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ORIGINAL PAPER

Paralyzed by shock: the portfolio formation behavior of peer-to-business lending investors

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Abstract

We examine investor behavior on a leading peer-to-business lending platform and identify an investment mistake that we refer to as default shock bias. First, we find that investors stop investing in new loans and cease diversifying their portfolio after experiencing a loan default. The default shock significantly worsens the risk–return profile of investors' loan portfolios. The defaults investors experience are often not beyond what would have been expected from the information that was provided by the platform ex ante. Second, investment experience on the platform is related to better investment decisions in general, but it does not reduce the default shock bias. These findings have important implications not only for the behavioral finance literature but also more generally for new forms of Internet-based finance.

Keywords Behavioral finance · Investment bias · Peer-to-business lending · Crowdlending · Risk-adjusted return on capital · Diversification

JEL Classification G21 · G23 · L31 · M14

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1 Introduction

In this article, we examine whether investors on a crowdlending platform exhibit an investment mistake, which we refer to as a *default shock bias*. A default shock bias occurs when investors cease diversifying their portfolio after experiencing a default in their existing portfolio, thereby worsening the risk–return profile of the portfolio.

Our findings add to the emerging literature in the field of crowdlending, in which empirical research has investigated the role of signaling on funding success and subsequent loan performance (Serrano-Cinca et al. 2015; Iyer et al. 2016; Lin et al. 2016). Lin and Viswanathan (2016) analyze whether there is a home bias in crowdlending and find that it not only exists but also cannot be explained by rational factors alone. More generally, our research aptly provides a novel explanation for why investors underdiversify their portfolios. Using data from the peer-to-business lending platform *Zencap*, which comprises information on 2196 investors, we investigate whether the experience of a loan default affects the investment behavior of retail investors and consequently has a negative effect on the risk–return profile of their investment portfolios.

Peer-to-business lending represents a new asset class for retail investors (Moreno-Moreno et al. 2019). Before the rise of peer-to-business lending platforms, the possibility to invest in small corporate loans tended to be available only to institutional investors (Cumming and Hornuf 2021). In contrast with banks, which frequently confront a large number of loan applications and potential borrowers, investors on peer-to-business lending platforms can only invest in the limited number of loans listed online. Therefore, peer-to-business lending investors may have difficulties in obtaining a diversified portfolio within a short time frame. Instead, they need to invest continuously in new loan projects to benefit from diversification. Furthermore, many retail investors have no experience with corporate loan investments and do not receive professional investment advice (Zhang 2022).

A natural benchmark for the investment mistake under scrutiny is sophisticated lenders such as banks. The literature on credit risk modeling and bank management shows that banks build portfolios using the principle of diversification and that they employ quantitative credit risk models to steer their loan portfolios (Hull 2015). Such models explicitly consider probabilities of default and losses given default of loans, their contribution to the portfolio risk, and their profitability. Moreover, banks rarely adopt their investment strategies after experiencing a loan default, as defaults are a well-anticipated part of their business model.

Although retail investors sometimes behave in line with what is referred to as ‘the wisdom of the crowd’ (Kelley and Tetlock 2013), on an individual level they can make various investment mistakes (Calvet et al. 2009). In addition, returns of retail investors are often driven by sentiments (Kumar and Lee 2006; Bollen et al. 2011). Evidence shows that retail investors, among others, underdiversify their portfolios (Goetzmann and Kumar 2008; Calvet et al. 2009), adhere to a local

bias (Seasholes and Zhu 2010), and experience the disposition effect (Shefrin and Statman 1985; Odean 2002). Because retail investors are more prone to exhibiting all sorts of biases, they may also be more likely than professional investors to suffer from a default shock bias. Laudenbach et al. (2021) provide some initial evidence on this conjecture based on data from a large German brokerage firm that shows that individual investors change their trading and risk-taking behavior after bankruptcies of mostly small firms nearby. A possible explanation for this finding is the well-documented overweighting of more recent or salient information by individuals (Tversky and Kahneman 1973), which, according to prior research, also exists in financial and real estate markets (Hirshleifer 2001; Bordalo et al. 2013; Fekrazad 2019).

The digitalization of financial services and the recent advent of new financial technologies might help make investment mistakes less likely. Digital innovations have the potential to support retail investors in their investment decisions. However, thus far, many new investment tools are yet to prove their value. In crowdfunding markets, evidence on the performance of retail investors is also mixed. For example, investors in equity crowdfunding platforms generate comparatively high returns on paper (Signori and Vismara 2018) but may realize smaller returns after they exit their investments. Analyzing data from the crowdlending platform Funding Circle, Mohammadi and Shafi (2017) show that institutional investors perform much better than individual lenders in using the observable information on the platform website.

Crowdfunding is one of the fastest growing innovations in recent financial history. In most cases, investors buy fixed-income products and have clear financial motives when entering these new markets (Rau 2020). Peer-to-business lending is a specific form of crowdfunding. First, unlike in peer-to-peer lending, in which borrowers seek to refinance their personal debt or capital needs for consumption purposes, peer-to-business lending involves the financing of firms. To render this type of business model sustainable, borrowers are obliged to provide sophisticated information on their current financial situation. While in theory anybody can provide capital for these loan projects, doing so requires at least some degree of financial literacy to understand the projects for which funding is sought. Second, investments in peer-to-business lending are possible with sums as low as 100 EUR. This makes losses relatively easy to accept. Consequently, an investor should continue making investments and improving the diversification of his or her portfolio independent of a default in his or her portfolio.

Furthermore, we address the question whether investors' experience mitigates the *default shock bias*. Using Swedish data on retail stock and mutual fund investors, Calvet et al. (2007, 2009) show that financially more sophisticated and better educated investors are less likely to underdiversify their portfolios. They also suffer less from risky share inertia and the disposition effect. Given that peer-to-business lending is an activity that does not rely on financial advice and that investors themselves must actively identify and choose investment projects on these markets, we expect more experienced investors to have a better risk–return profile and to suffer from the default shock bias to a lesser extent.

We begin by developing our hypotheses on why investors may suffer from the default shock bias and why more experienced investors may suffer less from this

bias. Then, we describe our data and outline the methods we apply. We next execute a series of tests to determine whether the default shock bias exists. Our findings are robust to different model specifications and dependent variables. In particular, we test whether loan defaults reduce the amount of new investments, the probability of a new investment, and the number of new investments. If investors indeed are affected by a default shock bias, we expect all these measures to decrease and the risk–return relationship of the overall portfolio to worsen if a loan in the portfolio has defaulted. To measure the risk–return profile, we construct value-at-risk (VaR) measures and determine the risk-adjusted return on capital (RAROC). We then examine whether the risk–return profiles improve as investors gain more experience and suffer less from the bias. Our data show support for the conjecture that experienced investors are affected by the default shock bias to a greater extent than less experienced investors. Our results remain robust after estimating a matching model and to different RAROCs based on different VaR estimates.

Our study is among the first to investigate the portfolio formation in peer-to-business lending. We draw on data from a predecessor of the market leader Funding Circle, which has recently surpassed the mark of 15 bn USD lent worldwide. Not only does our research shed greater light on existing investment biases, but it also informs policy makers and regulatory initiatives such as the FinTech Action plan that was proposed by the European Commission (2018).

2 Theory and hypotheses

Before we outline our hypotheses on possible behavioral biases, we devise a theory about how investors should rationally build a loan portfolio in peer-to-business lending.

2.1 A short theory of rational loan portfolio formation

Given the nature of their business, banks can be regarded as professional investors in loan portfolios. They use credit risk models and sophisticated tools based on these models to control risks and the risk–return relationship in their loan portfolios (Hull 2015). Beyond the mere regulatory requirements, which instruct them how to calculate the VaR, they typically run their own internal credit risk models for portfolio-steering decisions (Hull 2015).

The risk capital of financial institutions is a scarce resource that is meant to cover the losses from lending activities. Because the risk capital should be used efficiently, it has become a standard approach to consider the RAROC, which measures the portfolio return over the risk capital employed, when it comes to the optimal portfolio formations of financial institutions (Hull 2015). The RAROC is calculated as a fraction, with the numerator being the expected profit of the portfolio (i.e. the interest charged less the refinancing costs and expected loan losses) and the denominator

being the VaR.[1] The RAROC can also be employed for the decision on the expansion or reduction of certain lines of business (Buch et al. 2011). Investors make investments that increase the RAROC and refrain from making those that reduce the RAROC. The literature on risk capital allocation has examined the question of how to allocate the overall risk capital to the existing business lines to calculate a RAROC for every line of business (Perold 2005). However, in our setting, retail investors only invest in peer-to-business loans, so the risk capital allocation to several business lines is not required.

Banks hold large loan portfolios, which are generally well-diversified (Casu et al. 2006). From a RAROC perspective, this is perfectly rational. While the numerator of the RAROC approximately remains the same when adding or removing average profitable loans, the denominator decreases with an increasing number of loans, at least as long as the portfolio is not well-diversified. If a bank holds only a small portfolio, it should diversify into new loans, as the expected return remains unchanged if the loan has an average interest margin, but the RAROC will increase as a result of a smaller VaR.

For banks, loan defaults are a part of daily business and are considered in the numerator and the denominator of the RAROC ex ante. Extending new loans is also part of banks' regular business, independent of whether old loans are paid back or in default (Roy 2016). If the number of defaults is higher than anticipated in the calculations leading to the RAROC, the bank will seldom cease to extend loans[2] but will instead update its credit risk model.

