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Credit rationing in P2P lending to SMEs: Do lender-borrower relationships matter?

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A B S T R A C T

This paper studies the role of individual P2P investors that are acquainted with the borrower in mitigating credit rationing in P2P lending to SMEs. I use proprietary data provided by one of the biggest Dutch P2P lending platforms, on which personal acquaintances of the borrower are able to invest before other P2P investors do. I find that P2P investors invest more in loans of borrowers to whom they are personally acquainted. More initial investment by investors acquainted with the borrower is subsequently associated with a higher likelihood of obtaining a second loan from the P2P lender, larger investments by other P2P investors and lower ex post defaults. These results are consistent with informal lenders having superior information or monitoring skills and rational herding following informal investors' investment decisions.

1. Introduction

Recent years have witnessed increased popularity of crowdfunding as alternative to more traditional forms of financing. Especially peer-to-peer (P2P) lending has become increasingly popular, both in terms of consumer loans and business finance. Advances in information technology and a heavier post-crisis regulatory burden on banks, have allowed P2P lending platforms to gain a foothold in SME credit markets (De Roure et al., 2018). P2P platforms that are active in the SME credit market act as intermediaries between individual lenders and firms and they typically provide credit screening services combined with a system of posted interest rates (Wei and Lin, 2017; Franks et al., 2020). Firms use P2P platforms to obtain funding, partly from their social network and partly from the general public. Therefore they rely both on the credit risk screening reputation of the platform as well as their informal network of relationships.

Strong lender-borrower relationships are an important tool to reduce credit rationing of small and opaque firms (Cenni et al., 2015; Kirschenmann, 2016), because they generate valuable, tacit information that is not generated through transaction-oriented lending (e.g. Petersen and Rajan, 1994; Berger and Udell, 1995; Boot, 2000; Berger and Udell, 2002). Theories of informal finance predict that informal lenders help reduce adverse selection and moral hazard, because they have superior information and lower monitoring costs (Stiglitz, 1990; Ghatak, 1999; Giné, 2011) and they could use the threat of social sanctions to mitigate incentive problems (Besley et al., 1993; Besley and Coate, 1995; Karlan et al., 2009). However, informal finance lacks the scalability of formal finance (Degryse et al., 2016), which P2P lending platforms could provide (Allen et al., 2018). By formalizing credit terms and enforcement they allow informal lenders to finance their acquaintances at lesser social frictions (Lee and Persson, 2016). So P2P lending platforms combine aspects of formal lending procedures, with aspects of informal lending, thereby combining the information advantages of informal lending with the pooling and risk-sharing benefits of financial intermediation (Allen et al., 2019).

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This paper studies at the extensive margin whether the platform selects a (second) loan application to appear on the platform, and at the intensive margin what determines the size of P2P investments. Specifically, I analyze how P2P investments by investors from borrowers' social network affect the extensive and intensive margin. This is possible because the data allow for a distinction between P2P investors that are acquaintances of the loan applicant, who are allowed to invest first, and P2P investments made by the general public who can subsequently invest.

I use a proprietary dataset kindly provided by one of the largest crowdfunding platforms in the Netherlands for the period 2014–2017. In the Netherlands the crowdfunding market has grown most quickly in the area of P2P loans to small and medium-sized enterprises (SMEs). From the Dutch P2P lender I obtain investment level data of individual P2P loan contributions. I also obtain data on the project descriptions posted online from which I manually extract data on project characteristics like credit ratings, requested loan amount, maturity, interest rates, collateral and other contractual features.

My main findings are as follows. First, I find that the P2P lending platform is more likely to provide a second loan to firms that have financed a larger part of their first loan through acquainted P2P investors. Second, P2P investors that are acquainted with the borrower invest substantially more. Third, some investors on the platform appear to be diversified investors, whereas others are one-off investors, who are more likely to be acquaintances of the borrower and who invest on average the largest amounts. Fourth, when acquainted investors invest more, subsequently also investors unacquainted with the borrower invest more, which is an effect that appears to be driven by startup firms. Fifth, the extent to which a loan is financed by investors acquainted with the borrower is associated with significantly lower ex post defaults.

This paper makes two contributions to the P2P lending literature. First, this paper analyzes the role of informal P2P investors in a system with posted prices, whereas existing literature mostly investigates this in the context of an auction system.[1] For instance, in an auction system, Hildebrand et al. (2017) show that friends make successful funding more likely, Zhang and Liu (2012) show that friend endorsements weaken herding, Lin et al. (2013) show that friendships lower interest rates and ex post default rates and Iyer et al. (2015) show that auction interest rates better predict defaults than credit scores do. However, the potential role of informal investors in both systems is different. In an auction system the final outcome of the auction is an interest rate that reflects the market's assessment of credit quality. So superior, soft information provided by lender-borrower relationships is transmitted via interest rates visible to other investors active on the platform. In a system with posted prices, the platform implicitly signals that the interest rate it sets reflects borrower quality (Wei and Lin, 2017), which is often substantiated by a credit rating either provided by the platform or an external rating provider. To reduce information frictions, soft information can be transmitted to other investors by allowing better informed investors to invest first. So instead of interest rate adjustments, the amount friends invest could act as a signal to subsequent investors.[2]

Second, this paper contributes to the P2P lending literature that considers information provision in the context of optimal platform design. Vallee and Zeng (2019) show for a system with posted prices that sophisticated investors outperform by being able to better screen on the basis of hard information, potentially leading to adverse selection. By contrast, this paper analyzes how the provision of additional soft information by informal investors investing first could improve lending outcomes for other investors. Several large platforms have moved to a system with posted prices, despite the information dispersion benefits associated with an auction system. Franks et al. (2020) show that Funding Circle switched to posted prices because liquidity shocks drove prices away from information efficiency and Prosper's switch to posted prices resulted in higher defaults (Wei and Lin, 2017) and less experienced households disproportionately exiting the market (Liskovich and Shaton, 2017). Results in this paper suggest that having better informed investors invest first could alleviate some of the losses in informational efficiency when moving to a system with posted prices.

This paper also contributes to the literature on informal financing, most of which has focused on less developed countries (e.g. Ayyagari et al., 2010; Degryse et al., 2016; Allen et al., 2018), and studies informal-formal co-financing from multiple creditors. However, the distinction between formal and informal financing has become less clearcut (Allen et al., 2019), which makes it interesting to study both formal and informal finance as provided within the same platform. Despite the information and monitoring benefits of informal finance, Lee and Persson (2016) show in their theoretical model that informal finance could reduce risk taking to sub-optimal levels. Although Lee and Persson (2016) also show that the introduction of formal contracts to informal finance—an important benefit of P2P lending—helps promote risk-taking, this could be an alternative explanation for informal financing being associated with lower defaults.

This paper proceeds as follows. Section 2 discusses the relevant literature and develops hypotheses. Section 3 presents the data together with initial descriptive analyses. Section 4 provides regression results and Section 5 presents robustness checks. Finally, Section 6 concludes.

2. Literature and hypotheses

This literature review provides first a short overview of the credit rationing literature and a discussion of how credit rationing could

[1] Also note that these papers mostly study unsecured consumer lending, whereas this paper studies secured and unsecured business lending.

[2] For instance, the P2P platform *October* from France ensures that 51% of each project on the platform is financed by institutional investors with the remaining 49% open for financing by retail investors. P2P business lending platforms from the Netherlands typically allow the inner crowd to invest first. These Dutch platforms include *Collin Crowdfund*, *CrowdAboutNow*, *Geldvoorelkaar* and *Oneplanetcrowd*. Alternatively, platforms can differentiate pricing for different groups of investors, like informal and formal investors. For example, *MytripleA* from Spain allows friends and family to finance their part of the loan at a lower rate. Other platforms completely focus on relationship lending, like *Zirtue*, a US company that offers a relationship-based lending application that formalizes loans between friends, family and trusted relationships.

take place in the context of P2P lending. Next, I discuss the literature on informal finance to hypothesize why informal investors could mitigate credit rationing in the context of P2P lending.

2.1. Credit rationing

Information asymmetries are inherently part of credit markets and play a large role in theories of financial intermediation (Jaffee and Russell, 1976; Leland and Pyle, 1977; Stiglitz and Weiss, 1981). Through their screening and monitoring capabilities banks are well positioned to reduce these information asymmetries. Under relationship lending, banks acquire information over time by repeatedly interacting with the firm and its stakeholders, and thereby obtain information that could not have been obtained through a single interaction. Berger and Udell (2002) model relationship lending and its associated accumulation of soft information as solution to credit rationing due to asymmetric information. The relationship provides information that has value on top of hard information like credit scores and financial statements. As lenders posses more additional soft information, asymmetric information diminishes and they are less likely to credit ration a borrower (Boot, 2000).

Kirschenmann (2016) distinguishes two types of credit rationing: borrower rationing and loan size rationing. Under borrower rationing some borrowers are not provided with a loan at all, even though they might be creditworthy, but they are indistinguishable from borrowers who do receive a loan (Stiglitz and Weiss, 1981). Under loan size rationing at the current interest rate all borrowers receive a loan but demand a bigger loan than they finally receive (Jaffee and Russell, 1976). In the context of P2P lending both types of rationing can take place in two phases: first screening by the platform and second screening by the P2P investors. First, borrower rationing by the platform implies that a borrower is denied by the platform. In terms of loan size rationing, the size of the loan set by the platform determines the maximum loan, when loans are not allowed to be oversubscribed.[3] Second, when individual P2P investors engage in borrower rationing, they choose to refrain from financing a project, which does not preclude other P2P investors from financing it. When P2P investors ration the investment size, they invest a smaller amount such that it could take longer to finance a loan or a loan will not be financed at all.

Considering the evidence for credit rationing, Berger and Udell (1992) study equilibrium credit rationing and conclude that it is not a significant macroeconomic phenomenon. Banerjee and Duflo (2014) exploit variation in access to a targeted lending program and find evidence that small firms are severely credit constrained. Cenni et al. (2015) find that SMEs are most credit rationed but this reduces when their debt is more concentrated in one main bank. Kirschenmann (2016) uses loan applications and finds that small and opaque firms are more credit rationed, but this decreases over time with the length of the banking relationship. So credit rationing is mainly a problem for SMEs, for which asymmetric information problems are bigger, but can be reduced by stronger relationships between borrower and credit provider. Credit relationships could be stronger in relationship banking or because of informal ties between lender and borrower, which is a topic that is discussed next.

2.2. Informal finance and P2P investment rationing

In a classic sense, informal financing is defined as the financing that occurs without a formal financial intermediary, for instance through family and friends, interpersonal borrowing or trade credit. Here informal financing is defined as the financing obtained via social or business networks, but intermediated via a P2P-platform. Informal financing is typically used to support business operations and provides multiple benefits. First, it can reduce asymmetric information. For instance, goods suppliers may have superior information about their buyers, which gives them a comparative advantage in providing them trade credit (Petersen and Rajan, 1997). Second, informal lenders might be superior in monitoring and contract enforcement (Allen et al., 2018). Although P2P-platforms could also monitor borrowers, a network of connections that are used as social collateral to secure informal borrowing would strengthen this (Karlan et al., 2009). Third and related, informal financing creates a reciprocal insurance between informal lender and borrower that incentivizes the borrower to reduce risk taking (Lee and Persson, 2016). These benefits suggests that (i) platforms are more likely to select borrowers on their platform that have a larger group of acquaintances backing them, and (ii) P2P investors are willing to provide larger investments to borrowers they know than to borrowers with whom they have no acquaintance:

H1. **:***A platform is more likely to accept a loan application to appear on the platform when there is a larger group of potential P2P investors acquainted with the borrower.*

H2. **:***P2P investments are larger when P2P investors are acquainted with the borrower.*

Co-funding of formal and informal P2P investors can generate important complementarities in screening and enforcement. Madestam (2014) provides a formal model of the co-existence of formal and informal finance in which formal lenders have access to unlimited funds but are unable to control the use of credit, while informal lenders are better at preventing bad behavior but often lack funding. Enforcement of loans by informal lenders relies more on a loss of reputation (Karlan et al., 2009), whereas formal lending relies on formal legal institutions. Each type of lender may benefit from the existence of the other. Banks could decide to only provide a part of the loan, thereby pushing for the involvement of informal lenders who have better information to screen the borrower (Andersen and Malchow-Møller, 2006). Likewise, informal lenders may be willing to provide financing to an indivisible project when

[3] Platforms also determine the minimum loan amount, because when they use an "All-Or-Nothing" model (Cumming et al., 2019) loans that are not completely financed by P2P investors will not be financed at all.

they can obtain cheap additional financing from the formal sector (Degryse et al., 2016).

