Small Bus Econ (2019) 52:67–87
https://doi.org/10.1007/s11187-017-9986-z

Small business online loan crowdfunding: who gets funded and what determines the rate of interest?

Reabetswe Kgoroeadira · Andrew Burke · André van Stel

Accepted: 29 December 2017 / Published online: 22 February 2018

Abstract The advent of online peer-to-peer crowdfunding presents a new type and source of finance for small firms. This raises the question of whether this innovation makes any difference to the type of business that can secure funding and the amount that they pay for this finance. In this paper, we examine the American online peer-to-peer loan crowdfunding website www.prosper.com to answer these questions. We create and analyse a dataset of 14,537 small firm unsecured loan applications. We find that lenders in this market ignore business characteristics and focus on personal characteristics instead, particularly a person's credit score but also whether they are employed and provide a picture. This implies that entrepreneurs who want to raise finance in this market will need to use a very different pitch than the norm in the offline market—as personal rather than firm characteristics are the main determinants of securing funding and the price paid for it.

R. Kgoroeadira
Beryl Holdings, Sandton, South Africa
e-mail: reabetswe.kgoroeadira@gmail.com

A. Burke (✉) · A. van Stel
Trinity Business School, Trinity College Dublin, University of Dublin, Dublin 2, Ireland
e-mail: andrew.burke@tcd.ie

A. van Stel
e-mail: vanstela@tcd.ie

A. van Stel
Kozminski University, Warsaw, Poland

Keywords Crowdfunding · Peer-to-peer lending · Small business finance

JEL classification G10 · G23

1 Introduction

The development and application of advanced information technologies is altering the finance market (Han and Greene 2007; Short et al. 2017). Over the past few years, for profit peer-to-peer (P2P) lending websites have become a new innovative approach to mobilise and disseminate capital. P2P lending is a form of financing in which individuals (who are usually strangers) extend funds to others directly without going through financial institutions like banks. These P2P lending websites (platforms) act as intermediaries, via which lenders provide capital to borrowers for a variety of financial needs, including the provision of capital to small business owners. It is typically a form of debt finance.

The P2P platforms match individual borrowers with individual lenders. Both borrowers and lenders first have to go through a verification process (e.g. users have to provide a valid social security number, a valid bank account number, etc.) in order to be allowed access to the platform. Next, the platforms provide lenders with both financial and non-financial information of the borrowers to facilitate due diligence. Borrowers post their loan requests (so-called listings) on the websites, in particular the amount of money they wish to borrow and the interest rate they wish to pay for the loan. Borrowers also share (voluntary) information about themselves—both personal and financial—and lenders decide whether or not to contribute to their loan request. Every loan is underwritten by multiple individual lenders, each committing a fraction of the loan until it is funded in full. Lenders can see how many other lenders already have placed a bid on a listing. Once fully funded, the loan is originated and the lenders receive a pro rata share of the principal and interest payments until the loan reaches maturity or until the borrower defaults. The websites generate their revenue via service fees, which they collect from borrowers as well as lenders (Klafft 2008). Borrowers are afforded an opportunity to include text description in their loan request. In addition, most P2P lending websites allow borrowers to include a picture when requesting for a loan. If the purpose of the loan request is to finance a business, the borrower may use the text description and picture to provide some information on their business. In turn, lenders can utilise this information to make a compelling case for why they should extend credit to these borrowers. Lenders decide how much, if any, funding to offer.

The P2P lending landscape differs in at least three ways when compared to traditional lending institutions like banks. First, on P2P websites, individuals extend loans to small business ventures without ever physically meeting the business owners; all transactions take place online. In traditional lending, however, the role of both physical contact and site visits (if need be) forms an important and integral aspect in credit extension, decreasing information asymmetries. It may be argued therefore that information asymmetries in the particular case of P2P lending might logically be expected to be even more severe.

Second, hundreds of potential lenders assess and screen the credit requests from small business ventures at any given time. It could also be argued therefore that, as a crowd, individuals understand each other's business better than traditional lenders. For example, some individuals may have knowledge about the area where the borrower wishes to start the business; others might have expertise in the product or the technology or the feasibility of the business. Since lenders can observe when many other people are lending to a firm, they may take this as an indication that extensive due diligence has been conducted by the 'crowd'. Hence, viewed from this angle, information asymmetries may potentially be less severe on P2P websites.

Third, lenders extending credit to small businesses on P2P websites are non-experts in assessing credit risk and making small business lending decisions, which may affect their ability to conduct due diligence. Traditional lenders, on the contrary, are trained experts in conducting due diligence and assessing credit risk.

To the extent that information asymmetries and how they are managed may differ in the online P2P lending market, then the extent of extending credit to small business ventures may also differ. Therefore, the research question of this article is "Are the characteristics of successful loan applications and of the interest rate paid different in the P2P lending market, compared to traditional lending institutions?" This question is topical because it has yet to be established at an empirical level whether P2P lending merely crowds out traditional small business finance—if the characteristics are the same—or whether it actually provides finance to businesses that otherwise they would not get (i.e. business start-ups and young firms or businesses looking for small amounts of capital—unable to raise funds from business angels and venture capitalists)—if the characteristics are different. We investigate our research question by focusing on the US P2P crowdfunding website Prosper.com, examining what type of entrepreneurs gets loans and how much interest they pay.

Our paper fills an important gap in the growing literature on crowdfunding. Crowdfunding finance is typically classified as reward-based, donation-based, equity-based or lending-based (Mollick 2014). Research on reward-based crowdfunding is most popular (Kaartemo 2017), while research on equity-based crowdfunding is also emerging fast (e.g. Vismara 2016; Piva and Rossi-Lamastra 2017; Block et al. 2017). However, research on lending-based crowdfunding is less frequent even though this is a viable method of small business funding. The research that does exist on P2P lending is typically of a general nature, i.e. including loans for all purposes, not just small business funding (e.g. Lin and Viswanathan 2016; Lin et al. 2013; Zhang and Liu 2012). In the current paper, we specifically focus on P2P lending with the purpose of small business funding, and on the characteristics of these small businesses. This is not straightforward as the firm characteristics have to be filtered manually from the Prosper database on the basis of the text descriptions provided by borrowers. This effort is worthwhile though as it enables us to investigate whether indeed P2P small business lending has different characteristics than traditional small business lending (our main research question). Thus, a unique feature of our study is that we can distinguish between firm and personal characteristics, whereas extant research on P2P lending is restricted to personal characteristics only. This enables us to investigate the relative importance of personal versus firm characteristics in the P2P lending market for small businesses.

The paper proceeds as follows: In Sect. 2, we review the literature and set hypotheses relating to online P2P lending. In Sect. 3, we discuss how we created the dataset from information on the Prosper.com website. This section also provides details of our empirical methodology and model. In Sect. 4, empirical results are presented, and finally, we close with a discussion and conclusions in Sects. 5 and 6.

2 Theory and hypotheses

Traditional lending institutions face problems with regards to extending finance to small business ventures. These problems are largely accounted for by information asymmetries in capital markets, where borrowers are assumed to have more information about their prospective projects than lenders (Besanko and Thakor 1987; Berger and Udell 1995). If lenders are unable to determine the quality[1] of the business venture because they lack full information, they could raise the average price of capital (interest rates in the case of banks) to compensate for the higher risk. However, because of the average high interest rates offered, low-risk borrowers[2] (knowing their worth) lack the incentive to access finance; they may opt to go look elsewhere (Storey 1994; Parker 2009). Stiglitz and Weiss (1981) argue that banks may therefore find it optimal not to raise interest rates in conditions of access demand because by so doing, they will worsen the quality of the borrower pool (adverse selection). This arises because only high-risk borrowers are willing to pay higher interest rates.

Similarly, the change in interest rates may influence borrowers to undertake riskier projects (moral hazard) given that if the initiative becomes successful 'the business owner takes all' and banks do not share in the profits or success of the undertaken project (Burke and Hanley 2003, 2006). If the initiative fails however, it is the banks that lose the funds they have extended to the business owners.

Consequently, for these reasons, banks may opt to ration credit instead as an alternative of charging high interest rates (Stiglitz and Weiss 1981). Since business start-ups and young small firms are the most likely to be 'unknowns' to the bank, the problems of adverse selection and moral hazard would seem to be particularly acute in this area (Bhide 2000).

Information asymmetries may also be problematic because of the relatively high fixed costs of gathering information lenders may incur for small transactions (especially in the case of venture capitalists and business angels); consequently, lenders may opt not to extend credit to businesses looking for small amounts of capital (Storey 1994).

To date, much of the research has focused on two main approaches by which traditional lending institutions attempt to cope with challenges caused by information asymmetries when extending finance to small firms: *signalling* and *relying on social ties*.

The *signalling approach* emphasises the facilitative role played by the

(i) Personal wealth of the business owner (often measured through home ownership, Avery et al. 1998). To the extent that personal assets are at stake, greater personal wealth may serve as a signal of credit quality, potentially mitigating adverse selection common in lending decisions. Personal assets may also alleviate moral hazard problems; the possibility of losing assets enforces borrowers to select less risky projects (Stiglitz and Weiss 1981; Bester 1985; Besanko and Thakor 1987; Bester 1987; Avery et al. 1998).
(ii) Close relationships established between lenders and borrowers, which serve to improve information flow used to appraise credit risk (Sharpe 1990; Petersen and Rajan 1994; Berger and Udell 1995; Cole 1998);
(iii) Human capital of the business owner, typically measured by the owner's education level and work experience, in influencing the future prospects or performance of the business (Bates 1991; Cressy 1996).