A rational investor on a peer-to-business lending platform should strive to optimize the RAROC because, rather than the money invested, the capital at risk is the scarce resource. If, for example, an amount of 10,000 EUR is invested in loans and the 99.5% portfolio VaR amounts to 4,000 EUR, these 4,000 EUR are at risk and cannot be used as a quantity for financial planning, whereas the remaining 6,000 EUR are paid back with almost certainty and are not regarded as being at risk. If the investment is undertaken in a leveraged manner, at least 4,000 EUR should be used as equity, whereas the remainder can be financed through less expensive debt. Rational behavior would now be deemed as receiving the highest possible returns per employed capital at risk (i.e. optimizing the RAROC). For the peer-to-business investors, who largely have portfolios consisting of only a few loans, the diversification benefit is that investing in a new loan with a modest portfolio weight usually decreases the VaR and increases the RAROC.

The majority of investors can be assumed to hold other assets classes as well. In the context of our analysis, we do not have information on the overall investor portfolio. However, even with significant investments in other asset classes, the overall VaR can still be decreased as long as the peer-to-business loan portfolio, which is at the center of our analysis, is not fully diversified (Dorfleitner and Pfister 2014). Moreover, from a behavioral finance perspective, investors might view

[1] Typically, the unexpected loss is used, or the portfolio VaR at a 99.5% or a 99.9% level less the expected loss.

[2] An example for such a case is a severe recession in which many loan defaults erode the equity of a bank.

their peer-to-business loan portfolio as part of one mental account and other asset classes as part of a different mental account. Das et al. (2010) indicate that optimizing the risk–return profile of one mental account enhances the risk–return profile of the aggregated mental accounts and, thus, the overall portfolio.

2.2 Hypotheses

Personal experience affects future investment decisions and helps explain the heterogeneity in portfolio choices. Consistent with reinforcement learning theory (see Cross 1973; Kaustia and Knüpfer 2008), investors tend to repeat investment strategies that have resulted in favorable outcomes and avoid investment strategies that have resulted in less favorable outcomes. Investment decisions can be affected by both the personal investment experience (Kaustia and Knüpfer 2008; Choi et al. 2009; Chiang et al. 2011; Andersen et al. 2019) and the broader economic circumstances an investor has experienced, such as a recession or particular labor market conditions (Malmendier and Nagel 2011; Knüpfer et al. 2017; Laudenbach et al. 2021). Recent experimental research shows that investment decisions are strongly influenced by probabilities of gaining and losing and that the desire to avoid negative outcomes is pronounced and widely applicable (Zeisberger 2022). Andersen et al. (2019) show that stock investors who have suffered losses from defaults during a financial crisis subsequently change their risk-taking behavior. We therefore conjecture that even in comparatively good economic conditions, a default in the crowdlending portfolio may be a reason to alter investment behavior. Investors who experience a loan default may rationally conclude that they have erred when trusting the probabilities of default that were calculated and reported by the platform for a given loan rating (see Appendix Table A1). Consequently, investors may rationally reduce their exposure or stop participating in the new peer-to-business lending market altogether.

As diversification in this new asset class can only be achieved over time as more loans are posted on the platform, peer-to-business loan investors initially tend to have small portfolios and therefore can be severely affected by a default in their loan portfolio. Investors may thus rationally cease investing in peer-to-business loans if the number of defaults they experience is high relative to the number of loans in their portfolio and the expected probabilities of default that can be obtained from the platform. By examining the credit ratings and the predicted probabilities of loan default, each investor can obtain an expected probability of default for his or her portfolio. We apply a binomial test to analyze whether investors may rationally update their beliefs about the probabilities of default after they observe a default and consequently cease investing in peer-to-business loans. In our context, the binomial test measures the hypothetical probability of loan defaults in a given portfolio on the basis of the probabilities of default reported by Zencap and tests whether the realized probability statistically differs from the expectations an investor should rationally have (Norušis 2011). We refer to such behavior as bias if investors suddenly stop investing in new loans after experiencing a loan default and the binomial test provides no evidence that the probabilities of default initially reported by

the platform require a re-assessment. Moreover, if refraining from investing, which implies that investors stop diversifying their portfolio, also has a negative effect on the risk–return profile of a crowdlending portfolio, we classify this behavior as irrational and, thus, as a bias.[3] We formulate a first hypothesis as follows:

H1: Investors can suffer from a *default shock bias* that decreases their inclination to further invest in new loans and thereby deteriorates their risk–return profile.

Investors tend to make better investment decisions on traditional capital markets as they gain more experience (Nicolosi et al. 2009; Korniotis and Kumar 2011). Likewise, peer-to-business lending investors who have carried out more investments should be able to improve their investment skills as they gain experience in this new asset class. Experienced investors are also less prone to behavioral biases. Feng and Seasholes (2005) and Dhar and Zhu (2006) show that the disposition effect, or the tendency of investors not to realize losses, decreases with investor experience and sophistication. Calvet et al. (2009) find that more experienced investors are less likely to suffer from the disposition effect and to underdiversify their portfolios. In a similar vein, experience in peer-to-business lending should not only reduce underdiversification but also increase the capability of investors to deal with a larger number of investment opportunities, which they can subsequently use to improve their risk–return profiles. Furthermore, in an early study, Calvet et al. (2007) find that more sophisticated households generate higher returns because they invest more efficiently and more aggressively. We therefore expect experienced peer-to-business lending investors to be less likely to weaken their risk–return profiles when they experience a loan default. Thus:

H2: Investors with more experience improve their risk–return profile.

H3: Investors with more experience suffer less from the *default shock bias*, which increases their inclination to further invest in new loans and thereby improves their risk–return profile compared with less experienced investors.

3 Data

Because we assess the behavior of lenders over time, we need to construct peer-to-business loan portfolios for each lender. To this end, we first describe the original data set of loan campaigns and their associated investors and then present information on the peer-to-business loan portfolios. Note that the sample of 2,129 investors is the relevant sample on which our investigation is based and not the set of loans or defaulted loans.

[3] In our sample, 297 investors were affected by a default. Using a 5% significance level, a binomial test indicates that 33 investors were rationally able to conclude that the loan defaults they experienced were beyond what they would have expected from the information provided by the platform. To test whether a default shock bias exists in peer-to-business lending, we subsequently excluded these 33 investors from the empirical analysis.

3.1 Summary statistics of loan data

In our analysis, we use data from Zencap, the first and the largest German peer-to-business lending platform. Cumming and Hornuf (2021), who also study this platform, provide evidence that when making an investment decision, the crowd mostly relies on ratings that were conveyed by the platform, but not more sophisticated financial information such as the firm's equity or liabilities. They conclude that investors seem to believe that issues of adverse selection are largely irrelevant in these markets. We rely on the same data from the time of the inception of the platform in March 2014 until the merger of Zencap with the platform Funding Circle in November 2015. Since the merger, Funding Circle has become one of the world's leading crowdlending platform for corporate loans.

The platform facilitates loans for small and medium-sized firms. These firms post their loan projects with the requested principal amount as well as several company characteristics and financial information on the platform. Consistent with the estimated default risk, the platform assigns a risk rating ranging from A (best) to D (worst) and the corresponding interest rate to each loan. Investors can invest in the loan campaign within a pre-defined funding period.[4] If the invested sum reaches the principal amount at the end of the funding period, a loan campaign is deemed successful and the loan is funded. After receiving the funds, the borrowers re-pay their loans in the form of fixed monthly annuities.

During the observation period, 414 borrowers applied for a loan via the platform. Definitions of all variables appear in Table 1. Tables 2 and 3 show the descriptive statistics of these borrowers and the investors backing the loans. On average, the platform assigned a nominal interest rate of 7.4% to these borrowers. Not all of the firms were profitable. The net income ranges between a minimum of −346,300 EUR and a maximum of more than 1m EUR. In total, 367 loan applications were successful. Unlike on many equity crowdfunding platforms (Hornuf et al. 2018; Coakley et al. 2021), none of the borrowers engaged in a follow-up funding round on Zencap. The platform does not provide any particular information on the repayment status of the loans but states that within the observation period, only a handful of loans defaulted. We used the forum P2P-kredite.com to research which loans defaulted during the observation period. We observe five borrowers who declared insolvency before November 2015, or 1.4% of all successfully funded borrowers.[5] The number of insolvencies on P2P-kredite.com corresponds to the number of defaults Zencap reported to us, which gives us confidence that we have identified all loan defaults during our observation period. While by now more borrowers may have defaulted, we do not consider the defaults of successfully funded borrowers who declared insolvency after the observation period ended. This is because any default after November 15, 2015,

[4] In general, the funding period lasts 21 days. However, borrowers can extend the funding period to a maximum of 61 days.

[5] This figure is rather low compared with typical default rates in peer-to-peer-lending platforms. Dorfleitner et al. (2016) report default rates in peer-to-peer lending of 12 % to 14 %.