These arguments can also be applied to P2P lending in which the informal lenders are the investors acquainted with the borrower. The P2P literature shows that with an auction system P2P investors are able to outperform credit scores in default prediction (Iyer et al., 2015), and they can infer the creditworthiness of borrowers by observing lending decisions by other P2P investors (Zhang and Liu, 2012). In a system with posted prices, assuming acquainted investors have an information advantage, providing them the opportunity to invest first could serve to signal the quality of the project to investors unacquainted with the borrower. Acquainted investors could agree to invest first because a loan will only be distributed when the application is fully financed, which limits the risk associated with financing underfunded projects (Cumming et al., 2019). When unacquainted investors observe that borrowers' acquaintances finance a large part of the loan, this signal might capture part of the tacit information not included in credit ratings. That is, instead of being reflected in auction interest rates (Lin et al., 2013; Iyer et al., 2015), acquainted investors as a group signal the quality of a loan by financing a larger share. In addition, unacquainted investors could expect to benefit from the monitoring capabilities and reciprocal insurance created by acquainted lenders financing a larger share (Lee and Persson, 2016). Finally, more financing from acquainted investors could also proxy for social network strength, which might benefit firm performance (Gronum et al., 2012). Together these arguments support the following hypothesis:

H3. **:***When acquainted P2P investors finance a larger part of the loan, subsequent P2P investments by unacquainted P2P investors are larger.*

3. Data and method

This section first discusses the application process prospective borrowers go through when applying for a loan at the P2P lending platform. Next it provides a discussion of the data and descriptive analyses of characteristics of P2P investors and the distribution of P2P investments based on whether P2P investors are personally acquainted with the borrower. Finally, this section describes the regression methodologies and the variables used.

3.1. Application process

I use data from one of the largest P2P lenders from the Netherlands. The platform only provides loans and mainly serves small and medium-sized enterprises. The platform works with an extensive loan screening process. All applications are assigned an individual loan officer who helps the firm prepare the loan application. Subsequently, the loan application is screened by the platform and is assigned an internal credit rating by the platform itself and an external credit rating by an external rating agency. If the loan application is rejected by the platform, it will not appear online.

If the loan application is approved, the applicant is requested to prepare a pitch, which will eventually appear online if all goes well. The pitch contains a short summary, information about the entrepreneur, information about the firm, the financing needs and information on the terms and conditions of the loan contract. All the terms and conditions, e.g. interest rate, maturity and loan amount, are decided in advance and are the same for all P2P investors regardless of when they invest. Once the pitch has been approved by the platform, the pre-publication phase starts. During the pre-publication phase the application appears online in a closed environment that is only open to a select group of acquaintances of the borrower. The borrower can approach potential P2P investors by e-mailing their acquaintances a link to an investment environment not visible for all P2P investors.

During the pre-publication phase, acquaintances can invest in the project to make sure that the project is already partly financed when it is finally published. The platform explicitly encourages prospective borrowers to attract lenders during the pre-publication phase by stressing that this helps convince investors that do not know the borrower to invest in the post-publication phase. During the post-publication phase the project is open to all investors that have registered on the platform. It will remain open for 31 days. When the project has not been financed after 31 days, the platform decides whether this period will be extended. If after extension the project is not fully financed, the loan will not be extended. That is, the loan is only provided once the project is financed completely.

The platform has been very successful, because all loans that ended up being published online were also completely financed within 31 days. So conditional on selection by the platform, credit rationing by all P2P investors combined has not been a major issue so far. About 30% of loans are completely financed on the day they are published and another 30% is financed the next day. Usually the loan is already partly financed when it enters the post-publication phase: on average 14% is financed in the pre-publication phase when only the borrower's acquaintances are able to invest in it.[4] About 35% of the loans are in the pre-publication phase two days or less, with the median pre-publication phase lasting four days (compared to a median post-publication phase lasting one day).

Investors can either be professional investors (businesses) or private investors. About a quarter of investors in the sample consists of professional investors with three quarters being private investors. By law, private investors can invest in total a maximum of €80,000 via a single P2P lending platform. Professional investors have no restrictions on the total amount they are allowed to invest via a single P2P lending platform, but there are very few investors on the platform with a total exposure higher than €80,000.

[4] Note that adverse selection by potentially better informed, pre-publication investors is unlikely to be a major issue, because only ten loans have a pre-publication percentage higher than 50%, only two loans have a pre-publication percentage higher than 90% and there are no loans that are completely financed in the pre-publication stage.

3.2. Data

The dataset consists of three parts: credit applications, borrower data and transaction data. First, the dataset contains credit applications of SMEs for which I know which applications have been allowed to enter the platform and applications which have been denied and therefore do not appear online. For all credit applications the loan amount requested, the interest rate, the maturity of the loan, the internal credit rating and the external credit rating are known. For credit applications that are published online, I know when they are published online and I know the activation date of loans when they have been fully funded. For credit applications that are published, the borrower has prepared a pitch, which provides much more extensive information on top of the information from the applications, which I manually collect from the text of the pitch. Second, from anonymized lender data I obtain the lender ID and the date the lender registered on the platform. Third, the transaction data contains individual P2P investments, anonymized lender IDs, project IDs and a timestamp of each individual P2P investor's investment.[5]

The platform is fairly young. I kindly received data from their operations starting in May 2014 until January 2017. In total there are 1134 applications of which 1054 have complete information on internal and external credit score, interest rate, requested loan amount, maturity and a short description of the goal of the loan. I exclude 204 loan applications from the analysis because they are in progress so I have either no or incomplete transaction data for these loans. I am left with 850 applications of which 276 loans are eventually granted and 574 applications are either denied by the platform or withdrawn by the loan applicant and therefore never appear online.[6]

In selected analyses, I extend my sample to include a longer time period. First, I check whether the firms associated with the 850 applications ever apply for two loans. I perform this check for the sample period until January 2017 and for a subsequent period until the end of 2019. It turns out that 101 firms apply for two loans. Second, given average maturities of 4.5 years and the start of the platform in May 2014, I also collect default data of the 276 granted loans until the end of 2019 to obtain a more accurate picture of actual expected defaults.

Table 1 presents summary statistics for the regression analyses. All variables are defined below.[7] Panel A presents summary statistics for the platform selection analyses, specifically for platforms' selection decision conditional on firms previously having received a loan from the platform. The variable *Selection* shows that 90% of the firms whose first loan application was selected to appear on the platform also have their second loan application appear online. Panel B provides summary statistics for P2P investment analyses. Due to administrative cost, the platform does not allow P2P investments below €500 and investments can only be made in multiples of €500. The largest P2P investment is €22,500 and the average P2P investment is €1340. About 7% of the P2P investments are made in the pre-publication phase. A substantial part of the loan tends to be financed in the post-publication phase, because Panel C shows that on average about 14% of a loan is financed in the pre-publication phase. The difference between 7% and 14% is due to the fact that the average P2P investment in the pre-publication phase is about €2500, while in the post-publication phase it is about €1250.[8]

Panel C presents loan-level summary statistics for the default analyses. It shows that the loan amount ranges from €5000 to €1.5 million, with an average of about €200,000. With an average of 7.5%, posted interest rates are relatively high, which reflects the relatively high credit risks on SME loans that are mostly unsecured: on average only 7% is backed by physical collateral and defaults range from 4% to 15%, depending on the default definition. Outside collateral is relatively popular: 54% of loans have a personal guarantee and 30% of the loans have a third party guarantee. 34% of the loans feature agreements in which (some) existing loans are subordinated to the P2P loan and 32% of the loan contracts contain covenants. With about 4.5 years, average maturities are relatively short and about 34% of extended loans are to firms of less than one year old. Concerning incorporation, 37% of firms have personal liability, which includes sole proprietorship and partnerships. All other firms have limited liability and these are almost all corporations without listed shares, i.e. limited liability companies (LLC or "BV" in Dutch).[9]

3.3. Descriptive analyses

As a first assessment of the distribution of P2P investments and characteristics of P2P investors, Table 2 presents descriptive statistics. Panel A provides a simple distribution of P2P investments, starting at the minimum investment of €500 and moving upward in increments of €500. From and including €3000 and upwards, P2P investments are divided in buckets. In the total sample and the post-publication sample about 75% of the P2P investment is €500 or €1000. By contrast, in the pre-publication sample this is only about 60%. Especially from €2500 upwards there is significantly more mass in the right tail of the distribution for the pre-publication

[5] Note that in a small number of cases the same investor invests multiple times in the same project in the post-publication phase. These investments are added together. In one project the same investor invests both in the pre- and post-publication phase. These two investments are excluded from the sample.

[6] Note that 323 applications are denied and 251 are withdrawn, although the distinction between denied by the platform and withdrawn from the platform is not very clear in practice.

[7] Note that Appendix Table A.1 provides an overview of all variable definitions and Appendix Table A.2 provides separate summary statistics for pre-publication and post-publication samples.

[8] See also Appendix Table A.2.

[9] Note that there are a small number of firms organized as limited liability partnerships ("CV" in Dutch) in which the silent partner is not personally liable, but the managing partners are. These are labeled as personally liable. In addition, a few cases of firms with limited liability are organized as corporations ("NV" in Dutch).

Table 1
Summary statistics.