[1] Where quality stipulates the borrower credit risk such that high-quality borrowers are the low-risk borrowers most likely to pay back the extended funds, while low-quality borrowers are the high-risk borrowers who are less likely to pay back the extended funds.

[2] Those likely to pay back the extended funds.

In general, it is expected that individuals who are home owners, with pre-existing relationships with lenders, who have greater work experience, education and knowledge of the market, signal better credit quality and hence are likely to access credit from lenders. However, with unsecured loans as in the case of Prosper.com, then the ability to signal through collateral is eliminated. Hence, one might expect the adverse selection and moral hazard problems in the online peer-to-peer loan crowdfunding market to be much greater than in the traditional loan markets where the use of security/collateral is common. However, Berger et al. (2011) put forward an argument that the ability to provide collateral may still be useful in unsecured lending as it may be the case that collateral differences more often reflect observed quality differences across borrowers, e.g. owning a home indicates an ability to accumulate some capital and service a debt. Studies by Machauer and Weber (1998) report that collateral is independent of borrower type, while a study by Jimenez et al. (2006) shows that collateral is negatively related to *ex post* default on loans offered to young firms. The authors argue that *ex post* default may reflect high unobserved risk and hence *ex ante* information asymmetries.

Turning from the probability of getting funding to the cost of funding, there is evidence that the interest rate charged to small firms incorporates whether the borrower provides collateral, such that borrowers who provide collateral are afforded lower interest rates (Chan and Thakor 1987; Cowling et al. 2017). Burke and Hanley (2003, 2006) argue however that the collateral-interest rate relationship is not necessarily linear. Based on UK banking data, they observe a U-shaped relationship between wealth and interest rates.

The *social ties approach* emphasises the facilitative role played by the small business owner's direct and indirect connections to potential capital providers and demonstrates that endorsements and social alliances with prominent third parties, which serve as a reputation gesture, can assist small firms in gaining access to finance (Stuart et al. 1999). Microfinance institutions look to social ties to be able to implement joint liability lending (Hartley 2010). This logic extends to reducing information problems when considering extending credit to small firms is through relationship lending (Boot and Thakor 1994; Petersen and Rajan 1994; Berger and Udell 1995; Cole 1998; Harhoff and Körting 1998; Cowling et al. 2017). According to this literature, lenders acquire information over time through contact with the firm, and/or its owner and use this information in their decision to extend credit. The premise is based on the fact that borrowers will be able to build a reputation over time where lenders are able to observe their repayment behaviour. In general, these studies report that strong ties (in the sense of building a personal relationship) with lenders lead to greater availability of credit for small firms (Petersen and Rajan 1995; Berger and Udell 1995; Harhoff and Körting 1998).[3]

Studies concerned with factors that influence interest rates paid by small business borrowers postulate that closer relationships with creditors improve information flows which may allow more accurate assessment of risk and reduce information asymmetries which leads to lower rates of interest (Petersen and Rajan 1994; Berger and Udell 1995; Harhoff and Körting 1998; Keasey and Watson 2000).

Petersen and Rajan (1994) use data from the 1987 SSBF to find that close ties with creditors lead to lower rates of interest. Studies by Harhoff and Körting (1998), based on Finnish Bank data, and Keasey and Watson (2000), based on UK data, confirm Petersen and Rajan (1994) findings, by reporting that existence of a relationship with a creditor enables small firms to be charged lower interest rates. Berger and Udell (1995) on the other hand find that it is the duration of the relationship that determines the interest rates paid by small firms such that interest rates are lower when firms have longer pre-existing relationships with creditors. On the contrary, Binks and Ennew (1998) argue that longer relationships can lead to increased interest rate charges due to banks taking advantage of the firms' lock-in to the relationship.

Looking at the characteristics of P2P lending websites, loans in this market are unsecured. We contend, therefore, that information asymmetries in this market may not necessarily be solved by collateral as put forward by Bester (1985); since if a borrower defaults, lenders cannot confiscate collateral to compensate for the inherent risk. Hence, home ownership as a signal for borrower quality is very limited. We argue however that home ownership can still provide useful information to the lenders in this market in order to reduce information asymmetries. For example, if a borrower has previously managed to attain a mortgage loan [from elsewhere], and not default—this might bode well with lenders such that they associate home ownership

[3] The 'strength' of an interpersonal tie is a linear combination of the amount of time, the emotional intensity, the intimacy (or mutual confiding), and the reciprocal services which characterise each tie (Granovetter 1973).

with higher quality/calibre of borrowers (relative to those that rent). This logic leads to the hypothesis:

H1a: Small business owners, who own their homes, demonstrate better creditworthiness (relative to those that rent) and therefore are more likely to be extended credit by potential lenders.
H1b: Small business owners, who own their homes, demonstrate better creditworthiness (relative to those that rent) and therefore are more likely to pay lower interest rates.

A related issue is that of borrower personal credit scores (Berger and Frame 2007) as a means to estimate borrower quality. On P2P lending websites, borrowers are assigned credit scores based on previous credit history. There are also greater reputational costs for high credit score individuals from defaulting on a loan as this will cause their credit rating to drop which will reduce the probability that they get finance in the future and will increase the cost of any finance they secure. A very low credit grade person does not face the same reputational cost of default as their credit scores are already in the lowest categories. Therefore, moral hazard and adverse selection may be expected to be lower among high reputational borrowers. These considerations give rise to the following hypotheses.

H2a: Small business owners, with high credit ratings, demonstrate better credit risk (relative to those with low credit ratings) and therefore are more likely to be extended credit by potential lenders.
H2b: Small business owners, with high credit ratings, demonstrate better credit risk (relative to those with low credit ratings) and therefore are more likely to pay lower interest rates.

Information asymmetries in the P2P lending context may also be solved by the fact that hundreds of people are evaluating the credit request (Belleflamme et al. 2014; Mach et al. 2014; Macht and Weatherston 2014). Although lenders do not meet the person who is looking for business funds, we contend that when they see many people lending to a firm, they may take this as an indication that extensive due diligence has been conducted by the crowd. This, in turn, may increase the probability that additional bids are placed and hence the probability that the loan request gets fully funded. Hence we postulate that

H3: The likelihood that a loan request gets funded will increase with the total number of bids on it.

Another issue is that of borrower-lender relationships (relationship lending) which, according to traditional lending markets, plays an important role in information flow, subsequently reducing information asymmetries between lenders and borrowers (Petersen and Rajan 1994; Berger and Udell 1995) which leads to access to credit and cheaper credit. In the context of P2P lending, multiple lenders extend credit to a borrower. Moreover, lenders and borrowers do not know each other personally—therefore we argue that, in terms of social network theory (Granovetter 1973), relationships may be weaker compared to traditional lending markets. Even in this diminished state however, relationships in the form of returning borrowers should still play a role in providing signals of borrower quality, especially if the previous loan was successfully paid off. Hence, we postulate that

H4a: Pre-existing relationships (in the form of repeat borrowers) increases the probability that the potential lender will extend credit to small business owners.
H4b: Pre-existing relationships (in the form of repeat borrowers) result in lower interest rates paid for loans.

It is also agreed that older borrowers (firms) are thought to have longer track records than younger borrowers (firms) and are therefore likely to reduce information issues (Bhide 2000; Van der Zwan 2016). In the context of P2P lending, borrowers are not required to indicate their age or the age of the firm. They do however indicate whether they are seeking funds for an existing business or a new business. In general, therefore, it may be anticipated that the following will hold concerning observable firm characteristics:

H5a: Existing firms are more likely to be funded.
H5b: Existing firms are more likely to pay lower interest rates.

In traditional markets, business plans have become a major means through which lenders assess the risk of extending funds to borrowers (Burke et al. 2010). In the P2P context, borrowers are not required to produce a business plan. Instead, borrowers have an option to give extra information (about the business and why they are looking for funds) in the form of text descriptions or added pictures in the loan request. We contend that, similar to traditional lending markets, it is plausible that the optional information (text and pictures) may actually enable lenders on P2P websites to better screen borrowers (Mollick 2014; Kaartemo 2017; Moritz and Block 2016). Hence, we postulate that

> H6a: Borrowers that give additional information (in the form of text descriptions and/or pictures) are likely to attenuate information asymmetries; therefore will be more likely to be funded by lenders.
>
> H6b: Borrowers that give additional information (in the form of text descriptions and/or pictures) are likely to attenuate information asymmetries; therefore will be more likely to pay lower interest rates.

A well-known possible consequence of business failure is that access to finance to start anew may be severely hampered due to a stigma of failure (Ucbasaran et al. 2013; Simmons et al. 2014). In the context of P2P lending, we argue that these consequences may be somewhat less severe since borrowers have an opportunity to explain to lenders any delinquencies, judgements or bankruptcies through the optional text elaboration. Nevertheless, we still expect a negative impact of previous failure to repay debts as it may influence the confidence lenders have that their loan will be repaid:

> H7a: Borrowers who have previous failures (in the form of previous delinquencies and/or judgements) find it more difficult to access funds on P2P lending websites.

In the same vein, we postulate that extending credit to borrowers who have previous failures will come at a price; lenders will expect to be compensated for extending credit to those with previous failures such that

> H7b: Borrowers who have previous failures (in the form of previous delinquencies and/or judgements) are more likely to pay higher interest rates.

For the remainder of this paper, we test these developed hypotheses.