Table 1 Definition of variables

Borrower Variables	
EBIT	Earnings before interest and taxes of the firm applying for the loan project in EUR.
Employees	Number of employees in the firm applying for the loan project.
Equity	Equity capital of the firm applying for the loan project in EUR.
Foundation Year	The year in which the firm applying for the loan project was established.
Lenders	Total number of lenders backing a loan project.
Loan Duration	Duration of the loan in months.
Loan Rating	Rating of the loan as assigned by the platform. Ranging from A+ to D.
Net Income	Net income of the firm that applying for the loan project.
Investor Variables	
Age	Age of the investor at the time of the investment.
Gender	Gender of the investor (1 = female).
Portfolio Variables	
#Campaigns	Number of simultaneously active loan projects on the platform each month.
Distance	Mean distance of all active loan projects during a given month and the respective investor in kilometers.
ExpReturn	Expected return of the portfolio calculated as the weighed average of the expected returns of the loan projects the investor invested in each month. The expected return for each loan is calculated as the nominal yield times the invested amount minus the expected loss as described by the rating class.
Insolvency	Dummy variable indicating whether the borrower declared insolvency during the previous month (1 = insolvency).
#Investments	Total number of loans an investor invested in during the respective month.
Min Distance	Minimum distance of all active loan projects each month and the investor in kilometers.
NewInvAmount	Amount of new investments during the respective month in EUR.
NewInvestment	Dummy variable indicating whether the investor carried out at least one new investment during the respective month.
#NewInvestments	Number of new investments an investor carried out during the respective month.
Nominal Yield	Nominal yield of the loan project as assigned by the platform.
Principal Amount	Principal amount of the loan, in EUR.
RAROC	Risk-adjusted return on capital calculated as the expected return of the portfolio divided by the VaR of the portfolio.
Campaign Success	Dummy variable indicating whether the campaign was successful (1 = successful).
ToP	Time on platform of each investor in months. Calculated as the end of the current month minus the account creation date.
VaR	Value at risk of the portfolio. The VaR is a relative measure and is calculated as the risk capital over the total invested amount each month. A 99.5% VaR is used if not stated otherwise. For a detailed calculation of the VaR, see the Appendix.

would not have affected the investor behavior during our sample period. In total, 2,129 investors backed the loans that were available via the platform. Within the observation period, 297 of these investors experienced at least one loan default. Overall, 89% of the investors are male, and the average investor is 41 years of age.

Table 2 Descriptive statistics of the metric variables of borrowers and investors

Variable	N	Mean	SD	Min	Max
Borrower Characteristics					
EBIT	414	93,367.33	127,433.80	−379, 600	1,291,700
Employees	414	17.55	28.51	1	300
Equity	414	160,649.70	519,186.70	−1, 214, 900	7,492,967
Foundation Year	414	2001	17.19	1784	2014
Lenders	414	84.70	47.28	4	302
Loan Duration	414	34.01	13.80	6	60
Net Income	414	66,744.35	101,940.60	−346, 300	1,112,533
Nominal Yield	414	0.0738	0.0188	0.0408	0.1564
Principal Amount	414	72,183.57	46,889.03	10,000	250,000
Campaign Success	414	0.89	0.31	0	1
Investor Characteristics					
Age	2,129	40.89	12.57	18.44	107.16

Variables are defined in Table 1

Table 3 Descriptive statistics of the categorical variables of borrowers and investors

Borrower Characteristics						
Loan Rating	A+	A	B	C	C−	D
Absolute frequency	21	86	196	96	15	0
Relative frequency	5.07%	20.77%	47.34%	23.19%	3.62%	0.00%
Insolvency	1 (Yes)	0				
Absolute frequency	5	362				
Relative frequency	1.36%	98.63%				
Campaign Success	1 (Yes)	0				
Absolute frequency	367	47				
Relative frequency	88.65%	11.35%				
Investor Characteristics						
Gender	1 (Yes)	0				
Absolute frequency	239	1,890				
Relative frequency	11.23%	88.77%				

In general, borrower variables have 414 observations. For *Insolvency*, only the 367 successfully funded borrowers are considered. Investor variables have 2,129 observations. Variables are defined in Table 1

3.2 Construction and summary statistics of portfolio data

Because we are interested in investor-specific VaRs and RAROCs and annuity payments only occur once a month, our time dimension consists of 20 time intervals, each spanning one month. Investors on Zencap receive repayments in the middle of each calendar month. Our time intervals therefore start and end halfway through each calendar month starting on April 15, 2014, and ending on November 15,

Table 4 Descriptive statistics of the portfolios

Variable	N	Mean	SD	Min	Max
#Campaigns	42,580	34.75	16.63	6	61
Distance	42,580	320.32	260.84	149.22	7972.41
ExpReturn	20,398	0.06	0.01	0.03	0.13
Insolvency	20,398	0.0608	0.24	0	1
#Investments	20,398	10.32	17.18	1	315
Min Distance	42,580	55.31	259.53	0	7703.35
NewInvAmount	22,087	558.50	2014.29	0	130,000
NewInvestment	22,087	0.36	0.48	0	1
#NewInvestments	22,087	1.31	2.99	0	41
RAROC	20,398	0.23	0.17	0.03	1.24
ΔRAROC	18,265	0.02	0.05	−0.27	0.43
ToP	22,087	6.7015	4.82	0	19.87
VaR	20,398	0.42	0.32	0.04	1

Monthly data for 2,219 investors and 20 sample months. Variables are defined in Table 1. As many investors did not create their accounts at the time Zencap was launched but only over time, several portfolio variables are not available for all investors and sample months

2015. The monthly time intervals end immediately after the repayment date. After determining the 20 time intervals, we calculated how much money an investor had invested in his or her peer-to-business loan portfolio, considering every new investment undertaken as well as repayments from annuities during the respective month. As a result, we derived a peer-to-business loan portfolio for each investor and month, with the 20 monthly observation dates comprising the time dimension and the investor comprising the cross-sectional dimension of our data set.

Table 4 shows the descriptive statistics of the portfolio variables.[6] The investment behavior varies greatly within the group of investors and the respective month. Investors decided to invest in at least one new loan project every three months or in 36% of the monthly time intervals. The mean amount investors pledged is 559 EUR and is significantly above the minimum investment of 100 EUR that Zencap requests for a single investment. The number of new investments in loan projects ranges from 0 to 41 per month. On average, investors hold portfolios consisting of 10 different loans. The distribution of loan holdings is right skewed with a median of 5 investments (2 investments in the 25% quartile and 11 investments in the 75% quartile); that is many investors invest in a few loans, while a few investors invest in many loans. However, to achieve a well-diversified portfolio (i.e. one in which the

[6] The difference in the number of observations for some variables is due not to unobtainable information but to the absence of some observations, because some investors had not yet registered on the platform when Zencap was launched. Moreover, some observations of portfolio variables are not available for all investors and sample months. The variable $\Delta RAROC$ has fewer observations than RAROC, because at least two sample periods are necessary to calculate a change, which is not the case if an investor joined the platform during the last month.

Table 5 Descriptive statistics of the change of the RAROC

Variable	N	Mean	SD	Min	10th Pctile	Median	90th Pctile	Max
NewInvestment = 1								
ΔRAROC	6,422	0.0461	0.0714	−0.2676	−0.0465	0.0453	0.1305	0.4257
NewInvestment = 0								
ΔRAROC	11,843	−0.0007	0.0115	−0.1928	−0.0033	0	0.0004	0.2254

portfolio risk scales linearly with portfolio size), a portfolio of several hundred loans would be necessary.[7]

Diversification seeks to smooth out unsystematic risk events in a portfolio, which is impossible to achieve with the peer-to-business loan universe on a single platform. For example, the diversification by asset class and foreign asset diversification are impossible for an investor who is only active on Zencap. Our empirical analysis is therefore more modest and focuses on the risk–return profile of investors, which compares the estimated return with the risk of loss of a given portfolio. In accordance with modern portfolio theory, an improved risk–return profile, however, will move the portfolio of a lender closer to the efficiency frontier. We measure the effect of the investment decisions on the risk and return of the portfolio through several variables. The VaR at a 99.5% confidence level measures the relative loss risk of the portfolio. The descriptive analysis of the VaR shows that, on average, 99.5% of the losses will not exceed 42% of the portfolio value. The average expected return of the portfolios equals 6%. To measure the risk–return profile we combine the two measures and obtain the RAROC, calculated as the expected return of a portfolio over the VaR. The Appendix provides a detailed explanation of the portfolio VaR calculations and the calculation of the RAROC. To analyze the development of the risk–return profile over time, we calculate changes in the RAROC from the previous to the current month ($\Delta RAROC$). A positive $\Delta RAROC$ indicates an improvement of the risk–return profile, while a negative $\Delta RAROC$ implies a deterioration of the risk–return profile.

As Table 5 shows, the change of the RAROC is, on average, positive when investors make new investments, but in 17% of the cases, new investments result in a negative change of the RAROC. Investing in new loans will, in most cases, have a positive effect on the risk–return profile, but in some cases, it can have a negative or zero effect.

For every month and investor, we determine the investor's experience on the platform. We therefore obtain the number of loans in which an investor had invested during the previous month ($\#Investments_{i,t-1}$). Although the contribution of additional investments to the risk–return profile becomes smaller with an increase in

[7] Using numerical examples, Dorfleitner and Pfister (2014) show that to obtain constant per unit risk, which can be interpreted as having a well-diversified portfolio, the minimum number of loans ranges from approximately 200 (VaR at 95% level and loan probability of default of 5%) to more than 500 (VaR at 99.9% level and loan probability of default of 10%).

portfolio size, we still expect that additional investments positively contribute to the risk–return profile for all investors. Regarding the loan defaults, the descriptive analysis suggests that on 1% of the monthly intervals, an investor has already experienced at least one loan default. All five defaults on the platform occurred in the second half of the observation period. The first borrower defaulted on the 11th sample month, the second on the 18th sample month, and the last three borrowers on the 19th sample month. As a robustness test for a baseline specification, we also investigate the competitive environment of the loan campaigns. On average, 34 loan campaigns were active in a given month (i.e. 34 investment possibilities were available to lenders). While the average distance between these active loan projects and an investor amounts to more than 300 km, the distance between the closest active loan campaign and an investor is, on average, only 55 km.