	Mean	SD	Min	Max	N
Panel A: Selection analyses					
Selection (0/1)	0.90	0.30	0.00	1.00	70
Pre-pub. Percentage	0.30	0.34	0.00	1.00	70
Internal credit score (0–1)	0.53	0.17	0.21	0.92	70
External credit score (0–1)	0.36	0.23	0.08	0.95	70
Loan amount (mln)	0.30	0.21	0.05	1.20	70
Maturity (yrs)	4.21	1.22	0.50	7.00	70
Interest rate (%)	7.43	0.68	5.50	9.00	70
Startup (0/1)	0.24	0.43	0.00	1.00	70
Personal liability firm (0/1)	0.17	0.38	0.00	1.00	70
Bank loan (0/1)	0.36	0.48	0.00	1.00	70
Physical collateral (0/1)	0.51	0.50	0.00	1.00	70
Personal guarantee (0/1)	0.71	0.46	0.00	1.00	70
Third party guarantee (0/1)	0.23	0.42	0.00	1.00	70
Subordinated loans (0/1)	0.36	0.48	0.00	1.00	70
Covenant (0/1)	0.49	0.50	0.00	1.00	70
Panel B: P2P investment analyses					
Log P2P investment	6.81	0.73	6.21	12.32	37,159
P2P investment (th)	1.34	2.83	0.50	225.00	37,159
Pre-publication investment (0/1)	0.07	0.26	0.00	1.00	37,159
Number of projects per week	3.39	1.28	1.00	6.00	37,159
Time trend	6.94	1.94	0.01	9.71	37,159
Interest rate (%)	7.36	0.52	6.00	9.00	37,159
Maturity (years)	4.53	0.74	3.00	6.00	37,159
Internal credit score (0–1)	0.59	0.16	0.24	1.00	37,159
External credit score (0–1)	0.39	0.24	0.08	1.00	37,159
Startup (0/1)	0.27	0.44	0.00	1.00	37,159
Personal liability firm (0/1)	0.23	0.42	0.00	1.00	37,159
Bank loan (0/1)	0.13	0.34	0.00	1.00	37,159
Physical collateral (0/1)	0.13	0.34	0.00	1.00	37,159
Personal guarantee (0/1)	0.65	0.48	0.00	1.00	37,159
Third party guarantee (0/1)	0.42	0.49	0.00	1.00	37,159
Subordinated loans (0/1)	0.37	0.48	0.00	1.00	37,159
Covenant (0/1)	0.46	0.50	0.00	1.00	37,159
Negative mortgage statement (0/1)	0.08	0.27	0.00	1.00	37,159
Only one investment (0/1)	0.04	0.21	0.00	1.00	37,159
First investment (0/1	0.11	0.31	0.00	1.00	37,159
Pre-pub. Percentage (%)	0.12	0.10	0.00	0.98	34,446
Panel C: Default analyses					
>30 days overdue	0.15	0.36	0.00	1.00	276
>120 days overdue	0.14	0.35	0.00	1.00	276
Write-off	0.04	0.20	0.00	1.00	276
Pre-publication percentage (0–1)	0.14	0.15	0.00	0.98	276
Interest rate (%)	7.47	0.54	6.00	9.00	276
Loan amount (mln)	0.20	0.16	0.05	1.50	276
Maturity (years)	4.49	0.75	3.00	6.00	276
Internal credit score (0–1)	0.57	0.17	0.24	1.00	276
External credit score (0–1)	0.37	0.25	0.08	1.00	276
Startup (0/1)	0.34	0.47	0.00	1.00	276
Personal liability firm (0/1)	0.37	0.48	0.00	1.00	276
Bank loan (0/1)	0.14	0.35	0.00	1.00	276
Physical collateral (0/1)	0.07	0.26	0.00	1.00	276
Personal guarantee (0/1)	0.54	0.50	0.00	1.00	276
Third party guarantee (0/1)	0.30	0.46	0.00	1.00	276
Subordinated loans (0/1)	0.34	0.48	0.00	1.00	276
Covenant (0/1)	0.32	0.47	0.00	1.00	276

This table reports summary statistics for selection analyses in Panel A, P2P investment analyses in Panel B and default analyses in Panel C. Indicator variables are labeled (0/1), variables ranging from 0 to 1 as (0–1) and millions and thousands of euro's are indicated as (mln) and (th), respectively. Definitions of all variables are provided in Appendix Table A.1.

Table 2
Descriptive statistics P2P investments and P2P investors.

Panel A: Distribution of P2P investments

	Pre-	Post-	All
500	35.1%	48.8%	47.8%
1000	24.4%	27.3%	27.1%
1500	5.7%	5.6%	5.6%
2000	6.4%	6.2%	6.2%
2500	9.4%	5.8%	6.1%
[3000 - 5000)	3.0%	2.3%	2.3%
[5000 - 10,000)	9.6%	3.1%	3.6%
[10,000 - 15,000)	4.0%	0.7%	0.9%
[15,000 - 30,000)	1.7%	0.1%	0.2%
$\geq$ 30,000	0.7%	0.1%	0.1%
Total	100.0%	100.0%	100.0%

Panel B: P2P investors

	All investors		Only pre-		Only post-		Pre- and post-	
	$n = 4{,}561$		$n = 1{,}005$		$n = 2{,}811$		$n = 745$	
	$N = 41{,}338$		$N = 1{,}047$		$N = 22{,}419$		$N = 17{,}872$	
	μ	σ	μ	σ	μ	σ	μ	σ
Number of loans	36.17	33.86	1.15	0.83	24.85	20.62	52.43	40.27
P2P investment (th)	1.34	2.76	3.91	6.71	1.23	2.95	1.33	1.90
% of P2P investors who found the platform via:								
Business partner	3%	17%	2%	13%	3%	18%	4%	20%
Loan officer	6%	23%	7%	25%	4%	20%	10%	30%
Friend	36%	48%	40%	49%	35%	48%	32%	47%
Loan applicant	15%	35%	38%	49%	7%	26%	10%	30%
Media	9%	28%	2%	14%	12%	32%	7%	25%
Search engine	14%	34%	2%	13%	18%	39%	12%	32%
Other	19%	39%	10%	30%	20%	40%	25%	43%
P2P investment (th) of investors who found the platform via:								
Business partner	1.52	2.85	3.63	6.24	1.30	3.29	1.80	1.76
Loan officer	1.53	2.32	4.18	5.22	1.27	2.52	1.52	1.71
Friend	1.37	3.44	3.53	5.45	1.29	4.00	1.32	2.40
Loan applicant	2.32	5.67	4.59	8.61	1.87	5.55	1.50	2.06
Media	1.07	1.48	1.88	2.22	1.01	1.42	1.20	1.60
Search engine	1.21	1.60	2.66	3.04	1.16	1.65	1.28	1.47
Other	1.27	1.74	3.38	4.94	1.22	1.91	1.29	1.36

This table reports descriptive statistics for the distribution of P2P investments in Panel A and P2P investors in panel B. Panel A reports the distribution of P2P loans for loan sizes of €500, €1000, €1500, €2000 and €2500 and subsequently for loan size buckets from €3000 onwards. The column *Pre-* indicates the percentage of loan observations in the pre-publication part of the sample (N = 2,976), the column *Post-* indicates the percentage of loan observations in the post-publication part of the sample (N = 38,362) and the column *Total* indicates the percentage of loan observations in the total sample (N = 41,338). Panel B distinguishes investor samples next to *All investors*: *Only pre-* indicates investors that only ever invest in the pre-publication phase, *Only post-* indicates investors that only ever invest in the post-publication phase and *Pre- and post-* indicates investors that invest in both the pre- and the post-publication phase. n and N indicate the number of distinct investors and the number of observations in each sample, respectively. μ and σ indicate the mean and the standard deviation, respectively. *Number of loans* indicates the number of loans per investor and *P2P investment* indicates the investment made by an individual P2P investor. *% of P2P investors who found the platform* via indicates the percentage from the cross-section of P2P investors split according to how the investor found the platform. *P2P investment (th) of investors who found the platform* via indicates the P2P investment amounts in the investor-loan panel split according to how the investor found the platform.

investment distribution than for the post-publication investment distribution. Given that only acquaintances of the borrower invest during the pre-publication phase, this is consistent with my second hypothesis.

Panel B provides more descriptives on what distinguishes pre- and post-publication investors. For clarity, I split the sample in three main types of investors: investors that only ever invest in the pre-publication phase, investors that only ever invest in the post-publication phase and investors that invest in both the pre- and the post-publication phase. For comparison I also present a sample of all investors, which includes 4561 distinct investors in a sample of 41,338 observations.[10] The average P2P investor invests in about 36 loans with an average amount of €1340. By contrast, P2P investors that only invest in the pre-publication phase invest on average in about 1.15 loans with an average amount of €3910. In fact, from these 1005 distinct investors, 977 investors (97%) only ever invest in one loan, compared to the sample of 2811 investors that only invest in the post-publication phase in which 908 investors (32%) only ever invest in one loan. So investors that only invest in the pre-publication phase are more likely to register on the platform to just invest in the loan of an acquaintance. This is confirmed by the next two panels, which show that of the investors that only invest during the pre-publication phase 38% found the platform via the loan applicant (compared to 15% in the overall sample), with an average associated P2P investment of €4590.

The sample of 2811 investors that invests only in the post-publication period and the sample of 745 investors that invests in both the pre- and post-publication period appear to be more like portfolio investors. They invest in respectively 24.85 and 52.43 loans with average amounts of €1230 and €1330. The 745 pre- and post-publication investors might be attracted to the platform via acquaintances, judging from their pre-publication investments, and subsequently invest more broadly, also in firms they do not know personally. Consistently, their average investments are a bit larger than those of investors that only invest during the post-publication phase.

All in all, this suggests substantial investment size differences between P2P investors. However, the regression analyses will include P2P investor fixed effects, so the effect of *Pre-publication investment* will be mainly identified through the 745 P2P investors that invest in both the pre- and post-publication phase. Unreported summary statistics show that within this group the average pre-publication investment is €1790 (σ=€3580, $N = 1929$) and the average post-publication investment is €1280 (σ=€1570, $N = 15{,}943$). These within-investor group differences are smaller than the differences between investor groups, which suggest that the fixed effects estimator should provide a conservative estimate of the overall *Pre-publication investment* effect.

3.4. Methodology

I perform three types of analyses. First, I test for credit rationing at the platform level in terms of what determines which projects are selected by the P2P lender to appear on their lending platform. As a first pass, I model the selection of a loan based on its characteristics. Next, to test my first hypothesis, I limit the sample to firms that have made two loan applications during the sample period and test whether the second loan application is more likely to be granted when the first application features a higher percentage of pre-publication funding. As explanatory variables I use characteristics of the first loan (application). This also ensures that results are less likely to be biased by the platform possibly deciding simultaneously on loan characteristics and selection.

Using a probit regression I test what drives the probability of selection (θ_i):

$$\theta_i = Pr(h_i = 1|\text{Observed variables}) = Pr(\alpha + \beta_1 Pre - pub_i + \beta_2 LFC_i + \beta_3 Collateral_i) \tag{1}$$

where h_i is an indicator variable that equals one when a loan application is accepted and zero when it is either denied by the platform or withdrawn by the loan applicant. Pre - pub_i indicates the *Pre-publication percentage*, which is measured as the percentage of the requested loan amount financed in the pre-publication phase, expressed as a fraction. In selected specifications this variable is set to zero when the first loan application was denied to appear on the platform. In that case I include *First loan selected*, which is an indicator equal to one when the first loan is selected to appear on the platform and zero when it was denied or withdrawn. Following hypothesis 1, I expect β_1 to be positive.

Loan and firm characteristics. The vector LFC_i indicates loan and firm characteristics.[11] *Interest rates*, which are expressed as a percentage, are likely positively related to selection because they increase the project's attractiveness to lenders and therefore to the platform. The requested *Loan amount* is expressed in millions of euros and is decided by the P2P platform in consultation with the loan applicant. Requests for a larger *Loan amount* are more risky to the extent that they increase leverage and increase default incentives, so likely negatively related to selection. The *Maturity* of a loan is expressed in years and winsorized at the 99% level. Shorter maturities with loans being rolled over provide additional information that reduces asymmetric information problems, so a longer *Maturity* is likely to reduce the probability of selection. Shorter maturities can also be used to signal quality (less adverse selection) and lower borrowers' incentives to switch from low- to high-risk projects (asset substitution problem). (Steijvers and Voordeckers, 2009; Menkhoff et al., 2012).

Concerning credit risk, I include the *Internal credit score* provided by the platform itself and the *External credit score* provided by an external rating provider. Both are measured on a scale from zero to a hundred, but expressed here on a scale from zero to one. Higher scores indicate lower credit risk, which is expected to be positively associated with the probability of selection. To measure opaqueness, I include an indicator variable (*Startup*) equal to one when a firm is less than one year old and equal to zero otherwise. In addition, I include an indicator variable equal to one when the firm is a personal liability firm (*Personal liability*: either a sole proprietorship or a partnership) and equal to zero otherwise. Both are expected to be negatively related to selection.

The P2P platform could receive a lower rank in the priority of debt claims when there are other claimants. Anecdotal evidence

[10] Note that this is the complete sample, whereas the regression sample is slightly smaller due to the inclusion of industry fixed effects in all estimations.

[11] Note that I only have externally obtained balance sheet data on a limited set of firms, because many small, personal liability firms do not publicly report annual statements. The larger firms for which I do have balance sheet data are part of a robustness check discussed in Section 5.2

suggests that often when a borrower has an existing bank loan, the bank prefers to retain the sole right to collateral, forcing the P2P platform to provide an unsecured loan instead. Therefore, I also include an indicator variable *Bank loan* that is equal to one when the firm already has a bank loan and equal to zero otherwise. Having a bank loan serves as a quality signal, but could also imply that a bank already acquired the right of collateral and is unwilling to share this. Therefore, the expected effect on selection is unclear.