3 Methodology

3.1 Data collection

This study is the first empirical study that looks at small business loans (as opposed to general loans) in the context of P2P lending. To test the hypotheses derived, we have created a new and comprehensive dataset based on a combination of coding qualitative information and utilising secondary data, extracted from the publically available electronic archives of Prosper.com. In particular, although Prosper is a general platform for P2P lending, in the current paper, we specifically focus on P2P lending with the purpose of small business funding. This is not straightforward: although small business loans can easily be filtered from the Prosper data base, the firm characteristics have to be filtered manually from the Prosper database on the basis of the text descriptions provided by borrowers. This effort is worthwhile though as it enables us to investigate whether P2P small business lending has different characteristics than traditional small business lending (our main research question).

Because Prosper.com is the oldest and dominant P2P lending site, it is likely to serve as a broadly useful model for examining P2P lending efforts in financing small business ventures. The data include all the information seen by potential lenders when making the lending decisions. The unit of observation is the individual loan as opposed to a firm. Because these are personal loans for business purposes, lenders on Prosper.com primarily underwrite them based on the owners' credit profile as opposed to the firm's credit profile. Still, by meticulously going through the text descriptions provided by borrowers, we were able to create variables on some firm characteristics as well. This enables us to test the relative importance of personal versus firm characteristics in determining credit approval success.

There are four general types of information available in the data. First, the bulk of the data consists of the main credit information that Prosper.com obtains from the credit bureaus' reports (Experian), indicating borrower's credit history and their typical payment behaviour of any previous debt obligations (including external credit scores, mortgage payments and any delinquencies or judgements). With the exception of credit scores, all other credit information is publicised on the website. Instead of the raw credit scores obtained from credit reports, Prosper.com assigns an internally generated credit grade to each potential borrower based on their credit score and credit history, and publishes this internally generated credit grade on the website.

Second, the data contains two types of self-reported information shared by the potential borrowers on the website: (i) obligatory information which includes employment status and stated income of the potential borrowers, which is verified by Prosper, and (ii) optional information in the form of pictures and a free-form text elaborating as to why potential borrowers are good loan candidates, which is not verified by Prosper. This optional information often includes items such as intended use of the proceeds (including funding a business) and explanation of poor credit grades. Because there are no small business specific demographic data available from the data, such as firm age, firm size, industry distribution of firms etc., we used the optional data to create some of the demographic variables. For example, we were able to code the optional content for industry classification of the small business ventures and the firm age (classified only as a binary variable new firm or existing firm). We were able to classify the data according to loan purpose (for example, working capital, capital investment, etc.), and we were also able to create two additional variables (include picture and elaboration) as indicators of whether the potential borrower has availed additional information to attenuate information asymmetries.

Third, the data also contains loan-specific information including loan amount, interest rates offered by the potential borrower, the interest rates paid by those who manage to get funded, as well as an indication of any previous loans attained through Prosper (a variable which we use as a proxy for reputational effects).

Finally, after filtering out loan requests with the purpose of funding a business, we have information on the lending decision outcome for a population of 28,904 small business loan requests issued between August 2007 and August 2013. Of those, 4046 (13%) were successfully funded and 24,858 (87%) were rejected. The analysis that follows, however, is based on a sample of 14,537 loan requests. We use a sample rather than the entire population because the short and long-text descriptions from each loan request must be read and hand-coded when developing key variables. We adopted a simple random sampling technique, where every second case was randomly selected from the population. With simple random sampling, there is an equal chance that each unit from the population could be selected for inclusion in the sample.

To obtain the coded variables (industry, firm age and loan purpose), 5 postgraduate students were employed to code the sample of 14,537 loan requests (i.e. total 6 coders all sitting in 1 room for 30 days). As a starting point, approximately 10% of the data (1251 cases) were selected from the sample and coded by all 6 coders together to determine the unified code for each variable. Coders were then paired for cross referencing and inter-coder reliability purposes, resulting in three groups of two coding the remaining 90% of the data (per pair coded approximately 3750 cases). In instances where the pair of coders disagreed about classifying data—the case was brought to the attention of the team, discussed and then classified. Ten percent of each group's coded cases were checked for accuracy by a second pair of coders. On the rare occasion that coders made a large number of errors, they were asked to redo the coding and a second accuracy check of all recoded cases was performed.

In cases where there were no agreements even after discussion of cases, the case was dropped. We applied the following filtering criteria based on missing values: 766 cases (5% of initial sample) were dropped as they could not be classified by industry; 929 (6% of initial sample) were dropped as they could not be classified by firm age; 202 cases (1% of initial sample) were dropped as they could not be classified on the loan purpose; and 104 cases (0.7% of initial sample) were dropped as they had unidentifiable pictures. This resulted in a final sample of 12,526 loan requests (from 7834 small firms) of which 1417 (11%) were funded loans.

3.2 Factors driving credit allocation

The first question our study addresses is concerned with factors that drive the probability of funding in this market. The dependent variable is a decision of whether to extend credit or not.[4] Since this is a binary outcome, we use a multivariate probit regression model. To test

[4] A borrower is extended credit if his loan request attracts at least 100% of the requested loan size within the duration the listing (loan application) remains active to receive funding—for Prosper, this duration is typically 7 days (Zhang and Liu 2012). For our study period, partial funding was not permitted in this market. If a borrower failed to raise 100% of what they asked for within the duration of the listing, and they would still desire to borrow money, they would have to re-list the loan request on the website, and the bidding process by lenders on the loan application would start anew.

the hypotheses developed, we specify the following main equation:

$$\Pr\left(\text{Funding}|1\right)_i = \beta_1 \text{ Owner}_i + \beta_2 \text{ Firm}_i + \beta_3 \text{ Information}_i + \beta_4 \text{ Loan}_i + \beta_5 \text{ Control}_i \quad (1)$$

The dependent variable is coded as 1 for funded requests and 0 otherwise. In order for the borrower to get funded on Prosper.com, their loan request must attract 100% of the requested loan size—partial funding was not available. If the requested loan amount failed to reach 100%, the borrower had to re-list on the website. The expected influence of the independent variables not discussed in hypotheses 1–7 is explained below with full variable definitions provided in Table 1.

Regarding owner attributes, the expected impact of variables home_owner, credit_grade, delinquencies and judgments have been discussed in hypotheses 1a, 2a and 7a, respectively. For the borrower's income (variable income_range), we expect a positive impact on the probability of getting funded. Traditional financial markets like banking prefer borrowers who have higher income levels and hence greater capacity to repay the loan (Antoniades 2016). Similarly, regarding employment status, in traditional financial markets, full-time employees are generally considered to have a more stable income than part-time employees or self-employed, and may be considered less risky borrowers. Accordingly, their probability of getting funded may be higher.

Regarding firm attributes, the role of firm age was discussed in hypothesis 5a. Our data does not include the age of the firm; however, borrowers do indicate whether they are looking for funds for an existing firm or a new firm (that does not yet exist on the day of applying for a loan).

Regarding information attributes, the roles of repeat loans, inclusion of pictures and text elaboration in the loan application and the number of bids placed on a listing (variable bid_count) were discussed in hypotheses 4a, 6a and 3, respectively.

Regarding loan attributes, we control for loan size (variable requested amount) requested by the borrower. We also include a polynomial (squared) variable to control for non-linear effects. Next, we also include the maximum interest rate offered by the borrower

Table 1 Summary of regressors

Variable	Definition	Data source
Home_owner	Dummy variable, taking value 1 if borrower is a home-owner, as measured by an active mortgage loan on the borrower's credit report, and 0 otherwise. Verified by Prosper.	Listing
Credit_grade	Set of dummies indicating borrower's risk of default taking values AA (low risk), A, B, C, D, E and HR (high risk). The credit grade is assigned to the borrower by Prosper, based on the borrower's credit history.	Listing
Delinquencies	Number of times the borrower has been 60 or more days late with payments in the last 10 years.	Listing
Judgements	Dummy variable indicating whether the borrower declared bankruptcy within the last 10 years.	Listing
Income_range	Set of dummies indicating income range of the borrower classified in the following categories: 1 = \$0 or undefined; 2 = \$25k–\$49,999; 3 = \$50k–\$74,999; 4 = \$75k–\$99,999; 5 = \$100k +	Listing
Employment_status	Set of dummies indicating the employment status of the borrower classified in the following categories: 1 = full time, 2 = part time, 3 = self-employed, 4 = other	Listing
Existing_firm	Dummy variable, taking value 1 if firm already exists; 0 otherwise.	Coded
Repeat_loan	Indicator variable, taking value of 1 if the borrower has a prior loan that has been paid off or is current at the time of the listing; 0 otherwise. Repeat loans are visible to lenders on Prosper.com.	Coded
Include_picture	Dummy indicating whether potential borrower includes a picture in the loan request.	Coded
Elaboration	Dummy indicating whether potential borrower includes a text elaboration.	Coded
Bid count	Number of bids placed on a listing	Listing
Requested_amount	Loan amount requested by borrower	Listing
Offer_interest_rate	The maximum interest rate offered by the borrower when asking for a loan.	Listing
Final_interest_rate		Listing

Table 1 (continued)

Variable	Definition	Data source
	Interest rate paid by those who were extended credit	
Industry	1 digit SIC defined as 1 = construction; 2 = transport and utilities; 3 = services; 4 = retail trade; 5 = manufacturing; 6 = wholesale trade; 7 = agriculture; 8 = finance and real estate. Included as dummy variables.	Coded
Time	Month dummies, indicating the time at which the loan request was posted on Prosper.	Listing
Region	Set of US state dummies indicating the region the borrower is from.	Listing

This table lists all regressors developed from our sample data from Prosper. The table gives a definition of each variable, and it distinguishes between variables which were collected directly from the listing and variables which were coded

(variable offer_interest_rate) when asking for a loan. It is not clear what effect this variable will have on the credit allocation decision. Theoretical literature suggests that borrowers that offer high interest rates may be signalling that they are high risk (Stiglitz and Weiss 1981). However, given the fact that potential lenders are not professional risk assessors as in banks—they may be attracted to borrowers offering high interest rates with the view of attracting high returns. Burke and Hanley (2006) put forward the argument that interest rates may take a non-linear form. Hence, we include a polynomial (squared) variable to control for non-linear effects of the offered interest rates on the probability of the loan request being funded.