4 Method

To examine which factors influence investment behavior, we estimate the effects of several covariates on the investment decision of each investor i in each month t. In line with our hypotheses, we specify the following regression equation:

$$\begin{aligned} InvestmentDecision_{i,t} = {} & \alpha + \beta_1 \cdot Insolvency_{i,t-1} + \beta_2 \cdot \#Investments_{i,t-1} \\ & + \beta_3 \cdot Distance_{i,t} \\ & + \beta_4 \cdot ToP_{i,t} + \beta_5 \cdot Gender_i + \beta_6 \cdot Age_{i,t} \\ & + \beta_7 \cdot TimeFE_t + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where *Investment Decision* represents one of three different dependent variables: *ln(NewInvAmount)*, *NewInvestment*, and *#NewInvestments*. For the natural logarithm of the newly invested capital (*NewInvAmount*), we estimate ordinary least squares (OLS) regressions. In what follows, we refer to the regression using the dependent variable *ln(NewInvAmount)* as our *baseline specification*. *NewInvestment* is a binary variable that equals 1 if the investor makes at least one new investment during the respective month. We use a logit regression for this specification and report average marginal effects. Finally, because the number of new investments is a count variable and our data suffer from over-dispersion, we use a negative binomial model to examine the effect of the covariates on *#NewInvestments*. We report incidence rate ratios, which can conveniently be interpreted as multiplicative effects. Because fixed effects panel estimators generally do not allow us to identify time-invariant variables such as gender, we pool our observations and cluster the standard errors at the investor level, to account for the fact that the investment decisions of a particular investor are not independent across time.

To test H1, we include the explanatory variables $Insolvency_{i,t-1}$, which measures whether an investor experienced at least one loan default during the previous month. If this variable is negatively related to new investments, we will have some

initial evidence in favor of a default shock bias.[8] Furthermore, to assess the effect of investor experience as outlined in H2 and H3, we add the number of loans in the investor's portfolio during the previous month ($\#Investments_{i,t-1}$). To test H3, we estimate specifications that include an interaction between $\#Investments_{i,t-1}$ and $Insolvency_{i,t-1}$.

Prior research indicates that crowdlending investors may have a local bias (Lin and Viswanathan 2016). Therefore, we include the average distance between the investors and the active loan campaigns during each month ($Distance_{i,t}$) as a control variable. Moreover, we control for the time investors have been registered on the platform in month ($ToP_{i,t}$), their age, and their gender. The first variable could be taken as another—but arguably weak—proxy for experience, because some investors have been registered on the platform for a considerable amount of time, but never invested or only explored the platform for academic reasons. Prior research has shown that investor age an gender influence risk taking and investment behavior (Bajtelsmit et al. 1999; Barber and Odean 2001; Agnew et al. 2003). Furthermore, to account for general time trends we include time fixed effects for each month (*Time FE*), which capture, for example, the current number of loans offered on the platform. As a robustness test, we explicitly replace the time fixed effects with the number of simultaneously active loan projects on the platform during the current month ($\#Campaigns_{i,t}$).

In a next step, we analyze the determinants of changes in the risk–return profile of the portfolios. In particular, we are interested in whether additional investments improve an investor's risk–return profile in general. We use the investor data to determine the changes of the RAROC for investor i in a given month t and estimate the following regression equation:

$$\begin{aligned} \Delta RAROC_{i,t} = {} & \alpha + \beta_1 \cdot InvestmentDecision_{i,t} + \beta_2 \cdot Insolvency_{i,t-1} \\ & + \beta_3 \cdot \#Investments_{i,t-1} \\ & + \beta_4 \cdot Distance_{i,t} + \beta_5 \cdot ToP_{i,t} + \beta_6 \cdot Gender_i + \beta_7 \cdot Age_{i,t} \\ & + \beta_8 \cdot TimeFE_t + \epsilon_{i,t}, \end{aligned} \tag{2}$$

While our explanatory variables could have a direct effect on $\Delta RAROC$, an alternative explanation for our results on changes in the RAROC may be that the variable *Investment Decision* mediates the effects of the explanatory variables on $\Delta RAROC$. In other words, some of the effects of the explanatory variables on the dependent variable $\Delta RAROC$ could pass through *Investment Decision* as a mediator variable. Not including *Investment Decisions* in the model that explains $\Delta RAROC$ would then almost certainly result in overestimating the coefficients of the explanatory variables. We are therefore interested in the extent to which the effects of the explanatory

[8] Our identification strategy and the power of our tests do not rely on five loan defaults, but on 297 of the 2129 investors who were affected by insolvencies. A lack of power cannot explain our results.

variables pass through *Investment Decision* in our baseline specification and estimate several mediation models.[9]

5 Results

5.1 Determinants of new investment decisions

In the first part of our analysis, we investigate which factors drive investors to make new investment decisions. Table 6 displays the results. For the first three specifications, we find that *Insolvency* is significantly and negatively related to new investment decisions, which suggests that investors indeed cease investing after experiencing a default. The economic significance of the variable of interest is also high. All else being equal, our baseline specification suggests that investors who have experienced a default invest 68.3% less[10] than investors who have not experienced such an event during the previous month. This result provides strong evidence for H1 that investors inherit a default shock bias and cease investing in loans on the platform after experiencing a default.[11] Unlike banks, investors update their expectations about the probability of default of the peer-to-business loans offered on the platform after having experienced a single default and consequently adapt their investment behavior. Because we consider only investors who cannot be assumed to rationally update their expectation of the probabilities of default based on our binomial test, we regard this behavior as irrational.

Furthermore, we regard the number of previously invested loan projects as a proxy for experience and investor sophistication and find that the variable $\#Investments_{t-1}$ is significantly and positively related to new investment decisions for all specifications. This suggests that investors who have already invested in more loans and thus are more experienced are more likely to invest further. More precisely, our baseline specification indicates that investors who had invested in one additional loan during the previous month were 7.5% more likely to invest again.[12] This result provides initial evidence for H2 that experienced investors invest more to improve their risk–return profile.

Moreover, we include an interaction between *Insolvency* and investor experience in our baseline specification. Table 6 shows the results. The interaction between $\#Investments_{t-1}$ and *Insolvency* is significant and negative, which suggests that experience worsens the effect of the default shock if an insolvency occurs. Using the interaction term in Table 6, we plot predictions in Fig. 1. While the probability of

[9] For an overview of this still infrequently used approach in the finance literature, see MacKinnon et al. (2007).

[10] Calculated as $e^{-1.16} - 1 = -68.3\%$.

[11] Although the coefficient of *Insolvency* is positive but non-significant in specification (4), in combination with the interaction term, a default has a negative effect on new investments when investors have five or more loans in their existing portfolio: $0.2590 + 5 \cdot (-0.0555) = -0.0164$. Table 4 indicates that the mean number of loans in investors' portfolios is 10.

[12] Calculated as $e^{0.0720} - 1 = 7.5\%$.

Table 6 Results of the baseline regressions, as specified in Section 4

Dependent Variable	(1) ln(NewInvAmount)	(2) NewInvestment	(3) #NewInvestments	(4) ln(NewInvAmount)
$Insolvency_{t-1}$	−1.1583***	−0.2352***	0.5345***	0.2590
	(0.1489)	(0.0325)	(0.0646)	(0.1668)
$\#Investments_{t-1}$	0.0720***	0.0145***	1.0668***	0.0923***
	(0.0060)	(0.0007)	(0.0034)	(0.0056)
ln(Distance)	−0.1053	−0.0173	0.9729	−0.0805
	(0.1808)	(0.0230)	(0.1006)	(0.1697)
ToP	−0.1140***	−0.0223***	0.8782***	−0.1196***
	(0.0079)	(0.0013)	(0.0066)	(0.0075)
Gender	−0.5675***	−0.0783***	0.6994***	−0.5217***
	(0.1054)	(0.0179)	(0.0654)	(0.0993)
Age	0.0276***	0.0026***	1.0115***	0.0262***
	(0.0034)	(0.0004)	(0.0019)	(0.0032)
$\#Investments_{t-1}$ · $Insolvency_{t-1}$				−0.0555***
				(0.0049)
Constant	3.4991***		1.0635***	3.3962***
	(1.1195)		(0.0393)	(1.0656)
Time FE	Yes	Yes	Yes	Yes
N	17,930	17,930	17,930	17,930
Pseudo-/ Adj. R^2	0.1775	0.1623	0.0790	0.1952

The dependent variable is the natural logarithm of the amount an investor newly invested (OLS, specification (1)), a dummy variable indicating whether the investor carried out at least one new investment (logit, specification (2)), and the number of investments an investor newly undertook (negative binomial, specification (3)). All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. Coefficients reported are average marginal effects for the logit model and incidence rate ratios for the negative binomial model. In specification (4), we include an interaction between Insolvency and $\#Investments_{t-1}$. Investors who could rationally conclude that the probabilities of default are higher than would have been expected froma binomial test (significance level of 5%) are excluded from the analysis. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

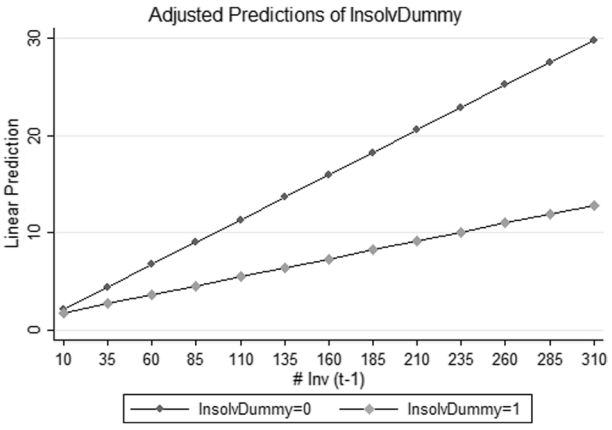

Fig. 1 Interaction term $Insolvency_{t-1}$ ×$\#Investments_{t-1}$: predictions

making new investments increases for all investors with more experience, the effect is weaker for investors who have encountered a default.