Collateral. I control for a number of contract features known to mitigate credit rationing. The use of collateral, indicated by $Collateral_i$, is one of the main instruments designed to prevent credit rationing. I include indicator variables for outside or physical collateral, *Physical collateral*, and inside collateral including *Personal guarantee* and *Third party guarantee*. When pledging a security interest in collateral, a creditor has a claim on a specific asset that has priority over unsecured (or subsequently secured) claimants (Avery et al., 1998). Because collateralized assets are controlled by the secured claimant, borrowers are unable to sell these assets. By contrast, personal and third party guarantees are general claims on personal wealth that put less restrictions on the borrower, but also on the creditor who could potentially seize personal assets in the event of non-repayment. Both inside and outside collateral are expected to reduce credit rationing.

I also include other contract features that are related to collateral. When collateral is inside collateral it involves assets inside the firm being pledged. It provides a priority of debt claims that reduces conflict of interest between multiple lenders (Menkhoff et al., 2012). This function of physical collateral could also be substituted by debt subordination, in which existing lenders agree to have their loans subordinated to the new loan contract. Existing lenders might be willing to agree to this when this increases the firm's survival probabilities or more generally when existing loan contracts are being renegotiated as result of the new loan. I include the variable *Subordinated loans*, which equals one when a firm already has existing loans which are subordinated to the P2P loan, and equals zero otherwise.

A restrictive covenant is another contractual feature that helps to reduce moral hazard (Voordeckers and Steijvers, 2006). It is included as an indicator variable: *Covenant* is equal to one when a loan has a restrictive covenant and equal to zero otherwise. Covenants serve to prevent borrowers from extracting funds from the firm and channeling them to personal uses or other firms they own. Restrictive covenants are typically tied to leverage or measures of firm performance and therefore require audited financial statements (Niskanen and Niskanen, 2004). Another contractual characteristic that is less studied in the literature, but is included in the dataset, is a (negative) mortgage statement that precludes borrowers from taking additional mortgages. It is include as an indicator variable *Negative mortgage statement*, which is equal to one when a contract contains this feature and equal to zero otherwise. Because it is used relatively infrequently, it could not be included in all analyses.

Second, I test for credit rationing at the level of individual P2P investors by running the following regression:

$$log\left(\text{P2P Investment}_{ij}\right) = \alpha_j + \beta_1 Pre\text{-}pub_{ij} + \beta_2 LFC_i + \beta_3 Collateral_i + \beta_4 T_{ij} + \kappa_i + \varepsilon_{ij} \tag{2}$$

where $P2P\ Investment_{ij}$ indicates the investment amount provided by P2P investor j to loan i. I take the natural logarithm of *P2P Investment* to adjust for skewness. The main variable of interest, $Pre\text{-}pub_{ij}$ or $Pre\text{-}publication\ investment_{ij}$, is an indicator variable that equals one when a P2P investment is made in the pre-publication phase and equal to zero otherwise. During the pre-publication phase only investors from the borrower's personal network can invest, so *Pre-publication investment* captures informal lending.

Following hypothesis 2, I expect β_1 to be positive. All analyses include P2P investor fixed effects indicated by α_j. P2P investor fixed effects control for unobserved heterogeneity of lender investment size preferences. The use of P2P investor fixed effects implies that I estimate a within-investor effect. That is, I ask whether the same P2P investor would choose a different investment size depending on whether the P2P investor personally knows the borrower or not.

The variables in the vectors LFC_i and $Collateral_i$ are all set before P2P investors decide on their investments. They are the same as before, but the requested *Loan amount* is omitted to prevent potential simultaneity. Instead I include *Number of projects per week*, which measures the number of projects open for investment on the platform in the same week a P2P investment is made and thus controls for possible competition from other projects on the platform. I include a time trend (T_{ij}) based on the date of investment of investor j in loan i to adjust for changes in investment amounts over time. NACE level 1 industry fixed effects (κ_i) are included to control for the possibility that firms from some industries could have stronger demand for their products than firms from other industries, which might be correlated with having a large set of acquainted lenders.[12]

To test hypothesis 3, I focus on a sample of P2P investments that are made in the post-publication phase only. I estimate Eq. (2) for this sample, including instead of the dummy *Pre-publication investment* the *Pre-publication percentage*, which is measured as the percentage of the requested loan amount financed in the pre-publication phase, expressed as a fraction. The *Pre-publication percentage* is known to post-publication investors when they see the loan application appear online. Investors also see the last five amounts invested by other investors, although these investors' identities are anonymized on the platform. According to Hypothesis 3, if the pre-publication percentage provides a signal of (tacit) quality, it should be associated with larger P2P investments in the post-publication phase.

P2P investor characteristics. P2P investors are uniquely identified and may register on the platform for different reasons. On the one hand, they could be portfolio investors. On the other hand, they could be approached by one of their social or business connections to provide financing for their loan. In the pre-publication phase borrowers explicitly ask their acquaintances to help finance the loan, but acquaintances could also play a role in the post-publication phase. In further analyses I try to identify this effect based on the number of

[12] Note that there are 16 distinct NACE level 1 industries in the dataset. Appendix Table B.2 shows a robustness check with SIC level 3 industry fixed effects based on a classification with 39 industries.

loans investors finance and how investors learned about the platform.

First, if lenders are attracted to the platform by borrowers they know, one would expect that their first loan is larger because it is to a borrower they know. A stronger indication of investors just registering on the platform to finance an acquaintance would be if they only ever make one investment on the platform. To test this, I define *Only one investment* which equals one if an investor only invests once on the platform, and equals zero otherwise. I also define *First investment* which equals one for each investor's first P2P investment made on the platform and equals zero otherwise. I expect that both are positively related to P2P investments.

When investors register on the platform they also indicate how they found the platform, where they can choose from *Business partner*, *Loan officer*, *Friend*, *Loan applicant*, *Media*, *Search engine* and *Other*. In further analyses I create indicator variables for each of these categories, excluding the category *Other*. I expect that larger P2P investments are made by investors that found the platform via a social connection with the borrower, which in this case is mostly likely to be identified as the loan applicant.

In a third set of analyses, I test how the probability (τ_i) of ex post nonperformance is related to loan and firm characteristics by running the following probit regression:

$$\begin{aligned} \tau_i &= Pr(z_i = 1 | \text{Observed variables}) \\ &= Pr(\alpha + \beta_1 Pre\text{-}pub_i + \beta_2 LFC_i + \beta_3 Collateral_i + \beta_4 \kappa_i) \end{aligned} \tag{3}$$

where z_i is an indicator variable that indicates nonperformance of loan *i*. I use three definitions of nonperformance: a loan is nonperforming (i) when it is more than 30 days overdue, (ii) when it is more than 120 days overdue or (iii) when it is written off. $Pre\text{-}pub_i$ indicates the *Pre-publication percentage*, which tests whether the extent of pre-publication investments is related to defaults. The vectors LFC_i and $Collateral_i$ include the same variables as in Eq. (1) and NACE level 1 industry fixed effects (κ_i) are included in selected specifications.

4. Regression analyses

This section presents regression results. First I evaluate Hypothesis 1 by testing whether positive selection by the platform of applicants' second loan application is related to the extent of pre-publication funding of the first loan. Second, I test Hypothesis 2 whether P2P investments are larger when P2P investors are acquainted with the borrower. Next, to test Hypothesis 3, I investigate whether financing by acquainted investors in the pre-publication phase affects the size of investment by other investors during the post-publication phase. Then I investigate to what extent different investor types are driving the effect of *Pre-publication investment* and proxy to what extent acquainted investors invest more in the post-publication phase as well. Finally, I estimate whether loans' ex post credit risk is related to financing by acquainted investors in the pre-publication phase.

4.1. *Selection of projects by the platform*

Table 3 presents marginal effects of the selection analysis in which a selection dummy, indicating a loan application is selected to appear on the platform, is regressed on loan and firm characteristics. Column (1) presents the results for all 850 loan applications in the sample, of which 276 are selected to appear on the platform. Results show that projects with a higher interest rate, lower requested loan amounts, a longer maturity and higher credit scores are more likely to be selected to appear on the platform. Column (2) considers only the second loan applications of firms that already made a loan application previously. For comparison purposes, exactly the same variables are included as in Column (1). That is, the characteristics of the second loan applications. The results of this selection analysis show that these loan applications appears to be mostly driven by the internal credit score and to some extent the maturity of a prospective loan.

The estimations in Columns (1) and (2) both suffer from potential simultaneity of the decision to select the loan application to appear on the platform and its characteristics. This is especially likely to be the case for the internal credit score that is provided to the application by the platform itself. Therefore, in Columns (3) to (6) the selection decision concerning a firm's second loan application is regressed on its first loan application's characteristics. Of the 101 firms that applied for their second loan in the sample, 67 are selected to appear on the platform.[13]

Column (3) provides the results of regressing the selection decision on the *pre-publication percentage* associated with the first loan application. The pre-publication percentage is set to zero when the first loan is denied to appear on the platform. The indicator *First loan selected*, which equals one when the first loan application was accepted to appear on the platform and zero otherwise, is included to control for this. In addition, loan characteristics of the first loan application are included. Results show that the *pre-publication percentage* of the first loan is significantly positively associated with a second loan being selected to appear on the platform, which is consistent with Hypothesis 1. An increase of one standard deviation of the *pre-publication percentage* of 0.34 is associated with an increase in the likelihood of the second loan being selected by about 23%. Also the *First loan selected* is positively associated with the likelihood of the second loan being accepted, whereas the other characteristics of the first loan application do not significantly influence the probability of the second loan being accepted.

Next, Columns (4) to (6) only consider the second loan applications for which the first loan application was accepted to appear on

[13] Note that of the 67 firms that have their second loan application accepted, 63 also have their first loan application accepted. Of the 34 firms that have their second loan application denied, 7 have their first loan application accepted.

Table 3
Selection of loan applications to appear on the platform.

	Selection and loan characteristics		2^{nd} loan selection and 1^{st} loan characteristics			
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-pub. Percentage			0.666**	0.601*	0.695*	4.893***
			[0.328]	[0.316]	[0.398]	[1.887]
First loan selected			0.294***			
			[0.096]			
Interest rate	0.026***	−0.008	0.010		−0.089	−0.476**
	[0.004]	[0.020]	[0.015]		[0.063]	[0.229]
Loan amount	−0.106**	0.129	−0.001		0.123	0.931**
	[0.052]	[0.217]	[0.151]		[0.163]	[0.382]
Maturity	0.017***	0.004*	−0.004		−0.053*	−0.149**
	[0.005]	[0.002]	[0.020]		[0.031]	[0.059]
Internal credit score	0.312***	0.007***	−0.047		−0.231	−2.156**
	[0.025]	[0.002]	[0.186]		[0.253]	[0.884]
External credit score	0.066*	0.002	0.085		−0.100	0.448**
	[0.037]	[0.001]	[0.122]		[0.182]	[0.225]
Startup					0.102	0.267***
					[0.083]	[0.086]
Personal liability firm					0.043	−1.245**
					[0.124]	[0.506]
Bank loan						0.248*
						[0.135]
Physical collateral						1.294**
						[0.526]
Personal guarantee						−0.603***
						[0.229]
Third party guarantee						−0.617**
						[0.260]
Subordinated loans						−0.368**
						[0.144]
Covenant						0.382**
						[0.160]
Observations	850	101	101	70	70	70
Pseudo R^2	0.713	0.348	0.505	0.102	0.214	0.592
N loans accepted	276	67	67	63	63	63

This table reports estimates of Eq. (1) in which the dependent variable is an indicator equal to one when a loan is selected to appear on the platform and zero when it is either rejected or withdrawn by the loan applicant. Column (1) reports estimates for the full sample of loans. Columns (2) and (3) report estimates for the sample of loan applications that have had a previous loan application at the P2P lending platform. Columns (4) to (6) restrict the sample to second loans for which the first loan was selected to appear on the platform. In Columns (1) and (2) selection is regressed on characteristics applying to the (second) loan application, whereas in Columns (3) to (6) selection of the second loan is regressed on the characteristics of the first loan application. Robust standard errors are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

the platform. Practically all of these second applications have some first loan pre-publication funding. Column (4) only includes the *pre-publication percentage* of the first loan, Column (5) adds the loan characteristics of the first loan and Column (6) adds the characteristics of the first loan application that are collected from its pitch on the platform. From this admittedly small sample two things stand out. First, the pre-publication percentage is positive and significant in all three specifications. Second, especially the characteristics related to the different types of collateral on the first loan are significantly associated with selection of the second loan, where physical collateral on the first loan is positively associated whereas (softer) guarantees on the first loan are negatively associated with selection. Conditional on the inclusion of collateral characteristics of the first loan, also other first loan characteristics become significant and the model fit improves markedly. Still, given the relatively small sample these result should be interpreted with some caution. Summarizing, based on an assessment of first and second loan applications I find evidence for Hypothesis 1 that a platform is more likely to accept a loan application to appear on the platform when there is a larger group of potential P2P investors acquainted with the borrower.