Finally, we control for the period in which the loan application was placed by including time dummies. We also control for the industry in which the business is active, as credit allocation decisions may differ across industries.

3.3 Factors driving interest rates paid

The second question we address in this study is concerned with factors that drive interest rates paid in this market. Given that it is unlikely that lenders will accept negative interest rates, we sensor the dependent variable at 0. Hence, we adopt a Tobit regression for our estimation. We consider the following equation:

$$\begin{aligned}\text{Interest rate}_i = \beta_1\,\text{Owner}_i + \beta_2\,\text{Firm}_i \\ + \beta_3\,\text{Information}_i + \beta_4\,\text{Loan}_i \\ + \beta_5\,\text{Control}_i \qquad (2)\end{aligned}$$

The dependent variable (interest) is the interest rate paid by each borrower on their funded loan. This interest rate was adjusted to provide the interest rate margin (i.e. actual rate—US Fed prime rate) so as to allow for a reliable comparison between data collected at different points in time. In terms of explanatory and control variables, we adopt the same regressors as those defined in Sect. 3.2 above.

3.4 Descriptive statistics

3.4.1 Mean values of model variables

In Table 2, we present the mean values for our explanatory and control variables. Statistics are presented separately for all loan requests (column 1), declined loans (column 2) and approved loans (column 3). In column 4, we show *t* tests to determine whether the mean values for the funded and declined loans are statistically different.

Column 1 of Table 2 shows summary statistics for the sample of 12,526 loan requests (from 7834 small firms) from which it is possible to profile the type of small business ventures that approach this market for funds. Using various characteristics from the loan requests, we found that typical firms approaching this market are started or owned by borrowers who are relatively in a poor credit situation: the majority (76%) fall into Prosper's lower credit grade categories (B, C, D, E or HR); on average, they have 6 delinquencies and at least 1 judgement record, indicating that they have previously failed to pay back loan commitments. These owners seem to be pursuing the business venture either as a sideline to their existing works or as a hobby, given the fact that 60% of the sample indicate full-time employment as their labour force activity. New firms make up around 30% of businesses approaching this market; the remaining 70% is made up of already established businesses. Relative to a representative sample of US small firms of which new ventures form around 10%, it appears that new firms are overrepresented in the P2P

Table 2 Mean values of model variables

Variable	(1) All loans	(2) Declined loans	(3) Funded loans	(4) *t* test
Number of loans	12,526	11,109	1417	
Owner attributes				
Home_ownership	0.49	0.48	0.58	6.8***
Credit_grade				
AA	0.11	0.09	0.22	15.1***
A	0.12	0.11	0.18	7.9***
B	0.15	0.15	0.18	3.3***
C	0.18	0.18	0.14	− 3.7***
D	0.15	0.15	0.15	− 0.07
E	0.09	0.10	0.07	− 2.7**
HR	0.20	0.22	0.05	− 15.5***
Delinquencies	6.1	6.5	2.9	− 9.6***
Judgements	1.7	1.8	0.4	12.1***
Income_range				
$0 or undefined	0.13	0.13	0.06	− 8.4***
$1–$24,999	0.10	0.11	0.08	− 3.2***
$25k–$49,999	0.27	0.27	0.28	1.4
$50k–$74,999	0.23	0.22	0.27	4.2
$75k–$99,999	0.11	0.11	0.14	3.2***
$100k +	0.16	0.16	0.17	0.83
Employment_status				
Full time	0.60	0.57	0.75	− 12.7***
Part time	0.02	0.02	0.01	2.3***
Self-employed	0.35	0.36	0.21	11.3***
Other	0.03	0.05	0.03	1.4*
Firm attributes				
Existing_firm	0.70	0.70	0.71	− 2.9*
Industry				
Construction	0.02	0.02	0.01	− 2.4**
Transport and utilities	0.02	0.02	0.02	− 1.3
Services	0.42	0.42	0.40	− 1.2**
Retail trade	0.31	0.31	0.30	1.1
Finance and real estate	0.16	0.17	0.20	3.8***
Agriculture	0.01	0.01	0.02	3.1
Wholesale trade	0.01	0.004	0.01	2.5
Manufacturing	0.05	0.05	0.05	− 0.7
Information attributes				
Include_picture	0.56	0.55	0.56	0.68**
Elaboration	0.97	0.97	0.97	− 2.5
Repeat_loan	0.04	N/A	0.39	N/A
Bid_count	39	20	191	1.6**
Loan contract attributes				
Requested amount	$10,430	$10,751	$7920	13.4***
Funded amount	$1821	–	$7864	N/A
Offer_ interest_ rate	24.1	24.5	21.3	− 12.1***
Final_ interest_rate	23.8	24.4	18.5	− 20.1***

Significant coefficients are indicated with *, ** and *** which stand for 0.10, 0.05 and 0.01 significance levels, respectively. Columns (1), (2) and (3) show mean values for all loan requests, declined loans and approved loans, respectively. Finally, column (4) presents *t* test/χ^2 statistics for differences in the means of the declined and approved loan requests

context. In terms of personal wealth, just under half of the prospective borrowers own their homes.

On average, these small business borrowers are looking for small amounts of money ($10,430), they are willing to pay a high price for credit (24%) and the majority (55%) of them are looking for working capital. In terms of industry distribution, most firms in the sample are found in the retail, services or finance industries. Moving on to column 3 of Table 2, we observe that of the 12,526 loan requests 1417 became funded loans, which translate to a success rate of 11%. So, this means that almost 9 out of 10 of those requesting a loan will not get it.

So far, we have profiled the type of firm that looks for funds in this market. Next, we attempted to gain insight on factors associated with funding success. Hence, from Table 2, columns 2 and 3, we show the summary statistics of declined and funded loans, respectively. In general, when comparing mean differences between funded and rejected loan requests for our explanatory variables, based on a standard *t* test, we found that statistically significant differences associated with credit approval are related to borrower credit grades, delinquencies, judgements, labour force status, home ownership, income range and inclusion of pictures. All these associations are significant at the 0.05 level or less.

3.4.2 Correlation matrix

The correlation matrix of the explanatory variables is presented in Table 3, as a test of multicollinear

Table 3 Correlation matrix

Variable	Requested amount	Interest rate	Income range	Credit grade	Judgements	Picture	Existing firm	Industry	Loan purpose	Homeowner	Repeat loan	Number of bids
Requested amount	1	−0.17**	0.18**	−0.41**	−0.23**	0.003	−0.04**	0.05**	0.06**	0.21**	−0.16**	0.16**
Interest rate		1	−0.06**	0.42**	0.18**	0.04**	0.003	−0.02	−0.02	−0.16**	0.06**	−0.23**
Income range			1	−0.19**	−0.09**	0.11**	−0.07**	0.02	0.03**	0.24**	0.09**	0.11**
Credit grade				1	0.37**	0.04**	0.05**	−0.05**	−0.03*	−0.30**	0.16**	−0.33**
Judgements					1	−0.03*	0.03*	−0.04**	−0.02	−0.12**	0.10	−0.12**
Picture						1	0.006	0.010	−0.009	0.03**	−0.08	0.01**
Existing firm							1	−0.020	−0.12**	−0.04**	0.04	0.04**
Industry								1	−0.016	0.04**	−0.07	0.03**
Loan purpose									1	0.02*	−0.03	0.02**
Homeowner										1	0.01	0.12**
Repeat loan											1	−0.14**
Number of bids												1

distortions. Generally, the correlation coefficients are low. The highest absolute value of the Pearson correlation coefficients as seen in Table 3 is that of credit grade and judgements, being 0.37. One may conclude that, although most values are significantly different from zero, this is not relevant considering their small values. Therefore, we did not anticipate any multicollinearity challenges when running regressions.

4 Results

4.1 Factors driving the probability of funding

Table 4 reports the results of the probit model which estimates the factors that drive the probability of a loan being funded.[5] Our results show that given the fact that borrowers indicate whether they are home owners or not in the loan requests provide useful information to potential lenders. In model (1) of Table 4, we find that similar to traditional lending, the supply of loans flows to the least risky entrepreneurs who are homeowners (H1a), confirming the importance of homeownership as a useful mechanism of eradicating information asymmetries in the P2P lending context, not as a form of collateral but in the form of borrower reputation as stipulated by Diamond (1989). Borrowers who are consistent in mortgage repayments seem to build a positive reputation, thus gaining access to loans in this context. Interestingly, the impact of home ownership applies to new firms only (model (3)), as the relationship is nonsignificant for existing firms (model (2)). This suggests that borrower reputation is considered particularly important for new firms.

