0.26	0.07	1.35
Number of Parallel Loans	The number of other competing loans on the platform on that day.	8,650	19.42	20.00	8.14	1.00	39.00
Cumulative Lag Number of Investments	The cumulative number of investments on the platform prior to this particular day	8,236	45.66	37.00	35.37	1.00	297.00
Cumulative Lag Bid Amount	The cumulative Euro value of investments on the platform prior to this particular day.	8,236	15755.05	10800.00	14976.37	100.00	118900.00