4.2. *Investment by acquaintances and P2P investment rationing*

Table 4 present analyses in which the dependent variable is the natural logarithm of P2P investment, log(P2P Investment$_{ij}$), so coefficients are interpreted as semi-elasticities. The effect of *Pre-publication investment* is positive and significant in all specifications, which confirms Hypothesis 2. In Column (1) the *Number of projects per week* is negatively associated with the size of P2P investments, suggesting that competition from other investments that are also open in the same week reduces the average P2P investment size. In Column (2) a *Time trend* is included and the *Number of projects per week* becomes insignificant. The negative effect of the *Time trend*

Table 4
P2P investment rationing and pre-publication.

	(1)	(2)	(3)	(4)
Pre-publication investment	0.131***	0.214***	0.207***	0.208***
	[0.032]	[0.024]	[0.023]	[0.023]
Number of projects per week	−0.030***	−0.002	−0.002	0.002
	[0.003]	[0.002]	[0.002]	[0.002]
Time trend		−0.125***	−0.123***	−0.128***
		[0.005]	[0.005]	[0.005]
Interest rate			−0.030***	−0.013*
			[0.007]	[0.007]
Maturity			0.016***	0.004
			[0.004]	[0.004]
Internal credit score			0.087***	0.137***
			[0.020]	[0.022]
External credit score			0.137***	0.140***
			[0.013]	[0.013]
Startup			−0.041***	−0.043***
			[0.006]	[0.006]
Personal liability firm			−0.060***	−0.041***
			[0.007]	[0.010]
Bank loan			−0.008	0.003
			[0.007]	[0.007]
Physical collateral				0.099***
				[0.012]
Personal guarantee				0.012*
				[0.007]
Third party guarantee				0.012*
				[0.006]
Subordinated loans				0.006
				[0.005]
Covenant				0.006
				[0.006]
Negative mortgage statement				0.032***
				[0.009]
Constant	6.922***	7.658***	7.742***	7.630***
	[0.018]	[0.034]	[0.072]	[0.073]
Observations	37,159	37,159	37,159	37,159
P2P investor fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.171	0.185	0.101
Number of investors	4335	4335	4335	4335
Number of loans	239	239	239	239

This table reports estimates of Eq. (2) in which the dependent variable is the natural logarithm of *P2P investment*. *Pre-publication investment* is an indicator variable that equals one when a P2P investment is made in the pre-publication phase and equals zero otherwise. Definitions of all other variables are provided in Appendix Table A.1. Estimations apply to the full sample of pre- and post-publication P2P investments during the period 2014–2017. All estimations include P2P investor fixed effects and industry fixed effects. Standard errors are clustered at the P2P investor level and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

might reflect the fact that all investments from the start of the platform are in the sample, and as time progresses investors are actively diversifying by investing smaller amounts. Once the time trend is included, in Columns (2) to (4) the size of the parameter of *Pre-publication investment* is relatively stable across specifications: Because P2P investor fixed effects are included, for the same investor a pre-publication investment is about 20% larger than a post-publication investment.

The effect of control variables is mostly as expected. Consistent with adverse selection, higher interest rates are associated with lower P2P investments. A longer maturity is associated with smaller P2P investments, although the effect is not consistently significant across specifications. As expected, credit risk is negatively related to the size of P2P investments: In Column (4) an improvement in external credit score of 10 points (scale 0–100) is associated with P2P investments that are larger by about 1.4% and the effect of the internal credit score is of similar size. Consistent with startups and firms with personal liability being small and opaque, they are associated with 4.3% and 4.1% smaller P2P investments, respectively. The effect of already having a bank loan is insignificant. Concerning collateral and similar loan contract features, *Physical collateral* is associated with P2P investments being larger by about 10%. Also *Personal guarantees* and *Third party guarantees* are associated positively with P2P investments, although their effect is relatively small and only significant at a 10% level. *Subordinated loans*, which captures whether the P2P loan is subordinated to existing loans of the firm and *Covenants* are not significantly related to P2P investments, but this could be due to the fact that in this sample controls for solvency and liquidity are lacking.[14] Finally, the effect of *Negative mortgage statement* is also positive and significant.

4.3. Pre-publication funding and post-publication rationing

The previous section established that in the pre-publication phase P2P investors conduct less rationing than in the post-publication phase. P2P investors in the pre-publication phase can only invest when they have personally received a link from the loan applicant, which indicates that pre-publication investors are acquainted with the borrower. Next I investigate whether the extent to which the loan is filled in the pre-publication phase serves to motivate post-publication investors to invest larger amounts. The idea is that if pre-publication investors have already filled the project to a greater extent, this could serve as a signal of quality to lenders unacquainted with the borrower. The signal emanates from a group of acquainted lenders that is likely to suffer less from asymmetric information and might use social leverage to mitigate incentive problems.

Column (1) of Table 5 presents the baseline results, which replicates Column (4) of Table 4 for a sample of post-publication P2P investments. The coefficients in Column (1) are mostly similar to those estimated for the entire sample. In Column (2) a loan's *Pre-publication percentage*, which is measured as a fraction, is added as explanatory variable. Consistent with Hypothesis 3, its effect is positive although the effect size is relatively small: an increase in the *Pre-publication percentage* of 10%, which is one standard deviation, is associated with a post-publication P2P investment that is larger by 0.7%. In Column (3) the sample is restricted to post-publication P2P investments that also have pre-publication P2P investments, i.e. in this sample the pre-publication percentage is never equal to zero. Here the effect of *Pre-publication percentage* is also positive and significant and similar in size to that found in Column (2).

If the signal provided by acquainted investors serves to alleviate asymmetric information, one would expect this to hold mostly for relatively small and opaque firms (Kirschenmann, 2016). Therefore, Columns (4) and (5) split the sample from Column (2) in P2P investments provided to startup firms and existing firms, respectively. Consistent with the variable *Startup*, startup firms are defined as firms less than one year old, i.e. firms applying for a loan in the same year they are founded. Existing firms are all other firms in the sample. The results in Columns (4) and (5) show that the *Pre-publication percentage* is only positive and significant in the sample with startup firms and insignificant in the sample with existing firms..[15] Another interesting result is that the effect of *Number of projects per week* is negative and significant in the sample with startup firms, while it is positive and significant in the sample with existing firms.

Summarizing, I find evidence consistent with Hypothesis 3 that when acquainted P2P investors finance a larger part of the loan, subsequent P2P investments by unacquainted P2P investors are larger as well. Consistent with acquainted investors alleviating asymmetric information for relatively opaque firms, this effect appears to be driven by startup firms.

4.4. P2P investor types: One-off versus portfolio investors

Table 2 showed a number of interesting patterns that I now investigate a bit further in a multivariate setting. For instance, of the 1005 investors that only ever invest in the pre-publication phase, 977 only invest in one loan. Arguably, a one-off investor that just registers on the platform to invest once, based on the invitation of an acquaintance, is likely solely motivated to help out a friend. In this section I first consider to what extent the effect of *Pre-publication investment* is driven by one-off investors, first-time investors and investors that indicate to have found the platform via the loan applicant. Second, I use these investor types to identify lenders likely to be acquainted with the borrower in a sample of post-publication investments to find out if similar acquaintance effects hold during the post-publication phase. Table 6 presents the results of these analyses, which all include industry fixed effects and a full set of control variables that are omitted for the sake of brevity.

First I consider the full sample of P2P investments. Column (1) of Table 6 investigates the differential effect on P2P investments of investors investing only once during the pre-publication phase. Column (1) of Table 6 replicates Column (4) of Table 4 and adds *Only one investment*, which is equal to one if a P2P investor only ever invests in one loan and equal to zero otherwise. I interact this variable with *Pre-publication investment*. Note that *Only one investment* and its interaction with *Pre-publication investment* are not identified in a P2P investor fixed effects model, so random effects are included instead. The main effect of *Only one investment* is positive and significant: investors that only invest once are associated with 30.1% larger P2P investments. Moreover, the interaction shows that when this investment takes place during the pre-publication phase it is higher by an additional 29.6%. Column (1) also shows that the main effect of *Pre-publication investment* is still significant and positive.[16]

Another possibility is that the effect of *Pre-publication investment* is driven by first-time investors. These investors are attracted to the platform via an acquaintance that asks them to invest in their project, and investors subsequently remain active on the platform. To gauge this effect, I define *First investment*, which is equal to one for the first investment of each investor and equal to zero otherwise. Compared to *Only one investment*, this variable has the advantage that P2P investor fixed effects can be included again. Column (2) of

[14] Appendix Table B.2 provides a robustness check for a smaller sample of firms that includes controls for liquidity and solvency. There I do find an effect of *Subordinated loans* and *Covenant* which is positive and significant for both.

[15] Note that an alternative specification based on interaction the *Pre-publication percentage* with the variable *Startup* provides consistent results: the interaction is positive and significant while the main effect of *Pre-publication percentage* becomes insignificant. These results are available upon request.

[16] Note that estimating the model from Column (4) of Table 4 with random instead of P2P investor fixed effects, the coefficient of *Pre-publication investment* equals 0.271 (results available upon request). This suggest that the effect of *Pre-publication investment* is partially, but not entirely, driven by one-off investors.

Table 5
Effect of pre-publication financing on post-publication investment rationing.