We also find that the supply of loans is more readily available to less risky entrepreneurs with high credit ratings (H2a) and to those indicating that they are repeat borrowers (H4a) with previous established repayment history within the P2P lending context. In fact, our proxy of a previously existing relationship 'Repeat_loans' does not appear in the probit results as shown in Table 4 because it predicts funding success perfectly. In traditional lending, by close and continued (physical) interaction, potential borrowers may provide the lenders with sufficient information about the firm's affairs, accumulated over time. The resulting information allows for inter-

[5] Due to missing values for some independent variables, the number of observations is smaller than indicated in Sect. 3.1.

Table 4 Probit estimates of factors driving credit approval

Variable	(1) General model (all)	(2) Existing firms (only)	(3) New firms (only)
Constant	−0.332	0.956***	0.423
	(−0.350)	(2.609)	(0.566)
Owner attributes			
Home_owner	0.134***	0.087	0.299***
	(2.685)	(1.483)	(2.850)
Credit_grade (AA)			
A	−0.263***	−0.210**	−0.421**
	(−2.858)	(−2.033)	(−1.982)
B	−0.397***	−0.339***	−0.498**
	(−4.019)	(−3.126)	(−2.334)
C	−0.662***	−0.717***	−0.415*
	(−6.079)	(−5.930)	(−1.863)
D	−0.921***	−0.906***	−0.881***
	(−7.468)	(−6.636)	(−3.424)
E	−1.373***	−1.421***	−1.255***
	(−9.741)	(−8.702)	(−4.336)
HR	−1.849***	−1.871***	−1.880***
	(−12.552)	(−11.033)	(−6.028)
Delinquencies	−0.170***	−0.124**	−0.263**
	(−3.239)	(−1.998)	(−2.417)
Judgements	−0.223		
	(−1.514)		
Income_range ($0–unable to verify)			
$1–$24,999	0.184*	0.098*	0.704**
	(1.666)	(0.719)	(2.445)
$25,000–$49,999	0.277***	0.210*	0.764***
	(2.874)	(1.879)	(2.787)
$50,000–$74,999	0.322***	0.265**	0.794***
	(3.280)	(2.351)	(2.856)
$75,000–$99,999	0.232**	0.093*	0.950***
	(2.093)	(0.730)	(3.135)
$100,000 plus	0.106*	0.013	0.671*
	(0.957)	(0.106)	(2.129)
Employment_status (full time)			
Part time	−0.450**	−0.492**	−0.465*
	(−2.435)	(−1.989)	(−1.472)
Self-employed	−0.107*	−0.137**	−0.140*
	(−1.947)	(−2.248)	(1.031)
Firm attributes			
Existing_firm	0.054		
	(1.041)		
Information attributes			
Include_picture	0.231***	0.179***	0.435***
	(4.138)	(2.695)	(3.788)
Elaboration	0.140	0.511	−0.348
	(0.561)	(1.365)	(−0.795)
Bid_count	0.008***	0.007***	0.011***
	(30.644)	(26.262)	(16.183)
Loan attributes			
Requested_amount ($1000)	−0.249***	−0.225***	−0.335***
	(−16.221)	(−12.844)	(−9.675)
SQ Requested_amount	0.003***	0.002***	0.004***
	(5.101)	(3.477)	(3.344)
Offer_interest_rate (%)	0.030*	0.014***	0.010**
	(1.702)	(3.494)	(1.304)
SQ Offer_interest_rate	−0.000		
	(−0.982)		
Time fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Number of observations	10,278	7249	2983
Pseudo R^2	0.481	0.473	0.549
Log likelihood	−1910	−1400	−459.2

T values are given in parentheses. Significant coefficients are indicated with *, ** and *** which stand for 0.10, 0.05 and 0.01 significance levels, respectively. This table reports the Probit regression results for factors driving credit approval on Prosper.com. The first regression presents estimates for the general specification for all loan requests. The last two regressions present estimates for (parsimonious) specifications for loans from existing firms only and for loans from new firms only. In all regressions, the dependent variable is binary taking the form 1 if the loan request was funded and 0 otherwise

temporal arrangements, reducing credit rationing (Cole 1998). In the P2P lending context, however, relationships in the traditional sense may not be feasible. First, borrowers and lenders do not meet; hence, interactions—which form an important element in reducing information asymmetries in traditional lending—are unavailable. Second, due to the sheer volume of potential lenders who could potentially extend credit per loan request, it may be impractical to form relationships as per Petersen and Rajan (1995). Although there are no physical interactions between borrowers and lenders in this context, our results corroborate Diamond's (1989) findings regarding the importance of building a reputation with a prospective lender, implying that a presence of a track record and the building of a reputation matter in reducing information asymmetries and adverse selection issues in the P2P lending market (see Sharpe 1990; Boot and Thakor 1994; Petersen and Rajan 1995; Berger and Udell 1995; Cole 1998).

Our results also demonstrate that firm-level characteristics have little impact on loan supply. We observe from model (1) of Table 4 that our variable 'Existing_Firm' is not significant. Hence, we do not find support for H5a. This result is counter to what is typically seen in banking literature (see Cole 1998; Coleman 2000), where the age of the firm is an important determinant of access to finance. This is largely due to the fact that older firms are thought to have longer track records; hence, they are likely to reduce information issues (Dunne et al. 1989; Good and Graves 1993; Honjo 2000). This result may occur because due diligence of business viability is hard to do online and hence may force lenders to rely on personal characteristics instead. Also, most lenders are not finance professionals and hence may not have the skills or inclination to do due diligence on business viability, whereas assessment of a person's credit worthiness is something that most people will have some experience of in life. Another possible explanation for this observation is that lenders may be extending credit based on personal idiosyncrasies—for example, they may be extending credit based on philanthropy (Agrawal et al. 2011; Belleflamme et al. 2014; Bruton et al. 2015; Mollick 2013; Mollick 2014; Schwienbacher and Larralde 2012) simply because they like the cause of the entrepreneur, regardless of firm age.

Interestingly, our results show support for Stiglitz and Weiss (1981) assertion that reducing information gaps in the form of conducting due diligence improves access to loans. We observe from model (1) of Table 4 that information asymmetries in the context of P2P lending may also be solved by the crowds. For example, unlike traditional lending where lenders screen loan applications in isolation to one another, in P2P lending, hundreds of potential lenders assess and screen the credit requests from small business venture at any given time. Our results show that crowds somehow help to reduce information asymmetries (H3); the variable 'Bid_count' is positive and significant at the 0.01 level, which suggests that prospective lenders perceive loan requests attracting a large number of potential lenders to have conducted a great deal of due diligence.

Interestingly, we also find that the amount (quantity) of narrative that borrowers provide does not influence funding success (H6a, first part); our information variable 'Elaboration' is not significant. Our results show that lenders respond positively to images in the form of pictures included in the loan request such that small business borrowers who include them are more likely to be extended credit (H6a, second part); our variable 'Include_picture' is positive and significant at the 0.01 level, suggesting perhaps that inclusion of a picture somehow verifies some information and humanises the process of lending on P2P websites. Therefore, our results seem to suggest that in the absence of human interactions, potential borrowers that include pictures could be giving prospective lenders information about the business context, or the product or even about the prospective borrowers which may be used by lenders to reduce information asymmetries.

If borrowers had late payments in previous loans, this negatively affects the probability of getting funding (variable delinquencies is significantly negative in model (1)). This finding supports H7a. On the other hand, previous bankruptcies (judgments) are not significantly related to credit allocation. This part of H7a is thus not supported.

Looking at the control variables, we observe a U-shaped relationship between loan amount requested and probability of funding—suggesting that borrowers seeking smaller loans on the one extreme and those seeking large loans on the other extreme are more likely to be funded. Our results also report that once borrower risk is accounted for—borrowers that offer higher interest rate are more likely to be extended credit, supporting results put forward by Hanley and Girma (2006). Finally, we find that similar to banks, prospective borrowers who indicate that they have some form of income and those who are in full-time employment are more likely to be extended credit (all these factors are significant at the 0.05 level or below).

In order to determine the economic importance of all statistically significant factors, we conducted average marginal effects. Table 5 reports the estimated average marginal effects of the explanatory variables after a probit model. We see in column 1 of Table 5 that the borrower quality dummy 'Credit_grade' is the single most important variable in the credit approval decision. We estimate that in comparison to a small business

Table 5 Marginal effects after Probit regressions

	All firms	Existing firms only	New firms only
Owner attributes			
Home_owner	0.014	0.009	0.025
	(0.005)***	(0.006)	(0.009)***
Credit_grade (ref AA)			
A	− 0.043	− 0.022	− 0.036
	(0.016)***	(0.011)**	(0.018)**
B	− 0.063	− 0.036	− 0.042
	(0.017)***	(0.011)***	(0.018)**
C	− 0.099	− 0.076	− 0.035
	(0.018)***	(0.013)***	(0.019)*
D	− 0.131	− 0.096	− 0.075
	(0.019)***	(0.014)***	(0.022)***
E	− 0.173	− 0.151	− 0.107
	(0.020)***	(0.017)***	(0.024)***
HR	− 0.201	− 0.199	− 0.160
	(0.019)***	(0.018)***	(0.026)***
Delinquencies	− 0.018	− 0.013	− 0.022
	(0.005)***	(0.007)**	(0.009)**
Income_range ($0 or undefined)			
$1–$24,999	0.020	0.010	0.060
	(0.011)*	(0.014)*	(0.024)**
$25k–$49,999	0.029	0.022	0.065
	(0.009)***	(0.012)*	(0.023)***
$50k–$74,999	0.034	0.028	0.068
	(0.010)***	(0.012)**	(0.024)***
$75k–$99,999	0.024	0.010	0.081
	(0.011)**	(0.013)*	(0.026)***
$100,000+	0.011	0.001	0.057
	(0.010)*	(0.013)*	(0.027)**
Employment_status (full time)			
Part time	− 0.040	− 0.052	− 0.040
	(0.014)***	(0.026)**	(0.027)**
Self-employed	− 0.010	− 0.015	− 0.012
	(0.023)	(0.019)*	(0.012)*
Information attributes			
Include_picture	0.024	0.019	0.037
	(0.005)***	(0.007)***	(0.010)***
Elaboration		0.014	− 0.030
		(0.023)	(0.037)
Bid_count	0.001	0.001	0.001
	(0.000)***	(0.000)***	(0.000)***
Loan attributes			
Requested amount ($1000)	− 0.025	− 0.024	− 0.029
	(0.002)***	(0.002)***	(0.003)***
Offer_interest_rate	0.001	0.002	0.001
	(0.000)***	(0.000)***	(0.001)
N	10,281	7249	2983