When assessing our control variables, we find several notable effects as well. The results indicate that the time an investor has been registered on the platform is negatively related to new investment decisions. Investors generally tend to invest more when they are new to the platform, while their propensity to continue investing declines over time. There are several plausible explanations for this type of investment behavior. Investors could begin investing by using a certain amount of capital that was previously set aside to test the platform, often referred to as *play money*. Subsequently, they observe how their investments develop without investing any additional capital. If they receive sufficient returns from the play money, they reinvest by using these returns for new investments. We find some evidence to support this kind of non-linear relationship for the time investors have spent on the platform when we include the squared term of *ToP* in Table A3 in the Appendix. However, if we test whether the investment behavior is driven by fresh liquidity and consider the aggregated loan repayments an investor has received, we find no evidence of such a relationship; on the contrary, the aggregated loan repayments are even negatively correlated with new investment decisions as Table A4 in the Appendix indicates, which is in line with our previous observation that investors generally cease to invest over time. Thus, a budget effect (i.e. the likelihood that the default shock bias is driven by less liquidity from loan repayments due to the defaulting loans) is an unlikely explanation in our setting.

Moreover, the data show that women and younger investors have a lower propensity to undertake new investments. The first result may be because women generally tend to trade less and are more risk averse than men (Barber and Odean 2001; Dwyer et al. 2002; Agnew et al. 2003). The lower propensity to invest by younger investors is consistent with the literature, which shows that older people tend to trade more (Agnew et al. 2003). Age may also serve as a proxy for wealth, as wealthier individuals invest more (Bajtelsmit et al. 1999). The coefficient of the mean distance of the active loan projects, however, is not significantly different from zero. This holds true for all three dependent variables. Thus, we find no evidence that geographic distance plays a role in peer-to-business lending.

5.2 Drives of changes in the risk–return profile of the portfolios

To investigate whether the investment behavior resulting from a loan default constitutes a bias, we examine how investment decisions, experience, and other controls affect the risk–return profile of the investors. As a starting point, we estimate four different specifications with $\Delta RAROC$ as the dependent variable. Table 7 displays the results. Specifications (1) and (2) include all explanatory variables from Table 6, except the *Investment Decision* during the current month. In specification (3) and (4), we add the *Investment Decision*. Specification (1) indicates that *Insolvency* has a significant, negative impact on $\Delta RAROC$, which serves as evidence of the default shock bias. In specification (2), *Insolvency* is positive, but in combination with the

Table 7 OLS regression results for changes in the RAROC

Dependent Variable	(1) ΔRAROC	(2) ΔRAROC	(3) ΔRAROC	(4) ΔRAROC
ln(NewInvAmount)			0.0069***	0.0070***
			(0.0002)	(0.0002)
Insolvency_{t-1}	−0.0060***	0.0002	0.0020*	−0.0016
	(0.0012)	(0.0016)	(0.0011)	(0.0012)
$\#\text{Investments}_{t-1}$	0.0003***	0.0004***	−0.0002***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(Distance)	−0.0010	−0.0008	−0.0002	−0.0003
	(0.0017)	(0.0017)	(0.0012)	(0.0012)
ToP	−0.0022***	−0.0023***	−0.0015***	−0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Gender	−0.0043***	−0.0041***	−0.0004	−0.0005
	(0.0011)	(0.0010)	(0.0007)	(0.0007)
Age	0.0002***	0.0002***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\#\text{Investments}_{t-1} \cdot \text{Insolvency}_{t-1}$		−0.0002***		0.0001***
		(0.0000)		(0.0000)
Time FE	Yes	Yes	Yes	Yes
N	17,882	17,882	17,882	17,882
Adj.R^2	0.0590	0.0603	0.2130	0.2135

Standard errors are clustered on investor level and reported in parentheses. Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. All variables are defined in Table 1. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

interaction term, it becomes negative again.[13] However, the significant, negative effect of *Insolvency* ceases to exist when we include *Investment Decision* in specifications (3) and (4). We therefore conjecture that the effect of *Insolvency* may pass through *Investment Decision* and consequently estimate a mediation model.

Performing a mediation model involves calculating three regressions. First, the dependent variable Δ*RAROC* is regressed on the explanatory variable *x*, and the regression coefficient of *x* should be significant (see Table 7, specification (1)). If there is no significant relationship between *x* and the explanatory variable, the conditions for a mediation model are not met. Second, our mediator variable *ln(NewInvAmount)* is regressed on *x* (see Table 6, specification (1)). Again, *x* should show a significant effect. For a mediation to occur, in a third model on Δ*RAROC* the regression coefficient of *Investment Decision* must be significant, and the coefficient

[13] Although the coefficient of *Insolvency* is positive but non-significant in specification (2), in combination with the interaction term, a default has a negative effect on new investments when investors have more than one loan in their existing portfolio: $0.0002 + 2 \cdot (-0.0002) = -0.0002$. Table 4 indicates that the mean number of loans in investors' portfolios is 10.

Table 8 Results of a mediation analysis explaining changes in RAROC

Effect	Mean	95% Confidence Interval	
$Insolvency_{t-1}$			
Average mediation	−0.00797	−0.00928	−0.00674
Average direct effect	0.00199	−0.00096	0.00468
% of total effect mediated	1.33612	0.84882	2.71226
$\#Investments_{t-1}$			
Average mediation	0.00050	0.00047	0.00052
Average direct effect	−0.00015	−0.00020	−0.00011
% of total effect mediated	1.44712	1.27226	1.68157
Age			
Average mediation	0.00019	0.00017	0.00021
Average direct effect	−0.00003	−0.00008	0.00002
% of total effect mediated	1.17623	0.86891	1.86408
Gender			
Average mediation	−0.00391	−0.00481	−0.00305
Average direct effect	−0.00036	−0.00243	0.00153
% of total effect mediated	0.91297	0.58684	1.85755
ToP			
Average mediation	−0.00078	−0.00086	−0.00071
Average direct effect	−0.00145	−0.00161	−0.00130
% of total effect mediated	0.35056	0.32385	0.37779

Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. N =17.882. The variables are defined in Table 1

of x must be smaller in absolute terms than that in the first model (see Table 7, specification (3)). We find that each of the three conditions holds for our explanatory variables *Insolvency*, $\#Investments_{i,t-1}$, $ToP_{i,t}$, *Gender*, and *Age*, which is strong evidence that these variables affect $\Delta RAROC$ by passing through *ln(NewInvAmount)*.

To quantify the extent of mediation and the direct effect of the explanatory variables, we report the average mediation, the average direct effect[14] (i.e. the remaining non-mediated effect), and the percentage of the total effect mediated in Table 8. The results of the mediation model indicate that mediation occurs for most explanatory variables and that this mediation is statistically significant at the 5% level. More precisely, the percentage of the total effect mediated is 35% for $ToP_{i,t}$ and 91% for *Gender*, whereas the mediated effect exceeds the direct effect and thus changes the direction of the relationship between the dependent and explanatory variables for *Insolvency*, $\#Investments_{i,t-1}$, and *Age*. For example, in the case of *Insolvency*, while we find a positive and statistically weak direct effect for loan defaults on $\Delta RAROC$ in specification (3) of Table 7, the actual effect runs through *ln(NewInvAmount)*.

[14] The direct effect in Table 8 corresponds to the coefficients of specification (3) in Table 7.

Table 8 shows that when a default occurs, investors cease to invest, which in turn worsens their risk–return profile to an even greater extent than the direct effect. As a result, the overall effect of *Insolvency* on $\Delta RAROC$ is negative. Thus, we should directly interpret the effect of the explanatory variables not on $\Delta RAROC$ but on the variable *ln(NewInvAmount)*.

To examine H2 and H3, we investigate the effect of experience on both the investment behavior and the risk–return profile. The results in Table 6 show that the number of loan projects in which investors have previously invested is significantly and positively related to new investment decisions, indicating that more experienced investors invest more. Moreover, the results in Table 7 show that more experienced investors also improve their risk–return profiles, in support of H2. For H3, we obtain no evidence to support the conjecture that the effect of the default shock bias is weakened with increased experience. Rather, the results in Table 6 show the opposite. To a large extent, experienced investors cease investing after experiencing a default shock. This behavior leads to an even stronger deterioration in the risk–return profile of the portfolio.

In summary, the investment behavior on a leading peer-to-business lending platform suggests that investors react to borrower defaults by ceasing to diversify their portfolios. Initially, we find a direct effect of insolvencies on the risk–return profile. By applying a mediation analysis, we find that only when investors cease investing does a borrower's default affect the risk–return profile of the investor's portfolio. In other words, the reaction to a default constitutes a bias because investors cease investing after experiencing a default and consequently reduce their RAROC. We consider this strong evidence in support of H1. In general, experience improves the risk–return profile, but it does not help in the case of insolvency.

5.3 Alternative explanations and robustness of results

The longer investors invest in peer-to-business loans, the more likely they will experience a default. At the same time, the longer investors are active on the platform, the more likely loan projects will have been offered to them and the less likely they will include the next loan project in their portfolio. Arguably, given the large number of loans that would be required to establish a well diversified portfolio, investors in our sample should have included almost any new loan to further diversify their portfolios. Nevertheless, in some cases experiencing a loan default may not trigger a default shock bias; instead, investors' length of time registered on the platform and their investments in more loans during that time could be causing the bias.