	Post-publication Investment sample		With pre-pub. Investment	Startup Firms	Existing Firms
	(1)	(2)	(3)	(4)	(5)
Pre-publication percentage		0.071***	0.075***	0.131**	0.009
		[0.025]	[0.025]	[0.066]	[0.031]
Number of projects per week	0.001	0.001	0.000	−0.018***	0.009******
	[0.002]	[0.002]	[0.002]	[0.005]	[0.003]
Time trend	−0.124***	−0.125***	−0.122***	−0.128***	−0.130***
	[0.005]	[0.005]	[0.005]	[0.007]	[0.005]
Interest rate	−0.011	−0.009	−0.011	−0.015	−0.001
	[0.007]	[0.007]	[0.007]	[0.018]	[0.008]
Maturity	0.005	0.006	0.007*	0.003	0.011****
	[0.004]	[0.004]	[0.004]	[0.011]	[0.004]
Internal credit score	0.142***	0.146***	0.127***	0.121***	0.218***
	[0.022]	[0.022]	[0.022]	[0.046]	[0.027]
External credit score	0.137***	0.139***	0.155***	0.258***	0.104***
	[0.014]	[0.014]	[0.013]	[0.035]	[0.014]
Startup	−0.044***	−0.043***	−0.041***		
	[0.006]	[0.006]	[0.006]		
Personal liability firm	−0.037***	−0.034***	−0.035***	−0.007	−0.046***
	[0.010]	[0.010]	[0.010]	[0.026]	[0.014]
Bank loan	0.002	0.003	0.002	−0.005	0.003
	[0.007]	[0.007]	[0.007]	[0.020]	[0.009]
Physical collateral	0.085***	0.086***	0.089***	0.100***	0.115***
	[0.011]	[0.011]	[0.012]	[0.029]	[0.015]
Personal guarantee	0.015**	0.017**	0.022***	0.010	0.043***
	[0.007]	[0.007]	[0.007]	[0.024]	[0.008]
Third party guarantee	0.016**	0.017***	0.011*	−0.008	0.017**
	[0.006]	[0.006]	[0.007]	[0.014]	[0.008]
Subordinated loans	0.003	0.003	−0.003	0.002	0.002
	[0.005]	[0.005]	[0.005]	[0.012]	[0.006]
Covenant	0.009	0.010*	0.013**	0.005	−0.000
	[0.006]	[0.006]	[0.006]	[0.018]	[0.007]
Negative mortgage statement	0.026***	0.026***	0.025***	−0.046*	0.068***
	[0.009]	[0.009]	[0.009]	[0.025]	[0.011]
Constant	7.565***	7.542***	7.543***	7.599***	7.441***
	[0.072]	[0.073]	[0.072]	[0.171]	[0.083]
Observations	34,446	34,446	32,576	9240	25,206
P2P investor fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.090	0.090	0.071	0.110	0.085
Number of investors	3420	3420	3282	2215	3120
Number of loans	239	239	221	80	159

This table reports estimates of Eq. (2) in which the dependent variable is the natural logarithm of *P2P investment*. The *Pre-publication percentage* is the fraction of the loan financed during the pre-publication phase. Definitions of all other variables are provided in Appendix Table A.1. The *Pre-publication percentage* is set to zero when there are no pre-publication investments. In Columns (1) and (2) the sample is limited to all P2P investments made in the post-publication phase during the period 2014–2017. In Columns (3) this sample is further restricted to post-publications investments that also have pre-publication investments. So investments with a *Pre-publication percentage* equal to zero are excluded from the sample here. Columns (4) and (5) split the sample in startup firms and existing firms, respectively, where startups are defined as firms applying for a loan in the year they are founded. All estimations include P2P investor fixed effects and industry fixed effects. Standard errors are clustered at the P2P investor level and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Table 6 presents the results of replicating Column (4) of Table 4 and including *First investment* and its interaction with *Pre-publication investment*. The main effect of *First investment* is positive but relatively modest: a first loan is associated with 6.6% larger P2P investments. However, when this first loan takes place during the pre-publication phase, it is associated with 39.6% larger P2P investments. The main effect of *Pre-publication investment* reduces to 15.1% in comparison with 20.8% in the baseline, so the effect of *Pre-publication investment* is partially driven by first-time investors. That is, part of the investors is initially attracted to the platform via an acquaintance who receives a relatively large investment, and they subsequently stay on the platform as portfolio investors. These are part of the 745 investors with both pre- and post-publication phase investments identified in Table 2.

To investigate this further, I consider how P2P investors found the platform, which is a question they are asked to answer when they register on the platform. They can choose from the categories, via a: *Business partner*, *Loan officer* from the platform, *Friend*, *Loan applicant*, *Media*, *Search engine* and *Other*. These categories are included as separate indicator variables that equal one when an investor indicates to have found the platform in this way, and equal to zero otherwise. The categories are mutually exclusive and the category *Other* is omitted from the estimations. Because these characteristics do not vary within P2P investors across investments, the main effects of the indicator variables are not identified in the investor fixed effects models, but their interaction with variables that vary

Table 6
P2P investor types and investment rationing.

	Full sample			Post-publication investments	
	X = Pre-publication Investment			X = Only one Investment	X = First Investment
	(1)	(2)	(3)	(4)	(5)
Only one investment dummy × X	0.296***				
	[0.059]				
First investment dummy × X		0.396***			
		[0.066]			
Business partner × X			0.038	0.279	0.187**
			[0.090]	[0.278]	[0.086]
Loan officer × X			0.111	0.242	0.206***
			[0.091]	[0.192]	[0.054]
Friend × X			0.034	0.418***	0.089***
			[0.057]	[0.102]	[0.034]
Loan applicant × X			0.655***	0.543***	0.432***
			[0.124]	[0.142]	[0.115]
Media × X			0.136	0.176	0.016
			[0.088]	[0.153]	[0.040]
Search engine × X			−0.008	0.026	0.047
			[0.066]	[0.116]	[0.036]
Business partner				0.130*	
				[0.073]	
Loan officer				0.117**	
				[0.056]	
Friend				0.008	
				[0.032]	
Loan applicant				0.170***	
				[0.066]	
Media				0.016	
				[0.044]	
Search engine				−0.033	
				[0.037]	
Only one investment dummy	0.301***			0.019	
	[0.040]			[0.076]	
First investment dummy		0.066***			0.009
		[0.013]			[0.026]
Pre-publication investment	0.214***	0.151***	0.142***		
	[0.023]	[0.022]	[0.044]		
Pre-pub. Percentage				0.079***	0.077***
				[0.025]	[0.025]
Observations	37,159	37,159	37,158	34,445	34,445
P2P investor fixed effects	No	Yes	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.121	0.195	0.192	0.100	0.186
Number of investors	4335	4335	4334	3419	3419
Number of loans	239	239	239	239	239

This table presents estimates of Eq. (2) for the total sample in Columns (1) to (3) and for a sample with only post-publication investments in Columns (4) and (5). Interactions are added as indicated by *X* in the column titles. *Only one investment* equals one for investors that only invest once on the platform and equals zero otherwise. *First investment* equals one for each P2P investor's first loan and equals zero otherwise. Columns (3) to (5) report interactions with dummies that indicate how a P2P investor learned about the platform with *Other* being the omitted category. Estimations without P2P investor fixed effects include P2P investor random effects instead. Definitions of all other variables are provided in Appendix Table A.1. All estimations include a full set of control variables and industry fixed effects, which are omitted for the sake of brevity. Standard errors are clustered at the P2P investor level and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

within investors and across investments are. Column (3) of Table 6 shows that P2P investors that found the platform via the loan applicant and invest during the pre-publication phase are associated with P2P investments that are 65.5% larger. Comparable to the result in Column (2), the main effect of *Pre-publication investment* is now partly captured by the interaction and therefore considerably smaller.

In addition to the pre-publication phase, acquaintances of the investor might also invest in the post-publication phase, so now I consider a sample of only post-publication investments. There are no cases in the sample in which for the same loan a pre-publication investor also invests in the post-publication phase, but a borrower might further tap its network in the post-publication phase.[17] Unfortunately, how an investor found the platform is an imperfect proxy for investor-borrower relationships, because unlike *Pre-*

[17] Note that in the raw data there was one case, but the corresponding two P2P investments have been excluded from the sample.

publication investment, it does not provide and indication of the investor-borrower relationship that is loan-specific. To mitigate this, I again consider investors that only invest once on the platform using *Only one investment* and investors' first investment on the platform using *First investment* and interact this with how investors found the platform.[18] The underlying identifying assumption is that if investors indicate, when they register on the platform, that they found the platform via the loan applicant, their first (and possibly only) investment will be in the loan of the loan applicant through whom they found the platform. The smaller size of the main effect of *Pre-publication investment* in Columns (1) to (3) suggests that this might capture at least part of the acquaintance effect in the post-publication phase.

Column (4) presents the results in which I replicate the baseline post-publication phase estimates from Column (1) of (Table 4) and add the interaction between *Only one investment* and indicator variables on how the P2P investor has found the platform. To identify the effect of *Only one investment*, the model is estimated using random effects instead of fixed effects. The coefficient of the interaction effect shows that investors that only invest once in the post-publication phase and found the platform via the loan applicant, have 54.3% higher P2P investments. The interaction of *Only one investment* with the indicator variable *Friend* shows a similar effect, although this is more difficult to interpret because it is unknown whether the friend in question is related to the loan applicant. The main effects show that investors that found the platform via a *Business partner*, a *Loan officer* from the platform or the *Loan applicant* are associated with larger P2P investments.

In Column (5) I replace *Only one investment* in the interactions with *First investment*. This again has the advantage that the model can be estimated using P2P investor fixed effects, which also implies that the main effect of the indicators measuring how investors know the platform can no longer be estimated. The interaction of *First investment* with the indicator variable that indicates an investor found the platform via the *Loan applicant*, confirms the results in Column (4). When a P2P investor registers on the platform and indicates to have found the platform via the *Loan applicant*, its first P2P investment during the post-publication phase is 43.2% larger than the other investments the investor makes during the post-publication phase. Also the interactions of *First investment* with *Business partner*, *Loan officer* and *Friend* are positive and significant, but again more difficult to interpret in a structural way. Combined these results confirm that also in the post-publication phase P2P investors acquainted with the borrower invest larger amounts, with the caveat that identification of these results is less strong than that obtained through the variable *Pre-publication investment*.

4.5. Pre-publication funding and ex post defaults

Given that investors that are acquainted with the borrower invest substantially more than those that are not acquainted with the borrower, and this positively affects the size of subsequent P2P investments and the likelihood of receiving a second loan, it is interesting to find out whether this is rational to do so. One the one hand, acquainted investors suffer from less asymmetric information and social relations mitigate incentive problems. On the other hand, acquaintances might not always invest rationally based on risks and return and part of their investment might reflect altruism. Therefore, in this section I investigate to what extent the *Pre-publication percentage* is related to ex post defaults.

Table 7 presents marginal effects for the analyses of nonperformance.[19] In the first two columns defaults are defined as loans being more than 30 days overdue, in the second two columns they are defined as loans being more than 120 days overdue and in the final two columns they are defined as loans that have been written off. For each of the categories *>30 days overdue*, *>120 days overdue* and *Write-off* a specification with and without industry fixed effects is estimated. In the sample about 15% of the loans (41 out of 276) is overdue and 4% of the loans (12 out of 276) are written off by the end of 2019.

The *Pre-publication percentage*, the fraction of the loan financed by a borrower's acquaintances is negatively related to nonperformance, in all specifications except Column (5). A one standard deviation increase in the pre-publication percentage (15%) is associated with a drop in the probability of default of about 6%.These results suggest that it might be rational for post-publication investors to base their investment decisions partly on the investment decisions made by pre-publication investors. Especially, because both the internal and external credit scores that are designed to predict the likelihood of defaults ex ante are not significantly related to defaults ex post. Credit assessment of small firms is notoriously difficult, especially in the Netherlands, which lacks a national credit registry for small firms. Given that the universe of loans at the platform is still small and lacks sufficient credit history, the performance of internal credit scores might still improve over time.

Concerning the control variables that are significantly related to observed defaults, interest rates and to some extent maturity are positively related to defaults. An increase in the interest rate of 1 percentage point is associated with an increase in the probability of nonperformance of 17%. Interestingly, whether borrowers have an existing bank loan is associated with the probability of default being lower by about 13%. This suggest that also bank screening of borrowers is effective.

5. Robustness checks

In this section I discuss three robustness checks. First, I test the robustness of the main results by replacing the dependent variable with a choice between a small investment (≤ €1000) and a large investment (> €1000) using logit models. Second, I consider whether the main analyses change when I incorporate firm-level controls and more fine-grained industry fixed effects. Finally, I consider possible sample selection effects affecting default estimates due to the platform selecting which loans appear online and which ones are

[18] Remember that during the post-publication phase 908 investors only invest in one loan.

[19] Note that Columns (5) and (6) do not contain estimated coefficients for *Physical collateral* because write-offs do not vary with this variable.

Table 7
Ex post defaults and pre-publication financing.