Standard errors are given in parentheses. Significant coefficients are indicated with *, ** and *** which stand for 0.10, 0.05 and 0.01 significance levels, respectively. This table presents the marginal effects after Probit models based on all variables set at their means. The marginal effects for categorical variables show how Pr (Approval = 1) is predicted to change as a particular factor variable changes from 0 to 1, holding all other independent variables at zero. The marginal effect of a continuous variable measures the instantaneous rate of change, which may or may not be close to the effect on Pr (Approval = 1) of a one unit increase in the independent variable

owner with credit grade in category AA, borrowers in category A are 4 percentage points less likely to get funded. Compared to the average probability of funding (11%), this translates to approximately 40% reduction in the likelihood of the loan application being approved. As the credit grades deteriorate, the impact becomes even more drastic.

For instance, borrowers in category C and those in category HR are 10 percentage points and 20 percentage points less likely to get funded which translate to 90 and 180% reduction in funding success, respectively. Similarly, in terms of borrower quality, home ownership is also important, albeit at a lesser impact relative to credit rating. Loan applications from borrowers who are homeowners are 1.4 percentage points more likely to be funded; this translates to approximately 13% increase in the likelihood of the loan application being approved relative to the average probability of funding.

Borrowers with previous *Delinquencies* are 1.8 percentage points (16%) less likely to have their applications approved. In terms of the information variables—'Include_picture' and 'Bid_count'—the impact of pictures is evident in the fact that compared to borrowers who opt not to include pictures in their loan application, we estimate that borrowers who do are 2.4 percentage points more likely to receive funding. Compared to the average probability of funding (11%), this represents a 23% increase in the likelihood of receiving funding. It is somewhat surprising that we find evidence that pictures seem to attenuate information asymmetries between lenders and borrowers, because pictures are optional and not verified by Prosper.com. A natural expectation therefore would be that lenders in this market would respond little to this type of ‘cheap talk’ given the fact that these pictures are optional. Yet, the fact that borrowers include a wide variety of (non-standardised) pictures and the market responds to them suggest that the information on the contrary is not treated as cheap talk by lenders in this market. Perhaps the pictures do indeed serve as some element of humanising the lending process. Interestingly, we also find strong support for the number of lenders and collective due diligence argument. For every one additional lender extending credit to a loan request, this increases the funding success of the loan by 0.6%; for every 10 persons, the funding increases by 6%, and for every 100 people, the likelihood of funding success increases by 60%.

Finally, being employed (as opposed to self-employed or part-time employed) increases the probability of funding which indicates that setting up or even running a business while holding down a full time job is a good approach to using career status to secure online P2P crowd loans which means that lean, part-time and hobby style ventures are going to find it easier to raise finance in this online financial market. Higher income is also associated with greater ease of securing funding but only in a concave inverse U-shaped manner. Once income exceeds $75,000, the marginal effect either declines which would be consistent with lenders using this as an indicator of spendthrift borrowers, i.e. one might expect that high-income borrowers, all things being equal, would be in a better position to save and not need to borrow. So those that do seek loans may be perceived as being disproportionately accounted for by people who are not good at managing their own finances and hence higher risk.

4.2 Factors driving interest rates on loans

In this sub-section, we examine the factors driving the interest rates actually paid. Table 6 reports the results of Tobit regressions explaining interest rates. Table 2 showed that average interest rates lie around 20% so that online P2P lending is a very expensive form of debt finance.

In terms of the drivers of these rates, we find that credit grades are the single most important determinant. We find that small business borrowers in higher risk credit categories will pay higher interest rates than those

Table 6 Factors driving cost of credit on Prosper

	(1)
Constant	4.756
	(1.197)
Owner attributes	
Home_owner	0.077
	(0.392)
Credit_grade (AA)	
A	0.750**
	(2.533)
B	1.730***
	(5.012)
C	3.131***
	(7.861)
D	3.915***
	(8.485)
E	6.118***
	(10.756)
HR	6.309***
	(10.142)
Delinquencies	0.131
	(0.604)
Judgements	0.375
	(1.586)
Employment_status (full time)	
Part time	− 0.611
	(− 0.792)
Other	− 0.112
	(− 0.185)
Self-employed	0.364
	(1.605)
Income_range ($0–unable to verify)	
$1–$24,999	− 0.654
	(− 1.293)
$25,000–$49,999	− 1.197***
	(− 2.748)
$50,000–$74,999	− 1.184***
	(− 2.673)
$75,000–$99,999	− 1.378***
	(− 2.905)
$100,000 plus	− 1.483***
	(− 3.129)
Firm attributes	
Existing firm	− 0.064
	(− 0.326)
Information attributes	

Table 6 (continued)

	(1)
Repeat loan	− 0.404**
	(− 2.117)
Include_picture	− 0.456**
	(− 2.105)
Elaboration	0.194
	(0.316)
Loan attributes	
Requested amount ($1000)	0.021
	(0.404)
SQ requested amount	0.003
	(1.267)
Offer interest rate (%)	0.539***
	(9.524)
Time fixed effects	Yes
Industry fixed effects	Yes
Regional effects	Yes
Number of observations	1390
Pseudo R^2	0.291
Log likelihood	− 3546

T values are given in parentheses. Significant coefficients are indicated with *, ** and *** which stand for 0.10, 0.05 and 0.01 significance levels, respectively. This table reports the Tobit estimates for factors driving cost of credit on Prosper.com. The dependent variable is the interest rate (less prime rate)

in premium credit grade categories (AA). This suggests that 'good types' defined in terms of credit rating get their loans at a lower interest rate (H2b).

In contrast to the credit allocation decision, homeownership is not significant in Table 6. Hypothesis 1b is thus not supported. Similarly, variables delinquencies and judgements are not significant (H7b not supported).

In terms of firm attributes, we observe from model (1) of Table 6 that the coefficient on our variable of interest Existing_firm is not significant (H5b). Thus, we do not find evidence that lenders on Prosper.com incorporate firm-level characteristics when pricing loans. In fact, our result seems to suggest that the pricing of loans in this context may possibly be relatively idiosyncratic—the interest rate on the funded loans may depend more on personal reputation of the small business owner than on the observed characteristics of the firm. This finding seems counter to the results found in small finance literature based on traditional forms of lending (see Keasey and Watson 2000; Cressy and Toivanen 2001; Cowling 1999) where firm age is one of the key determinants of pricing credit.

Interestingly, in terms of the information variables, the significant negative coefficient of the variable Repeat_loan suggests that building a relationship in this context translates to cheaper credit as suggested by the model of Petersen and Rajan (1994). Hence, we find support for H4b. A number of theoretical papers predict that the relative cost of finance in the second borrowing period will be cheaper such that banks reward survivors (Diamond 1989; Besanko and Thakor 1987). In P2P lending, we find a similar phenomenon.

The negative and statistically significant coefficient on the Include_picture variable suggests that by reducing the information gap by including a picture in the loan requests, small business borrowers will pay almost a half a percentage point interest less than those who do not include a picture (H6b). This result appears to suggest that lenders value pictures as a mechanism of reducing information asymmetries—even though these pictures are not verified by Prosper.com. We do not find a similar effect for text elaboration though.