To causally analyze the default shock bias and to address potential selection issues, we estimate the treatment effect of experiencing a default the previous month on the newly invested capital by means of a propensity score matching model (Rosenbaum and Rubin 1983). Defaults occurred on three different dates; therefore, we estimate three treatment effects on the investment decisions in the following month. First, we model the probability of experiencing a default in a given month (propensity score) for all individuals by using a logit regression. We include gender, age, the time on the platform, and the average number of invested loans during

Table 9 Propensity score matching model

	$\ln(\text{NewInvAmount})_{12}$	$\ln(\text{NewInvAmount})_{19}$	$\ln(\text{NewInvAmount})_{20}$
ATT	−1.5836***	−0.5471*	−0.7736**
	(0.6053)	(0.3291)	(0.3090)
N	807	1257	1257

Average treatment effect on the treated (ATT) of a default on the invested amount during the ensuing month. Propensity scores are estimated using a logit regression and (transformations) of the independent variables gender, age, experience, and the average number of investments in the first three months on the platform. Specifications of the propensity scores vary for the different defaults to ensure a balanced propensity score for each propensity score matching. The propensity scores for the invested volume in the 12th and the 19th months are estimated using gender, age, the natural logarithm of the average number of invested loans during the first three months on the platform, and four categories for the ToP. For the 18th month, the propensity score is estimated using gender, categories for age, categories for the previously invested amount, and the natural logarithm of the ToP. We apply a one-to-many matching algorithm with replacement and a caliper of 0.2 for the standard deviation of the logit of the respective propensity score. Abadie–Imbens standard errors are reported in parentheses. Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. All variables reported below are defined in Table 1. * $p < 10\%$, ** $p < 5\%$, and *** $p < 1\%$

the first three months on the platform as covariates. In this way, we ensure that our dependent variable and the default shock bias variable are not simultaneously determined by one of these variables. To obtain balanced propensity scores for each of our three estimations, we use different specifications of the propensity score and also include different transformations of the covariates. Second, we match individuals who have experienced a default in a given month with individuals of the control group based on the propensity score. We apply a one-to-many matching algorithm with a caliper of 0.2 for the standard deviation of the logit of the respective propensity score. We ensure that the common support condition holds and that the distribution of the propensity score is balanced in the treatment and control groups. Third, we estimate average treatment effects on the treated using Abadie-Imbens standard errors (Abadie and Imbens 2011).

Table 9 shows that the average treatment effect of a default on the invested amount the following month is significant and negative for each of the three specifications. These results provide further evidence that peer-to-business loan investors suffer from a default shock bias and that investors ceasing to invest after an insolvency occurs is not an artefact of, for example, having more experience or of being active on the platform for a somewhat longer period.[15]

After experiencing a default, investors may not rationally update their expectations of a loan default based on the significance level we have assumed so far. In Table 10, we therefore use a slightly different sample that is based on a modified definition of investors who rationally update their expectations on the probability of default. First, in specifications (1) and (2) we include all investors who have

[15] We estimate a similar propensity score matching model using a one-to-one matching algorithm. This matching technique results in too few observations, and the average treatment effects on the treated are not significantly different from zero.

experienced a loan default, regardless of whether updating their expectations would be rational or irrational according to the binomial test. Second, we relax our definition of a rational investor compared with the baseline specifications and apply a binomial test with a 10% (vs. 5%) significance level in specifications (3) and (4). With this new significance level, an additional 37 investors could rationally have concluded that the loan defaults they experienced were beyond what they would have expected from the information provided by the platform. We consequently excluded these investors from the analysis. In Table 10, we focus on our baseline specification and our baseline specification with the interaction between $\#Investments_{i,t-1}$ and $Insolvency_{i,t-1}$. The results regarding the default shock bias remain largely robust, regardless of the definition of investors who rationally update their expectations of a loan default. In specifications (1) and (3), the insolvency dummy is significantly and negatively associated with new investment decisions. Moreover, the results indicate that more experienced investors tend to invest to a larger extent than less experienced investors.

In Fig. 2, we test the default shock bias for different leads and lags. We find that investors anticipate the defaults two periods ahead of the announcement date, which may be due to late payments by the borrower that we cannot observe in our data. We also find that the effect of a default is strongest for lag1 and lag2 in all three models. It could be argued that investor behavior in four of five loan default events is influenced by unobserved factors after the observation period ends. However, we find no further defaults during that two-month period, and no significant macroeconomic events like an interest rate raise occurred. Moreover, Table 9 shows that the effect of the default shock bias holds for period 12 alone, even for a matched sample, arguably the most convincing statistical test. The coefficient for period 12 is even greater than those for periods 19 and 20. The effect size in period 12 is three times greater than that in period 19 and twice as large as that in period 20. In addition, the effect in period 19 is only significant at the 10% level. Thus, if anything, investor defaults in period 12 are the driving force behind our result. The loan defaults in periods 19 and 20 are comparatively less important.

Table A5 in the Appendix includes the interaction between *Insolvency* and the rating of the defaulted loan, to test whether lenders are shocked more if a loan in default has a better rating. In our sample, we observe three loans in default with a B rating, one with a C rating, and one with a C- rating. Thus, the interaction term indicates the effect after a loan with a B rating defaults. We find that the default shock is significantly stronger when a B-rated loan defaults than when loans rated with a C or a C- do so. Furthermore, in Table A6 in the Appendix we investigate whether the number of defaults that an investor experiences affects the default shock bias. In our sample, 198 investors experienced one default, 55 experienced two defaults, 9 experienced three defaults, and one investor experienced four and later even five defaults. For all specifications, we find that $\#Defaults_{t-1}$ is significantly and negatively related to new investment decisions, which suggests that investors cease investing after experiencing one or more defaults. The effect becomes even stronger if investors experience more than one default. In the baseline specification,

Table 10 OLS regression results for the investment behavior with varying definition of rationally updating investors

Dependent Variable	All investors		Irrational investors ($\alpha = 0.1$)	
	(1)	(2)	(3)	(4)
	ln(NewInvAmount)	ln(NewInvAmount)	ln(NewInvAmount)	ln(NewInvAmount)
Insolvency_{t-1}	−1.1410***	0.1136	−1.1773***	0.4936***
	(0.1313)	(0.1479)	(0.1724)	(0.1902)
$\#\text{Investments}_{t-1}$	0.0720***	0.0923***	0.0719***	0.0920***
	(0.0059)	(0.0056)	(0.0060)	(0.0056)
ln(Distance)	−0.1201	−0.0956	−0.0946	−0.0736
	(0.1786)	(0.1679)	(0.1830)	(0.1716)
ToP	−0.1134***	−0.1188***	−0.1145***	−0.1205***
	(0.0079)	(0.0074)	(0.0080)	(0.0075)
Gender	−0.5641***	−0.5165***	−0.5566***	−0.5106***
	(0.1042)	(0.0982)	(0.1086)	(0.1018)
Age	0.0279***	0.0267***	0.0283***	0.0270***
	(0.0033)	(0.0032)	(0.0035)	(0.0033)
$\#\text{Investments}_{t-1} \cdot \text{Insolvency}_{t-1}$		−0.0538***		−0.0580***
		(0.0048)		(0.0049)
Constant	3.5710***	3.4616***	3.3966***	3.3101***
	(1.1068)	(1.0548)	(1.1344)	(1.0795)
Time FE	Yes	Yes	Yes	Yes
N	18,315	18,315	17,485	17,485
Adj. R^2	0.1778	0.1946	0.1776	0.1962

In columns 1 and 2, we consider all investors in the sample. In columns 3 and 4, we exclude investors who may rationally conclude that probabilities of default are higher than expected from a binomial test with a significance level of 10%. All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

the variable of interest $\#Defaults_{t-1}$, for example, suggests that investors who experienced two defaults invest 91% less.[16]

Moreover, we calculate the change of the RAROC with different VaR levels. Tables 11, 12, and 13 present the results using a 95%, 97%, and 99% VaR, respectively. As the probability of default for A-rated loans equals 0.6% according to the platform, the VaR of an investor's portfolio can amount to zero for these VaRs. Because we cannot calculate the RAROC for a VaR of zero, the number of observations decreases with a lower probability threshold of the VaR. We find that the results for H1 and H2 remain robust when measuring the RAROC differently. However, while we found no support for H3 previously, our robustness analysis indicates that experience has a positive effect on investors' risk–return profiles in the case of a default if investors are less risk-averse. More precisely, Table 11

[16] Calculated as $e^{(-1.21 \cdot 2)} - 1 = -91.1\%$.

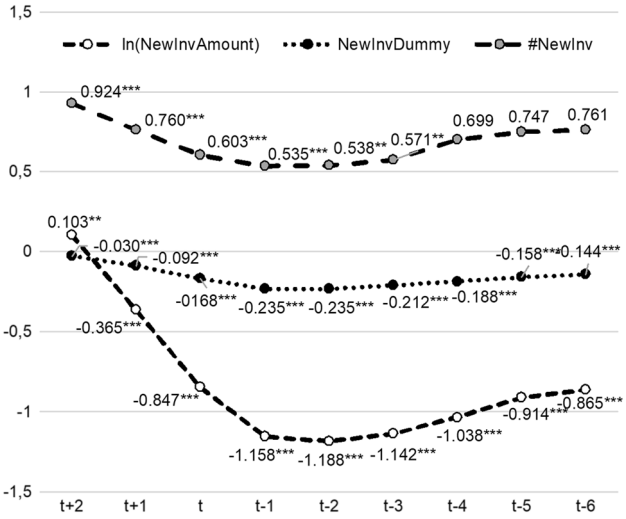

Fig. 2 Sensitivity analysis using different leads and lags. This figure shows the coefficients of *Insolvency* using different leads and lags for three different dependent variables: *ln(NewInvAmount)* (OLS regressions), *NewInvestment* (logit regression), and *#NewInvestments* (negative binomial regression). Models are specified as in Table 6

shows that, with a VaR of 95%, the interaction term in specification (2) is positive and statistically significant, which implies that in the case of a default, more experienced investors who are willing to take some risk improve their RAROC.