	> 30 days overdue		> 120 days overdue		Write-off	
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-publication percentage	−0.400**	−0.428**	−0.433**	−0.498**	−0.170	−0.397**
	[0.190]	[0.191]	[0.200]	[0.200]	[0.114]	[0.172]
Interest rate	0.160***	0.187***	0.166***	0.192***	0.062*	0.187**
	[0.046]	[0.051]	[0.046]	[0.051]	[0.032]	[0.075]
Loan amount	0.183	0.230	0.135	0.175	0.262**	0.605***
	[0.159]	[0.186]	[0.150]	[0.175]	[0.107]	[0.170]
Maturity	0.045	0.037	0.054*	0.051	0.025	0.082**
	[0.030]	[0.034]	[0.029]	[0.032]	[0.020]	[0.037]
Internal credit score	0.051	0.085	0.063	0.097	−0.136	−0.107
	[0.139]	[0.157]	[0.139]	[0.157]	[0.088]	[0.137]
External credit score	−0.151	−0.172	−0.140	−0.161	−0.019	−0.033
	[0.103]	[0.110]	[0.101]	[0.108]	[0.062]	[0.077]
Startup	−0.017	0.015	−0.029	0.003	0.003	0.004
	[0.045]	[0.050]	[0.044]	[0.048]	[0.028]	[0.040]
Personal liability firm	−0.035	−0.070	−0.049	−0.092	−0.026	−0.058
	[0.073]	[0.082]	[0.070]	[0.076]	[0.050]	[0.040]
Bank loan	−0.137***	−0.134***	−0.134***	−0.132***	−0.015	0.036
	[0.035]	[0.046]	[0.034]	[0.045]	[0.028]	[0.071]
Physical collateral	−0.007	0.064	0.005	0.072		
	[0.099]	[0.130]	[0.100]	[0.127]		
Personal guarantee	0.015	−0.037	0.016	−0.038	−0.020	−0.021
	[0.065]	[0.079]	[0.065]	[0.078]	[0.049]	[0.049]
Third party guarantee	0.018	0.021	0.021	0.022	0.012	0.041
	[0.048]	[0.051]	[0.047]	[0.051]	[0.031]	[0.038]
Subordinated loans	0.026	−0.004	0.017	−0.014	−0.025	−0.029
	[0.043]	[0.043]	[0.043]	[0.043]	[0.019]	[0.026]
Covenant	0.042	0.025	0.047	0.026	0.008	0.006
	[0.050]	[0.054]	[0.050]	[0.053]	[0.028]	[0.035]
Observations	276	227	276	227	256	174
Industry fixed effects	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.158	0.215	0.169	0.235	0.182	0.419
N nonperforming loans	41	36	40	35	12	10

This table reports marginal effects of a probit regression of Eq. (3) in which the dependent variable is an indicator variable equal to one when a loan is nonperforming and equal to zero otherwise. The *Pre-pub. Percentage* is the fraction of the loan financed during the pre-publication phase. Definitions of all other variables are provided in Appendix Table A.1. In Columns (1) and (2) nonperforming is defined as a loan being more than 30 days overdue. In Columns (3) and (4) nonperforming is defined as a loan being more than 120 days overdue. In Columns (5) and (6) nonperforming is defined as a loan being written off. These estimations do not include estimates for *Physical collateral* because there are no firms with physical collateral whose loans are written off. *N nonperforming loans* indicates the number of loans that are nonperforming as of the end of 2019, consistent with the dependent variable used in each probit model and according to the definition of nonperforming loans used in each of the respective Columns (1) to (6). Industry fixed effects are included in Columns (2), (4) and (6). Robust standard errors are reported in square brackets and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

denied.

5.1. Logit models for small versus large P2P investments

From Table 2, Panel A, it is clear that 75% of the P2P investments are €1000 or less, with 48% of the investments being €500 and 27% being €1000. This is followed by a relatively long tailed distribution of larger investment amounts. In the analysis, the natural logarithm is taken to adjust for this power-law distribution. A simpler, possibly more robust way to consider the P2P investment decision, is to frame it as a choice between a small and a large investment. Therefore, I define the dependent variable as an indicator equal to one when the investment is larger than 1000 and equal to zero otherwise and re-estimate the main analyses presented in Table 4.

Appendix Table B.1 present the results of this robustness check. To mimic the main analyses, Columns (1) to (4) present conditional fixed effect logit estimates. The effect of *Pre-publication investment* is positive and significant in all specifications. The most extensive fixed effects specification in Column (4) shows that an investor is 2.5% more likely to make a large P2P investment (> €1000) when it occurs in the pre-publication phase. The sign of the control variables is mostly consistent with those in Table 4, although not all controls are consistently significant.

5.2. Firm control variables and SIC level 3 industry fixed effects

In the analyses in Table 4, if pre-publication investors would consistently invest larger or smaller amounts in firms with particular characteristics not yet controlled for, results on *Pre-publication investment* might be biased. Therefore, I redo the main analyses for a subsample of firms for which data on firm-level control variables is available. This excludes most firms with personal liability, which results in a sample with limited liability companies (LLCs) and corporations. Still the availability of firm-level data remains an issue, so I choose three variables that are relatively widely available. These are the *Current ratio*, the *Solvency ratio* and *Total assets* winsorized at the 99% level. The *Current ratio* is defined as current assets over current liabilities and the *Solvency ratio* is defined as total equity over total assets, both expressed as a fraction. In addition, I control for industry fixed effects using a more fine-grained SIC level 3 industry classification. Data on these ratios and the SIC level 3 industry classification of each firm is obtained from Bureau van Dijk's Amadeus database.

Appendix Table B.2 presents a replication of the analyses in Table 4 for a sample with firm control variables and industry fixed effects. It shows that the results on *Pre-publication investment* are comparable, in terms of positive sign and significance and the size of the effect is even a bit larger than in the baseline estimates in Table 4: around 28% instead of 21%. The *Solvency ratio* is positively related to P2P investments. The effect of the *Current ratio* is positive in selected specifications and the effect of *Total assets* is indeterminate across specifications. Finally, note that the effects of *Subordinated loans* and *Covenants* were insignificant in Table 4, but are now positive and significant, respectively. Taken together, the main result that P2P investors make larger investments in loans of borrowers they know personally appears to be robust to the inclusion of firm controls and more fine-grained SIC level 3 industry fixed effects.

5.3. Sample selection effects

The sample used in this paper is not randomly drawn from the applicant population, which implies that sample selection bias could be an issue. This has been studied in the seminal work by Boyes et al. (1989) and more recently by Jacobson and Roszbach (2003) and Marshall et al. (2010). If the platform's decision on which loans to select to publish online and which ones to reject is correlated with the error terms in my estimations, sample selection effects might be an issue. As indicated by Boyes et al. (1989), if the lender (P2P platform) would rely only on credit scores to select loans to finance, sample selection occurs according to a deterministic rule based on borrowers' observable characteristics such that sample selection does not bias the estimates. However, if the platform would also apply a subjective or non-systematic assessment and if this assessment would be correlated with the error terms in my estimations, sample selection could lead to biased estimates. This could be an issue, because the results in Table 3 show that at least for a firm's second loan application the platform bases its selection decision on its assessment of a firm's ability to tap its social network to obtain funding in the pre-publication phase.

To asses to what extent sample selection could be an issue, I consider as robustness check the approach suggested by Boyes et al. (1989) that is designed to avoid sample-selection bias in credit-scoring models. The procedure they suggest is to estimate a bivariate probit model, that consists of two simultaneous equations, one in which the dependent variable indicates the binary decision to provide a loan or not and another equation in which the dependent variable indicates whether a default occurred on a loan. In a robustness check I apply a similar procedure for my default analyses. First I consider the the sample of 850 loan applications from Column (1) of Table 3. Second, I estimate this equation together with Eq. (3) in a bivariate probit model.[20]

As indicated by Jacobson and Roszbach (2003), the size of the correlation between the errors of the two bi-variate probit equations provides an indication of the extent to which non-systematic increases in default risk are correlated with non-systematic tendencies to select loans to appear on the platform. In replicating the analyses from Table 7 using a bi-variate probit, the correlation between the error terms is relatively low when defaults are defined as more than 30 days or more than 120 days overdue, around 0.22, and somewhat larger for write-offs, around 0.65. Also the marginal effects of the default equation of the bivariate probit model are qualitatively very similar to those in Table 7. This indicates that the default analyses are not biased by the platform's selection decision and more generally it suggests that sample selection is likely not a major issue.

6. Conclusion

This paper studies the role of acquainted P2P investors in mitigating credit rationing in P2P lending to SMEs. I use a proprietary dataset provided by one of the largest Dutch P2P lending platforms on which investors personally acquainted with the borrower are allowed to invest before other investors. Considering the extensive margin, I find that when investors have shown with their first loan that they are able to finance a larger percentage using investments from acquaintances, this positively affects the probability of being granted a second loan by the platform.

Considering the intensive margin, I find that within investors' portfolios, investments are 20% larger when investors know the borrower personally. Next to portfolio investors, there are also one-off investors active on the platform. These investors are more likely to be personally acquainted with the borrower and their investments are around 30% larger. A similar effect applies to investors' first investment on the platform. These effects are identified based on borrowers' acquaintances investing first, but similar effects are observed for investors that likely also know the borrower but invest when the project is open to all investors.

On average 86% of the funding is obtained during the time the project is open to all investors, despite larger average P2P investments by acquaintances before that time. The platform urges loan applicants to tap their social network for funding before the project is published online, arguing that this makes it more likely that projects will eventually be fully funded. This is corroborated by

[20] Note that the results of these estimations are available upon request.

evidence in this paper, which shows that when a borrower's social network provides more financing before the project is open to all investors, this is subsequently associated with larger investments, as well as with substantially lower ex post defaults and a higher probability to receive a second loan from the platform. This suggests that it is rational for P2P investors and the platform to take the acquainted lenders investment decision into account.

These findings apply to the effect of social networks in a P2P lending platform with posted prices and thereby complement the literature based on auction lending platforms that finds social networks are associated with a higher likelihood of successful funding (Hildebrand et al., 2017) and lower default rates (Iyer et al., 2015; Lin et al., 2013). This literature also finds that in an auction setting social networks are associated with lower interest rates, whereas this paper shows that in a posted price setting they are associated with larger investments by other borrowers not acquainted with the lender.

These findings also complement those on optimal platform design. When moving to a system with posted prices, the informational efficiency associated with an auction system is reduced (Franks et al., 2020; Liskovich and Shaton, 2017). Instead, certain investors could benefit from having more information or better abilities to process information. Vallee and Zeng (2019) show that the latter can lead to adverse selection with platforms reducing the provision of information to all investors to maximize lending volumes. By contrast, the results in this paper suggest that less well informed investors could benefit from observing the investment decisions of better informed ones. Therefore, a platform design that guards against adverse selection (Vallee and Zeng, 2019), while allowing for information transmission between investors, might be able to attract more funding from the (less informed) crowd.

There are several limitations attached to the findings in this paper.[21] First, all projects that appear online are also completely funded (even though this need not be the case in the future). This implies that for the fully funded projects, smaller P2P investment amounts (intensive margin) are fully compensated by more P2P investors investing (extensive margin). So even though the exposure of informal P2P investors is larger, in the current sample firms are not overall credit rationed on the intensive margin because of smaller P2P investments. Second, the dataset is relatively small in terms of the number of loans and firms applying for a loan twice. In addition, firm control variables are not available for all firms. Third, acquainted investors are identified as those investors directly approached by the firm to invest in the project. This identification is imperfect because firms might also approach potential P2P investors to whom they are not personally acquainted.

Appendix A. Variable definitions and summary statistics

Appendix Table A.1
Variable definitions.