In Table 7, we compile predicted probabilities for factors driving interest rate at representative values. The baseline case is an individual with Prime credit grade A, income range $25k–$49,999, with previous delinquencies and judgements, who rents their home, running an existing business, who opts not to include a picture but gives a text elaboration—this borrower has an 11% likelihood of funding success and is likely to pay approximately 13.7% interest rate. Compared to the baseline case, a borrower with a premium credit grade AA, full time employed income range $50k–$74,999, no past due loans, who is a homeowner, who includes a picture has a 20% chance of getting a loan request funded at a cost of almost 12.5% interest rate; this translates to a probability of funding that is twice as likely than the base case, with an interest rate that is only 1.2 percentage point less. This renders the credit grade as an influential determinant of the price. Whilst, compared to the baseline case, a high-risk borrower with a HR credit grade, full time employed, income range $75k–$99,999 with delinquencies and who rents their home, has a 1% chance of being funded and can expect to pay as high as 30% interest rate. Being delinquent in the past on loan obligations only reduce the probability

Table 7 Predicted margins at represented values

Actual cases		Interest rate
Full-time employed, Prime credit grade AA, income range $50k–$74,999, no past due loans and no judgments, homeowner, existing firm, image, elaborate	0.20	12.5%
Full-time employed, Prime credit grade AA, income range $50k–$74,999, no past due loans and no judgments, rent home, existing firm, no image, elaboration	0.15	13.0%
Self-employed, Prime credit grade AA, income range $25k–$49,999, no past due loans and no judgments, rent, new firm, no image, elaboration	0.12	13.3%
Full-time employed, Prime credit grade A, income range $25k–$49,999, no past due loans and no judgments, homeowner, existing firm, image, elaboration	0.16	13.5%
Full-time employed, Prime credit grade A, income range $25k–$49,999, past due loans and judgments, rent home, existing firm, no image, elaboration	0.11	13.7%
Self-employed, Prime credit grade A, income range $50k–$74,999, past due loans and judgments, rent home, existing firm, no image, elaboration	0.10	13.7%
Full-time employed, Prime credit grade B, income range $50k–$74,999, past due loans and judgments, rent home, existing firm, no image, elaboration	0.09	14.5%
Self-employed, credit grade C, income range $25k–$49,999, past due loans and judgments, home owner, existing firm, image, elaboration	0.07	15.6%
Full-time employed average credit grade D, income range $25k–$49,999, no delinquencies, no judgement, rent, existing firm, image, elaboration	0.06	16.5%
Self-employed credit grade D, income range $25k–$49,999, no delinquencies, no judgement, rent, existing firm, image, elaboration	0.06	16.9%
Full-time employed credit grade E, income range $25k–$49,999, delinquencies, no judgement, homeowner, existing firm, image, elaboration	0.06	19.7%
Self-employed, credit grade E, income range $25k–$49,999, delinquencies, judgement, rent, existing firm, image, elaboration	0.05	20.1%
Full-time employed, high risk credit grade HR, income range $75k–$99,999, past due loans and judgments, homeowner, new firm, image, elaboration	0.03	22.9%
Self-employed, high risk credit grade HR, income range $75k–$99,999, past due loans and judgments, rent home, new firm, no image, elaboration	0.02	27.3%
Self-employed, high risk credit grade HR, income range $1–$24,999, past due loans and judgments, rent home, new firm, no image, no elaboration	0.01	30.1%

Requested loan amount set at the mean $10,430. In this table, we present predicted probabilities of interest rate at represented values conducted after two-stage Heckman regressions, with actual cases extracted from the population of loan requests

of funding by 0.56 percentage points which seems to support our argument that lenders in this market are forgiving.

4.3 Summary of results

We have found that, while some owner attributes are important determinants of credit allocation and the interest paid on P2P business loans, others are not. In particular, a favourable credit profile considerably increases the probability of funding while it decreases the interest rate paid (H2a and H2b supported). Homeownership also increases the probability of funding, but it does not affect the interest rate (H1a supported; H1b rejected). Finally, delinquencies decrease the probability of funding, but judgments do not (H7a partly supported), whereas for funded loans, both variables are not significantly related to the interest rate paid (H7b rejected).

Regarding firm attributes, we neither find a significant relation of existing firms with the probability of getting funded nor with the interest rate paid (H5a and H5b rejected).

Regarding information attributes, the number of bids placed on a listing increases the probability of funding (H3 supported). Furthermore, repeat borrowers who successfully paid off their previous loan have a higher probability of getting funded and their interest rate is also lower (H4a and 4b supported). Finally, whereas the provision of a picture in the loan request is positively associated with credit allocation and negatively with the interest rate paid, this does not hold for providing extensive text descriptions about the business (H6a and 6b partly supported). All in all, information attributes seem to be quite important in determining loan application success.

5 Discussion

Regarding crowdfunding literature, lending-based crowdfunding as studied in the present paper is distinct from the other three forms of crowdfunding identified in the literature, i.e. reward-based, donation-based and equity-based crowdfunding (Mollick 2014). Potential investors in reward-based and donation-based crowdfunding base their decision to invest in characteristics of the product they fund (reward-based) or the cause of the campaign (donation-based), while in equity-based funding, investors are interested in obtaining ownership share of a promising company (Short et al. 2017; Kaartemo 2017).

In P2P lending, incentives of investors are purely financial though as they seek to fund a loan against the highest interest rate at the lowest risk. As such, this form of crowdfunding comes closest to small business lending in a traditional sense. Indeed, our research shows that P2P lending depicts a new online small business unsecured loan market. Although collateral is not required, we find that the supply of loans tends to flow to the least risky entrepreneurs, those who are homeowners (i.e. with a track record of repaying mortgage payments) with high credit ratings. In our findings, we also demonstrate that firm-level characteristics have little impact on loan supply while reducing information asymmetries through volunteering information (importantly though, pictures rather than text) improves access to loans. Our results have key implications for small business finance theory. To recap, the vast research trajectory emanating from the seminal work of Stiglitz and Weiss (1981) identifies three key features relating to small firm loan finance and the impact of asymmetric information which include the key roles of collateral, refraining from using high interest rates to avoid moral hazard and adverse selection issues, due diligence, and the inferred direct physical contact in borrower-lender interactions. From our results, we find that the relative importance of these influences change. First, the general insight we get from the study is that borrower reputation, stipulated by credit grades, is the single most important determinant of credit allocation. The significance of using the credit grade helps to reduce the problem of adverse selection. The cost of defaulting will result in poorer scores—which are quantifiable to a 24% reduction of probability of funding. Moreover, reputations which were previously limited to person networks and regions in traditional offline lending markets are now less bounded and can go viral online very quickly so that the reputational cost of default is much greater in the online environment. Since those with higher credit grades have most to lose in this environment, it is, therefore, probably not too surprising that credit grade is the single most important determinant of the access to and cost of funding.

Second, we see from the results that collateral, which was such an important determinant in reducing adverse selection issues in Stiglitz-Weiss's (Stiglitz and Weiss 1981) research trajectory, in the P2P lending, it is less important, particularly for determining the interest rate paid. Thirdly, closely associated with the second point is that in the absence of being able to use collateral to keep interests low and just ration credit to low-risk borrowers, the online crowd funding unsecured lenders appear to take on high-risk small-firm borrowers by seeking compensation through high interest charges—commensurate with rates of return those sought by high-risk investors such as venture capitalists.

Third, the general insight we get from the study is that due diligence, although still an important factor, in the P2P lending context is conducted by the crowd. This new feature, unique to P2P lending, introduces the importance of collective intelligence as a means of reducing information asymmetry and associated adverse selection issues. Furthermore, our results shift focus from physical interactions between individual borrowers and lenders inferred in Stiglitz-Weiss's theory and to a multiple lender to individual borrower relationship over the internet. Effectively rendering physical contact, which was previously seen an important aspect of reducing information asymmetry and adverse selection issues in theory, relatively less important.

6 Conclusion

The advent of online peer-to-peer crowdfunding presents a new type and source of finance for small firms. It involves new types of lenders, financial intermediary and methodology in terms of applying for small firm finance. This raises the question of whether this innovation makes any difference to the type of business that can secure funding and the amount that they pay for this finance. In this paper, we examine the American online peer-to-peer loan crowdfunding website www.prosper.com to answer these questions. We create and analyse a dataset of 14,537 small firm unsecured loan applications. We find that a self-employed, low credit grade, renter with relatively low income will be less likely to secure funding and pay an interest rate of 30% per annum for a business loan, whereas an employed, high credit grade homeowner will secure a loan much more easily and typically pay 12.5%. Worryingly, we find that lenders in this online market ignore business characteristics as it is usually the opportunity in the business that allows entrepreneurs to escape the constraints of their own personal financial circumstances and raise external money, whereas this online market ties them to their own personal circumstances. So unsecured online P2P loan funding is high cost debt with rates of interest commensurate with returns sought by venture capitalists. The need to be employed implies that its use for start-up ventures will be constrained to those suitable for pilot/lean launches which can be trialled while the entrepreneur is still holding down a job. Start-ups requiring an entrepreneur to be fully engaged in the venture (i.e. not in full time employment) will find it difficult to secure finance unless they are launched by a team where one of the entrepreneurs stays in employment in order to raise funding. Therefore, this new form of finance may suit higher risk ventures that want loan instead of equity finance. However, the type of entrepreneur who can get this finance at a relatively low cost is the same type that would be able to do so in the offline traditional loan market. In this sense, it is a case of new technology but same old story. In contrast, we find that a lack of importance is attached to the business characteristics. We also find features such as providing a picture increasing the probability of funding and reducing the cost of finance. Importantly though, the provision of a text description of the business, arguably the feature of a P2P loan application that comes closest to a business plan in the traditional offline market, is not related to funding success. Together, these results imply that entrepreneurs who want to raise finance in this market will need to use a very different pitch than the norm in the offline market—a business plan appears redundant in this market as personal characteristics of entrepreneurs are the main determinants of securing funding and the price paid for it. So more effort in terms of building up one's own credit rating rather than writing a business plan seem more worthwhile in this market for small firm finance.

A limitation of our paper is that the study is only based on evidence from the USA. Future research should focus on other parts of the world as well. Moreover, firm characteristics are hard to obtain from P2P lending websites as these are mainly designed for general loan purposes, not specifically for small businesses. At the same time, the fact that we have been able to collect and use firm characteristics at all—most notably whether the loan request was done for a new or existing firm—is a significant step forward in P2P lending literature for small business loans.

References

Agrawal, A., Catalini, C., & Goldfarb, A. (2011). *The geography of crowdfunding*, NBER Working Paper No. 16820, Cambridge, MA: National Bureau of Economic Research.