As another robustness check, we use two alternative measures for investment behavior as explanatory variables when analyzing changes in the RAROC. Table 14 reports the results. Our results explaining $\Delta RAROC$ hardly change when we use different explanatory variables to measure the investment behavior. Finally, in Table A2 in the Appendix, we replace the time fixed effects with the number of loan campaigns currently offered on the market. We find that market phases with more active campaigns increase the likelihood of an investment being made, which is consistent with rational portfolio formation behavior.

Finally, it could be argued that investors who experience a default in their peer-to-business loan portfolio could still optimally diversify their overall portfolio outside the peer-to-business lending domain. While we cannot test this conjecture, because we do not know the entire universe of individual investments—a problem most empirical studies on portfolio choice suffer from—we argue that it would at least be rational to continue investing in the peer-to-business loan domain. Moreover, it seems highly unlikely that for the investors who experienced a default, it is suddenly and systematically more efficient to make outside investments, while the same does not hold for the control group of investors who did not experience a default in their loan portfolios.

Table 11 OLS regression results for changes in the RAROC with robustness tests for the RAROC

	RAROC with 95 % VaR			
	(1)	(2)	(3)	(4)
	ΔRAROC	ΔRAROC	ΔRAROC	ΔRAROC
ln(NewInvAmount)			0.0118***	0.0120***
			(0.0003)	(0.0003)
Insolvency_{t-1}	−0.0095***	−0.0146***	0.0048*	−0.0130***
	(0.0027)	(0.0034)	(0.0028)	(0.0030)
$\#\text{Investments}_{t-1}$	0.0002***	0.0001	−0.0005***	−0.0008***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
ln(Distance)	−0.0021	−0.0022	−0.0021	−0.0025
	(0.0038)	(0.0038)	(0.0028)	(0.0029)
ToP	−0.0045***	−0.0045***	−0.0031***	−0.0030***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Gender	−0.0058*	−0.0059**	0.0007	0.0003
	(0.0030)	(0.0030)	(0.0022)	(0.0023)
Age	0.0003***	0.0003***	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\#\text{Investments}_{t-1} \cdot \text{Insolvency}_{t-1}$		0.0002**		0.0007***
		(0.0001)		(0.0001)
Constant	0.0899***	0.0902***	0.0508***	0.0513***
	(0.0241)	(0.0244)	(0.0181)	(0.0184)
Time FE	Yes	Yes	Yes	Yes
N	11,405	11,405	11,405	11,405
Adj.R^2	0.0484	0.0487	0.1525	0.1555

The RAROC is calculated on the basis of a 95% VaRs. Standard errors are clustered on the investor level and reported in parentheses. Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. All variables reported below are defined in Table 1. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

6 Conclusion

Rational investors should strive to diversify their loan portfolio to a great extent to achieve the best possible risk–return profile. In contrast with the stock market, in which investors can invest in funds and have a large range of stocks from which to choose, obtaining a diversified loan portfolio in peer-to-business lending is not possible immediately. Investors must invest continuously in several subsequent loan campaigns posted on the platform over time. We show that investors are paralyzed by the shock they experience when a loan in their portfolio defaults. Thereafter, they invest in fewer new loans and cease diversifying their portfolios. The default shock bias results in a deterioration of the risk–return profile of their portfolios. Furthermore, by using a binominal test, we control for investors who may rationally cease investing by updating their expectations of a default after experiencing a default in

Table 12 OLS regression results for changes in the RAROC with robustness tests for the RAROC

	RAROC with 97 % VaR			
	(1)	(2)	(3)	(4)
	ΔRAROC	ΔRAROC	ΔRAROC	ΔRAROC
ln(NewInvAmount)			0.0099***	0.0100***
			(0.0003)	(0.0003)
Insolvency_{t-1}	−0.0075***	−0.0072***	0.0041*	−0.0069***
	(0.0021)	(0.0025)	(0.0022)	(0.0023)
$\#\text{Investments}_{t-1}$	0.0002***	0.0002***	−0.0004***	−0.0006***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
ln(Distance)	0.0028	0.0028	0.0026	0.0024
	(0.0033)	(0.0033)	(0.0028)	(0.0028)
ToP	−0.0041***	−0.0041***	−0.0028***	−0.0027***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Gender	−0.0036	−0.0036	0.0017	0.0015
	(0.0022)	(0.0022)	(0.0017)	(0.0017)
Age	0.0003***	0.0003***	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
$\#\text{Investments}_{t-1} \cdot \text{Insolvency}_{t-1}$		0.0000		0.0004***
		(0.0001)		(0.0001)
Constant	0.0617***	0.0617***	0.0297*	0.0298*
	(0.0214)	(0.0214)	(0.0179)	(0.0178)
Time FE	Yes	Yes	Yes	Yes
N	13,089	13,089	13,089	13,089
Adj.R^2	0.0537	0.0537	0.1603	0.1619

The RAROC is calculated on the basis of a 97% VaRs. Standard errors are clustered on the investor level and reported in parentheses. Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. All variables reported below are defined in Table 1. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

their portfolios. Moreover, in general, more experienced investors are better able to improve their risk–return profiles. When a default occurs, the impact of experience on the RAROC is mixed. While more experienced and risk-averse investors reduce their risk–return profiles, experience helps improve the RAROC if investors are less risk-averse.

The default shock bias results in fewer investments in peer-to-business loans and a weaker portfolio performance. Platforms providing this form of investment should try to reduce the effects of this investment bias. A credit risk tool provided by the platform could help investors better understand the risk of defaults and improve their investment decisions. Such a tool could help investors invest in a way that optimizes the risk–return profile of their portfolio. A possible explanation for the default shock bias could be that lenders judge the probability of default events by the ease with which they come to mind (Tversky and Kahneman 1973). Another alternative

Table 13 OLS regression results for changes in the RAROC with robustness tests for the RAROC

	RAROC with 99 % VaR			
	(1)	(2)	(3)	(4)
	ΔRAROC	ΔRAROC	ΔRAROC	ΔRAROC
ln(NewInvAmount)			0.0079***	0.0080***
			(0.0002)	(0.0002)
Insolvency_{t-1}	−0.0086***	−0.0019	0.0005	−0.0035**
	(0.0015)	(0.0019)	(0.0014)	(0.0016)
$\#\text{Investments}_{t-1}$	−0.0086***	−0.0019	0.0005	−0.0035**
	(0.0015)	(0.0019)	(0.0014)	(0.0016)
ln(Distance)	−0.0008	−0.0006	0.0000	0.0000
	(0.0022)	(0.0021)	(0.0014)	(0.0014)
ToP	−0.0028***	−0.0028***	−0.0019***	−0.0018***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Gender	−0.0056***	−0.0054***	−0.0011	−0.0012
	(0.0013)	(0.0013)	(0.0009)	(0.0009)
Age	0.0002***	0.0002***	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\#\text{Investments}_{t-1} \cdot \text{Insolvency}_{t-1}$		−0.0003***		0.0002***
		(0.0001)		(0.0000)
Constant	0.0795***	0.0791***	0.0479***	0.0480***
	(0.0163)	(0.0161)	(0.0120)	(0.0120)
Time FE	Yes	Yes	Yes	Yes
N	16,609	16,609	16,609	16,609
Adj.R^2	0.0586	0.0596	0.1918	0.1922

The RAROC is calculated on the basis of a 99% VaRs. Standard errors are clustered on the investor level and reported in parentheses. Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. All variables are defined in Table 1. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

that could help quell the default shock bias is an automatic portfolio builder tool in line with the current trend of robo-advice, in which investors no longer make active investment decisions but merely indicate the amount they wish to invest and the risk they are willing to take.

Secondary markets are another potential solution to alleviate the default shock bias (Lukkarinen and Schwienbacher 2020), the development of which platform owners and managers could play an active role. Secondary markets would allow lenders to buy and sell loans to balance their peer-to-business loan portfolio at any time. Because the reduced diversification in loan portfolios that results from the default shock bias stems from investors ceasing investing, rather than the default of a loan itself, liquid secondary markets would allow lenders to sell loans they anticipate will default and exit the market. Selling loans on secondary markets would drive down prices and potentially warn lenders that a default might soon occur. By

Table 14 OLS regression results for changes in the RAROC with robustness tests for the RAROC

Dependent Variable	(1) ΔRAROC	(2) ΔRAROC	(3) ΔRAROC	(4) ΔRAROC
Investment Behavior	0.0427***	0.0430***	0.0078***	0.0078***
	(0.0009)	(0.0009)	(0.0003)	(0.0003)
Insolvency_{t-1}	0.0009	−0.0019	0.0028**	−0.0021
	(0.0011)	(0.0012)	(0.0013)	(0.0016)
$\#\text{Investments}_{t-1}$	−0.0001***	−0.0001***	−0.0003***	−0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(Distance)	−0.0001	−0.0001	−0.0025**	−0.0026**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
ToP	−0.0015***	−0.0015***	−0.0014***	−0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Gender	−0.0007	−0.0008	−0.0023***	−0.0025***
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Age	0.0000	0.0000*	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\#\text{Investments}_{t-1} \cdot \text{Insolvency}_{t-1}$		0.0001***		0.0002**
		(0.0000)		(0.0001)
Constant	0.0304***	0.0305***	0.0575***	0.0579***
	(0.0097)	(0.0097)	(0.0099)	(0.0099)
Time FE	Yes	Yes	Yes	Yes
N	17,882	17,882	17,882	17,882
Adj.R^2	0.1972	0.1975	0.2167	0.2175

The change of the RAROC is estimated using different measures of the investment behavior as the dependent variable. The variables for investment behavior are *NewInvestment* in specifications (1) and (2) and *#NewInvestments* in specifications (3) and (4). Standard errors are clustered on investor level and shown in parentheses. Investors who could rationally conclude that probabilities of default are higher than expected from a binomial test (significance level of 5%) are excluded from the analysis. All variables reported below are defined in Table 1. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

preparing lenders for a default to happen, secondary markets could at least mitigate the default shock bias.