Variable	Definition
Selection (0/1)	Indicator equal to one when a loan is selected for appearance on the platform and zero otherwise.
P2P investment (th)	The loan amount invested by investor j in loan i in thousands of euros.
Pre-publication loan dummy (0/1)	An indicator variable that equals one when a P2P investment is made in the pre-publication phase and zero otherwise.
Pre-pub. Percentage (0–1)	The fraction of the requested loan amount financed in the pre-publication phase.
Internal credit score (0–1)	The credit score given by the platform to firm, measured on a scale of 0 to 1 with higher scores indicating less risk.
External credit score (0–1)	The credit score given by an external rating provider to the firm, measured on a scale of zero to one with higher scores indicating less risk.
Loan amount (mln)	The amount of the requested loan measured in millions of euros.
Maturity (years)	The maturity of the requested loan in years.
Interest rate (%)	The interest rate on the requested loan measured in percentage.
Startup (0/1)	Indicator equal to one when a firm is less than one year old, and zero otherwise.
Personal liability firm (0/1)	Indicator equal to one when the firm applying for a loan has personal liability, and zero otherwise.
Bank loan (0/1)	Indicator equal to one when a borrower already has an existing bank loan, and zero otherwise.
Physical collateral (0/1)	Indicator equal to one when a loan is secured by physical collateral, and zero otherwise.
Personal guarantee (0/1)	Indicator equal to one when a loan is secured by a personal guarantee, and zero otherwise.
Third party guarantee (0/1)	Indicator equal to one when a loan is secured by a third party guarantee, and zero otherwise.
Subordinated loans (0/1)	Indicator equal to one when existing loans are subordinated to the P2P loan, and zero otherwise.
Covenant (0/1)	Indicator equal to one when a loan contract features one or more covenants, and zero otherwise.
Negative mortgage statement (0/1)	Indicator equal to one when a loan contract features a negative mortgage statement that precludes borrowers from taking additional mortgages, and zero otherwise.
Number of projects per week	The number of projects open for investment on the platform per week.
Time trend	Time trend based on date of investment by P2P investor j in loan i.
Only one investment (0/1)	Indicator equal to one for investors who only ever invests in one loan on the platform, and zero otherwise.
First investment (0/1)	Indicator equal to one for each investor's first investment on the platform, and zero otherwise.
>30 days overdue (0/1)	Indicator equal to one when repayment on a loan is more than 30 days overdue, and zero otherwise.
>120 days overdue (0/1)	Indicator equal to one when repayment on a loan is more than 120 days overdue, and zero otherwise.
Write-off (0/1)	Indicator equal to one when a loan has been written off, and zero otherwise.
Business partner (0/1)	Indicator equal to one when an investor has found the platform via a business partner, and zero otherwise.
Loan officer (0/1)	Indicator equal to one when an investor has found the platform via a loan officer from the P2P lending platform, and zero otherwise.

(continued on next page)

[21] I thank two anonymous referees for pointing out these limitations.

Appendix Table A.1 (*continued*)

Variable	Definition
Friend (0/1)	Indicator equal to one when an investor has found the platform via a friend, and zero otherwise.
Loan applicant (0/1)	Indicator equal to one when an investor has found the platform via the loan applicant, and zero otherwise.
Media (0/1)	Indicator equal to one when an investor has found the platform via media channels, and zero otherwise.
Search engine (0/1)	Indicator equal to one when an investor has found the platform via an internet search engine, and zero otherwise.
Current ratio (0–1)	Ratio of current assets to current liabilities.
Solvency ratio (0–1)	Ratio of total equity to total assets.
Total assets (mln)	Total assets expressed in millions of euros and winsorized at 99%.

This table provides a definition for the variables used in the regression analyses. The *Current ratio*, the *Solvency ratio* and *Total assets* are obtained from Bureau van Dijk's Amadeus database. All other variables are generously provided by the P2P platform. Indicator variables are highlighted with (0/1), variables ranging from 0 to 1 are indicated as (0–1), percentages are indicated as (%) and millions and thousands of euros are indicated as (mln) and (th), respectively.

Appendix Table A.2
Summary statistics for pre- and post-publication samples.

	Mean	SD	Min	Max	N
Panel A: Pre-publication					
Log P2P investment	7.18	1.00	6.21	11.51	2713
P2P investment (thousands)	2.55	5.15	0.50	100.00	2713
Number of projects per week	3.53	1.31	1.00	6.00	2713
Interest rate (%)	7.28	0.56	6.00	9.00	2713
Maturity (years)	4.53	0.72	3.00	6.00	2713
Internal credit score (0–1)	0.61	0.16	0.24	0.90	2713
External credit score (0–1)	0.38	0.24	0.08	1.00	2713
Startup	0.27	0.44	0.00	1.00	2713
Personal liability firm (0/1)	0.25	0.43	0.00	1.00	2713
Bank loan (0/1)	0.12	0.33	0.00	1.00	2713
Physical collateral (0/1)	0.12	0.32	0.00	1.00	2713
Personal guarantee (0/1)	0.58	0.49	0.00	1.00	2713
Third party guarantee (0/1)	0.41	0.49	0.00	1.00	2713
Subordinated loans (0/1)	0.35	0.48	0.00	1.00	2713
Covenant (0/1)	0.47	0.50	0.00	1.00	2713
Negative mortgage statement (0/1)	0.06	0.24	0.00	1.00	2713
Only one loan dummy	0.32	0.47	0.00	1.00	2713
First loan dummy	0.41	0.49	0.00	1.00	2713
Panel B: Post-publication P2P investments					
Log P2P investment	6.79	0.70	6.21	12.32	34,446
P2P investment (thousands)	1.25	2.54	0.50	225.00	34,446
Pre-publication investment (0/1)	0.00	0.00	0.00	0.00	34,446
Number of projects per week	3.38	1.28	1.00	6.00	34,446
Interest rate (%)	7.37	0.52	6.00	9.00	34,446
Maturity (years)	4.53	0.74	3.00	6.00	34,446
Internal credit score (0–1)	0.59	0.16	0.24	1.00	34,446
External credit score (0–1)	0.39	0.24	0.08	1.00	34,446
Startup	0.27	0.44	0.00	1.00	34,446
Personal liability firm (0/1)	0.23	0.42	0.00	1.00	34,446
Bank loan (0/1)	0.13	0.34	0.00	1.00	34,446
Physical collateral (0/1)	0.13	0.34	0.00	1.00	34,446
Personal guarantee (0/1)	0.66	0.47	0.00	1.00	34,446
Third party guarantee (0/1)	0.42	0.49	0.00	1.00	34,446
Subordinated loans (0/1)	0.37	0.48	0.00	1.00	34,446
Covenant (0/1)	0.46	0.50	0.00	1.00	34,446
Negative mortgage statement (0/1)	0.08	0.27	0.00	1.00	34,446
Pre-pub. Percentage	0.12	0.10	0.00	0.98	34,446
Only one loan dummy	0.02	0.15	0.00	1.00	34,446
First loan dummy	0.08	0.28	0.00	1.00	34,446

This table reports summary statistics separately for a sample of pre-publication investments in Panel A and for a sample of post-publication investments in Panel *B. indicator* variables are highlighted with (0/1), variables ranging from 0 to 1 are indicated as (0–1), percentages are indicated as (%) and millions and thousands of euro's are indicated as (mln) and (th), respectively. Definitions of all variables are provided in Appendix Table A.1.

Appendix B. Robustness checks

Appendix Table B.1
P2P investment rationing and pre-publication: Logit estimations.

	(1)	(2)	(3)	(4)
Pre-publication investment	0.074**	0.017***	0.013**	0.025**
	[0.036]	[0.004]	[0.007]	[0.011]
Number of projects per week	−0.037***	−0.000	−0.000	0.001
	[0.004]	[0.000]	[0.000]	[0.001]
Time trend		−0.012***	−0.010**	−0.019**
		[0.002]	[0.004]	[0.008]
Interest rate			−0.002***	−0.001
			[0.000]	[0.001]
Maturity			0.001*	0.001
			[0.001]	[0.001]
Internal credit score			0.008	0.025*
			[0.005]	[0.014]
External credit score			0.011*	0.021**
			[0.005]	[0.010]
Startup			−0.003**	−0.007**
			[0.002]	[0.003]
Personal liability firm			−0.006**	−0.003
			[0.003]	[0.002]
Bank loan			−0.003**	−0.003
			[0.001]	[0.002]
Physical collateral				0.019**
				[0.009]
Personal guarantee				0.007**
				[0.003]
Third party guarantee				0.006**
				[0.003]
Subordinated loans				−0.000
				[0.001]
Covenant				0.002
				[0.002]
Negative mortgage statement				0.004
				[0.003]
Observations	20,549	20,549	20,549	20,549
P2P investor fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Pseudo R^2	0.036	0.191	0.209	0.214
Number of investors	957	957	957	957
Number of loans	239	239	239	239
Number of y = 1	6585	6585	6585	6585

This table reports marginal effects of conditional P2P investor fixed effects logit estimations. The dependent variable is a dummy equal to one when *P2P investment* is larger than €1000 and zero when *P2P investment* equals either €500 or €1000. *Pre-publication investment* is an indicator variable that equals one when a P2P investment is made in the pre-publication phase and equals zero otherwise. Definitions of all other variables are provided in Appendix Table A.1. Estimations apply to the full sample of pre- and post-publication P2P investments during the period 2014–2017. All estimations include industry fixed effects. Standard errors are clustered at the P2P investor level and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Appendix Table B.2
P2P investment rationing and pre-publication: Firm controls and SIC level 3 industry fixed effects.

	(1)	(2)	(3)	(4)
Pre-publication investment	0.247***	0.281***	0.280***	0.281***
	[0.040]	[0.034]	[0.035]	[0.034]
Number of projects per week	−0.091***	0.004	0.003	0.006
	[0.006]	[0.005]	[0.005]	[0.006]
Current ratio	0.270	0.548*	0.411	1.127**
	[0.329]	[0.303]	[0.459]	[0.470]
Solvency ratio	0.154***	0.097***	0.048**	0.021
	[0.021]	[0.018]	[0.019]	[0.020]
Total assets	−0.006	0.010***	0.002	−0.015***
	[0.004]	[0.004]	[0.004]	[0.005]
Time trend		−0.148***	−0.143***	−0.149***
		[0.006]	[0.006]	[0.007]
Interest rate			0.004	0.008
			[0.013]	[0.015]

(*continued on next page*)

Appendix Table B.2 (*continued*)

	(1)	(2)	(3)	(4)
Maturity			0.020***	0.032***
			[0.007]	[0.008]
Internal credit score			0.231***	0.245***
			[0.042]	[0.043]
External credit score			0.134***	0.089**
			[0.035]	[0.036]
Startup			−0.025	−0.029
			[0.029]	[0.030]
Personal liability firm			−0.136*	−0.178**
			[0.073]	[0.074]
Bank loan			−0.055***	−0.072***
			[0.017]	[0.021]
Physical collateral				0.047
				[0.047]
Personal guarantee				0.002
				[0.014]
Third party guarantee				0.013
				[0.017]
Subordinated loans				0.027**
				[0.014]
Covenant				0.025*
				[0.013]
Negative mortgage statement				0.209***
				[0.042]
Constant	6.634***	7.774***	7.434***	7.337***
	[0.032]	[0.052]	[0.128]	[0.149]
Observations	16,917	16,917	16,917	16,917
P2P investor fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.109	0.225	0.232	0.131
Number of investors	3289	3289	3289	3289
Number of loans	91	91	91	91

This table reports estimates of Eq. (2) in which the dependent variable is the natural logarithm of *P2P investment*. This robustness checks adds industry fixed effects and firm control variables: the *Current ratio*, the *Solvency ratio* and *Total assets* winsorized at 99%. Definitions of all other variables are provided in Appendix Table A.1. Estimations apply to the full sample of pre- and post-publication P2P investment during the period 2014–2017, to the extent firm level control variables and industry are available. Next to industry fixed effects based on a SIC level 3 industry classification, all estimations include P2P investor fixed effects. Standard errors are clustered at the P2P investor level and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

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