Antoniades, A. (2016). Liquidity risk and the credit crunch of 2007–2008: evidence from micro-level data on mortgage loan applications. *Journal of Financial and Quantitative Analysis, 51*(6), 1795–1822.

Avery, R., Bostic, R., & Samolyk, K. (1998). The role of personal wealth in small business financing. *Journal of Banking and Finance, 22*, 1019–1061.

Bates, T. (1991). Commercial bank financing of white and black owned small business start-ups. *Quarterly Review of Economics and Business, 31*(1), 64–80.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: tapping the right crowd. *Journal of Business Venturing, 29*(5), 585–609.

Berger, A. N., & Frame, W. S. (2007). Small business credit scoring and credit availability. *Journal of Small Business Management, 45*(1), 5–22.

Berger, A., & Udell, G. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business, 68*, 351–381.

Berger, A., Cowan, A., & Frame, S. (2011). The surprising use of credit scoring in small business lending by community banks and the attendant effects of credit availability, risk and profitability. *Journal of Financial Services Research, 39*, 1–17.

Besanko, D., & Thakor, A. (1987). Collateral and rationing: sorting equilibria in monopolistic and competitive credit markets. *International Economic Review, 28*(3), 671–689.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *The American Economic Review, 75*(4), 850–855.

Bester, H. (1987). The role of collateral in credit markets with imperfect information. *The European Economic Review, 31*, 887–899.

Bhide, A. V. (2000). *The origin and evolution of new businesses*. New York: Oxford University Press.

Binks, M., & Ennew, C. (1998). Private Businesses and their Banks, Forum of Private Business Bank Survey, 1998, University of Nottingham Business School.

Block, J., Hornuf, L., & Moritz, A. (2017). Which updates during an equity crowdfunding campaign increase crowd participation?. *Small Business Economics*. First Online: 24 May 2017.

Boot, A., & Thakor, A. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review, 35*(11), 899–920.

Bruton, G., Khavul, S., Siegel, D., & Wright, M. (2015). New financial alternatives in seeding entrepreneurship:

microfinance, crowdfunding and peer-to-peer innovations. *Entrepreneurship Theory and Practice, 39*(1), 9–26.

Burke, A., & Hanley, A. (2003). How do firms pick safer ventures? A theory relating the importance of risk aversion and collateral to interest rates and credit rationing. *Journal of Entrepreneurial Finance and Business Ventures, 8*(2), 13–24.

Burke, A., & Hanley, A. (2006). Bank interest margins and business start-up collateral: testing for convexity. *Scottish Journal of Political Economy, 53*(3), 319–334.

Burke, A., Fraser, S., & Greene, F. J. (2010). The multiple effects of business planning on new venture performance. *Journal of Management Studies, 47*(3), 391–415.

Chan, Y. S., & Thakor, A. V. (1987). Collateral and competitive equilibria with moral hazard and private information. *The Journal of Finance, 42*(2), 345–363.

Cole, R. (1998). The importance of relationships to the availability of credit. *Journal of Banking and Finance, 22*, 959–997.

Coleman, S. (2000). Access to capital and terms of credit: a comparison of men and women owned small businesses. *Journal of Small Business Management, 20*(3), 37–52.

Cowling, M. (1999). The determination of bank-small business loan premia in the UK. *Applied Economics Letters, 65*, 251–253.

Cowling, M., Matthews, C., & Liu, W. (2017). The role of loan commitment terms in credit allocation on the UK small firms loan guarantee scheme. *International Review of Entrepreneurship, 15*(1), 15–28.

Cressy, R. (1996). Commitment lending under asymmetric information: theory and tests on UK start-up data. *Small Business Economics, 8*(5), 397–408.

Cressy, R., & Toivanen, O. (2001). Is there adverse selection in the credit market? *Venture Capital, 3*(3), 215–238.

Diamond, D. (1989). Reputation acquisition in debt markets. *Journal of Political Economy, 97*(4), 828–862.

Dunne, T., Roberts, M. J., & Samuelson, L. (1989). The growth and failure of US manufacturing plants. *The Quarterly Journal of Economics, 104*(4), 671–698.

Good, W., & Graves, R. (1993). Small business support programs: the views of failed versus surviving firms. *Journal of Small Business and Entrepreneurship, 10*, 66–76.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology, 78*(6), 1360–1380.

Han, L., & Greene, F. (2007). The determinants of online loan applications for small businesses. *Journal of Small Business and Enterprise Development, 14*(3), 478–486.

Hanley, A., & Girma, S. (2006). New ventures and their credit terms. *Small Business Economics, 26*, 351–364.

Harhoff, D., & Körting, T. (1998). Lending relationships in Germany: empirical results from survey data. *Journal of Banking and Finance, 22*, 1317–1354.

Hartley, S (2010), Kiva.org: Crowd–sourced microfinance and cooperation in group lending, SSRN Working Paper, Social Science Research Network, available as papers.ssrn.com/sol3/papers.cfm?abstract_id=1572182.

Honjo, Y. (2000). Business failure of new firms: an empirical analysis using multiplicative hazard model. *Journal of Industrial Economics, 18*, 557–574.

Jimenez, G., Salas, V., & Saurina, J. (2006). Determinants of collateral. *Journal of Financial Economics, 81*(2), 255–281.

Kaartemo, V. (2017). The elements of a successful crowdfunding campaign: a systematic literature review of crowdfunding performance. *International Review of Entrepreneurship, 15*(3), 291–318.

Keasey, K., & Watson, R. (2000). Interest rate premia on UK small firm bank borrowing: a research note. *Journal of Business Finance & Accounting, 27*, 247–259.

Klafft, M. (2008). "Online peer-to-peer lending: a lenders' perspective" (July 14, 2008). In H. R. Arabnia & A. Bahrami (Eds.), *Proceedings of the International Conference on E-Learning, E-Business, Enterprise Information Systems, & E-Government, EEE 2008* (pp. 371–375), Las Vegas: CSREA Press. Available at SSRN: http://ssrn.com/abstract=1352352

Lin, M., & Viswanathan, S. (2016). Home bias in online investments: an empirical study of an online crowdfunding market. *Management Science, 62*(5), 1393–1414.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending. *Management Science, 59*(1), 17–35.

Mach, T, Carter, C., & Slattery, C (2014). Peer-to-peer lending to small businesses finance, Economics Discussion Series, Divisions of Research & Statistics and Monetary Affairs Federal Reserve Board, Washington, DC, Working Paper No. 2014–10. Available at SSRN: http://ssrn.com/abstract=2390886 or https://doi.org/10.2139/ssrn.2390886

Machauer, A., & Weber, M. (1998). Bank behavior based on internal credit ratings of borrowers. *Journal of Banking & Finance, 22*(10), 1355–1383.

Macht, S. A., & Weatherston, J. (2014). The benefits of online crowdfunding for fund-seeking business ventures. *Strategic Change, 23*(1–2), 1–14.

Mollick, R. (2013). Swept away by the crowd? Crowdfunding, venture capital, and the selection of entrepreneurs, SSRN working paper, available at SSRN: http://ssrn.com/abstract=2239204 or https://doi.org/10.2139/ssrn.2239204

Mollick, E. (2014). The dynamics of crowdfunding: an exploratory study. *Journal of Business Venturing, 29*, 1–16.

Moritz, A., & Block, J. H. (2016). Crowdfunding: a literature review and research directions. In D. Brüntje & O. Gajda (Eds.), *Crowdfunding in Europe* (pp. 25–53). New York: Springer.

Parker, S. C. (2009). *The economics of entrepreneurship*. Cambridge: Cambridge University Press.

Petersen, M., & Rajan, R. (1994). The benefits of lending relationships: evidence from small business data. *Journal of Finance, 49*, 3–37.

Petersen, M., & Rajan, A. (1995). The effect of credit market competition on lending relationships. *Quarterly Journal of Economics, 110*(2), 407–443.

Piva, E., & Rossi-Lamastra, C. (2017). Human capital signals and entrepreneurs' success in equity crowdfunding. *Small Business Economics*, forthcoming. First Online: 20 November 2017.

Schwienbacher, A., & Larralde, B. (2012). Crowdfunding of entrepreneurial ventures. In D. Cumming (Ed.), *The Oxford Handbook of Entrepreneurial Finance*. Oxford: Oxford University Press.

Sharpe, S. (1990). Asymmetric information, bank lending and implicit contracts: a stylised model of customer relationships. *Journal of Finance, 45*, 1069–1087.

Short, J. C., Ketchen, D. J., McKenny, A. F., Allison, T. H., & Ireland, R. D. (2017). Research on crowdfunding: reviewing the (very recent) past and celebrating the present. *Entrepreneurship Theory and Practice, 41*(2), 149–160.

Simmons, S. A., Wiklund, J., & Levie, J. (2014). Stigma and business failure: implications for entrepreneurs' career choices. *Small Business Economics, 42*(3), 485–505.

Stiglitz, J., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review, 71*, 393–410.

Storey, D. J. (1994). *Understanding the small business sector.* London: Routledge.

Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly, 44*(2), 315–349.

Ucbasaran, D., Shepherd, D. A., Lockett, A., & Lyon, S. J. (2013). Life after business failure: the process and consequences of business failure for entrepreneurs. *Journal of Management, 39*(1), 163–202.

Van der Zwan, P. (2016). Bank loan application success of innovative and non-innovative SMEs. *International Review of Entrepreneurship, 14*(4), 483–502.

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics, 46*(4), 579–590.

Zhang, J., & Liu, P. (2012). Rational herding in microloan markets. *Management Science, 58*(5), 892–912.