Our Study has several limitations. First, while Zencap provided us with the investor and borrower data, it declined from providing data on loan defaults and late payments. While loan defaults are publicly discussed in online forums and can be precisely determined, late payments, which we could not identify, could also trigger a bias. However, if late payments also trigger a default shock bias we would expect our coefficients to provide a lower bound for the default shock bias that results from a loan default. Second, our observation period is rather short. A longer period would have led to more loan observations and enable greater insights into learning effects. Third, more demographic information on the investors, such as income, could aid in examining the effect of the behavioral bias and experience in more detail. Moreover, an analysis that explores whether investors suffer from this investment bias when investing in other asset classes that are dominated by institutional investors would be

promising. Equity crowdfunding, which enables retail investors to provide equity to start-ups, could be a relevant setting in this context.

Appendix

Calculation of the RAROC

To measure the risk–return profile of investors in peer-to-business lending, we must obtain the RAROC. Therefore, we divide the expected return of the portfolio by the risk capital. Considering the low interest rates for retail investors within the observation period, refinancing costs should be negligible in this context. Thus, we calculate the expected portfolio return as the interest charged minus the expected loan losses (*ExpReturn*). Moreover, the VaR is a common proxy for risk capital (see, e.g. Prokopczuk et al. 2004). Thus, we estimate the RAROC as follows:

$$RAROC = \frac{\text{Expected Portfolio Return}}{\text{Risk Capital}} = \frac{ExpReturn}{VaR}. \tag{3}$$

To estimate the RAROC, we calculate the VaR of each portfolio. In a first step, we obtain the average default correlation between the borrowers in a portfolio. Düllmann and Scheule (2003) use data on German small and medium-sized enterprises and empirically estimate their asset correlation by the size of the corporation and the probability of default (PD). Using a maximum-likelihood estimator, they obtain asset correlations for small corporations between 0.009 and 0.04. Our data set mainly consists of small corporations. Therefore, we assume an asset correlation of 0.025 for corporations in different industries. The correctness of this figure is confirmed by the more recent empirical results of Scheule and Jortzik (2020).

As the asset correlation of corporations in the same industry tends to be higher, we choose a higher value of 0.04 for interindustry correlation. Furthermore, the platform provides an estimate of the average PD for each rating class (see Table A1).

With the asset correlation and the PD of the corporations, we next determine the probability of two borrowers to default simultaneously. This probability is given by the joint probability of default (JPD). Assuming a bivariate Gaussian distribution, we calculate the JPD as follows:

$$JPD_{i,j} = \Phi(c_i, c_j, \rho_{i,j}^{asset}), \tag{4}$$

where c_i is $\Phi^{-1}(PD_i)$. We follow Frye (2008) and calculate the default correlation between two borrowers as

$$Default\ correlation = \rho_{i,j} = \frac{JPD - PD_i \cdot PD_j}{\sqrt{PD_i \cdot (1 - PD_i) \cdot PD_j \cdot (1 - PD_j)}}, \tag{5}$$

where PD_i and PD_j are the PDs of each loan, according to their rating classes.

Table A1 Probability of Default of the loans

Loan Rating	A+	A	B	C	C−	D
Expected PD in %	0.6	1.5	2.3	3	4	5

The values of the average expected PD are derived from the peer-to-business lending platform. The platform did not provide an average PD for rating class C−. Therefore, we interpolate with the average PDs of rating classes C and D

As most portfolios contain several loans, we estimate an average default correlation using the following formula:

$$\rho_{av} = \frac{2}{\left(\sum_{i=1}^{n} v_i\right)^2 - \sum_{i=1}^{n} v_i^2} \cdot \sum_{i<j} \rho_{ij} \cdot v_i \cdot v_j, \tag{6}$$

where v_i and v_j represent the invested amounts in loans i and j.

In a second step, we follow Ieda et al. (2000) and first calculate the 99.5% VaR for a homogeneous portfolio. Therefore, we examine the probability that n of N borrowers will default and calculate the smallest m such that

$$\sum_{n=0}^{m} \int_{-\infty}^{\infty} \left\{ \Phi\left(\frac{c - \sqrt{\rho} u}{\sqrt{1-\rho}} \right) \right\}^n \left\{ 1 - \Phi\left(\frac{c - \sqrt{\rho} u}{\sqrt{1-\rho}} \right) \right\}^{N-n} \phi(u) du \binom{N}{n} \geq 0.995. \tag{7}$$

In this context, we calculate the c on the basis of the average PD of each portfolio. We obtain the VaR of a homogeneous portfolio by multiplying m with the average invested amount in a loan.

In a final step, as suggested by Ieda et al. (2000), we obtain the VaR of a heterogeneous portfolio by multiplying the VaR of a homogeneous portfolio with

$$\frac{\sqrt{\rho + \left(\frac{\sqrt{\sum v_i^2}}{\sum v_i} \right)^2 (1-\rho)}}{\sqrt{\rho + \frac{1-\rho}{N}}}. \tag{8}$$

In this way, we correct for the likelihood that investors hold heterogeneous portfolios and for benefits through diversification. We divide the VaR of the portfolio by the total amount invested each month to measure the portfolio risk relative to the portfolio value.

Additional tables

In Tables A2, A3, A4, A5, A6 we present further robustness checks.

Table A2 Results of the baseline regressions, as specified in Sect. 4 with #Campaigns instead of time dummies

Dependent Variable	(1) ln(NewInvAmount)	(2) NewInvestment	(3) #NewInvestments	(4) ln(NewInvAmount)
Insolvency_{t-1}	−1.1699***	−0.2337***	0.5355***	0.2001
	(0.1482)	(0.0320)	(0.0638)	(0.1669)
$\#\text{Investments}_{t-1}$	0.0711***	0.0142***	1.0654***	0.0906***
	(0.0058)	(0.0006)	(0.0033)	(0.0055)
ln(Distance)	−0.1485	−0.0247	0.9452	−0.1254
	(0.1807)	(0.0232)	(0.0962)	(0.1700)
ToP	−0.1361***	−0.0253***	0.8651***	−0.1435***
	(0.0068)	(0.0012)	(0.0060)	(0.0066)
Gender	−0.5886***	−0.0824***	0.6795***	−0.5464***
	(0.1068)	(0.0180)	(0.0657)	(0.1014)
Age	0.0278***	0.0027***	1.0119***	0.0265***
	(0.0034)	(0.0004)	(0.0020)	(0.0033)
#Campaigns	0.0126***	0.0016***	1.0162***	0.0115***
	(0.0017)	(0.0003)	(0.0015)	(0.0017)
$\#\text{Investments}_{t-1}$ · Insolvency_{t-1}				−0.0538***
				(0.0048)
Constant	1.6650		0.5383	1.5170
	(1.0397)		(0.3216)	(0.9792)
N	17,930	17,930	17,930	17,930
Pseudo-/ Adj. R^2	0.1691	0.1541	0.0746	0.1857

The dependent variable is the natural logarithm of the amount an investor newly invested (OLS, specification (1)), a dummy variable indicating whether the investor carried out at least one new investment (logit, specification (2)), and the number of investments an investor newly undertook (negative binomial, specification (3)). All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. Coefficients reported are average marginal effects for the logit model and incidence rate ratios for the negative binomial model. In the last specification, we include an interaction between Insolvency_{t-1} and $\#\text{Investments}_{t-1}$. Investors who could rationally conclude that the probabilities of default are higher than would have been expected from a binomial test (significance level of 5%) are excluded from the analysis. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

Table A3 Regression results explaining the investment behavior in peer-to-business lending including non-linear effects of ToP

Dependent Variable	(1) ln(NewInvAmount)	(2) NewInvestment	(3) #NewInvestments	(4) ln(NewInvAmount)
Insolvency_{t-1}	−1.1657***	−0.2411***	0.5241***	0.3425**
	(0.1516)	(0.0331)	(0.0645)	(0.1633)
$\#\text{Investments}_{t-1}$	0.0726***	0.0145***	1.0681***	0.0943***
	(0.0061)	(0.0007)	(0.0035)	(0.0058)
ln(Distance)	−0.0997	−0.0159	0.9792	−0.0718
	(0.1805)	(0.0230)	(0.1016)	(0.1688)
ToP	−0.2719***	−0.0409***	0.7585***	−0.3212***
	(0.0283)	(0.0038)	(0.0163)	(0.0262)
ToP^2	0.0088***	0.0011***	1.0089***	0.0112***
	(0.0014)	(0.0002)	(0.0013)	(0.0013)
Gender	−0.5694***	−0.0779***	0.6993***	−0.5211***
	(0.1049)	(0.0179)	(0.0659)	(0.0982)
Age	0.0275***	0.0026***	1.0115***	0.0260***
	(0.0034)	(0.0004)	(0.0019)	(0.0032)
$\#\text{Investments}_{t-1} \cdot$				−0.0592***
Insolvency_{t-1}				(0.0049)
Constant	3.6798***		1.2402	3.6198***
	(1.1157)		(0.7661)	(1.0581)
Time FE	Yes	Yes	Yes	Yes
N	17,930	17,930	17,930	17,930
Pseudo-/ Adj. R^2	0.1810	0.1644	0.0815	0.2008

The dependent variable is the natural logarithm of the amount an investor newly invested (OLS, specification (1) and (4)), a dummy variable indicating whether the investor carried out at least one new investment (logit, specification (2)), and the number of investments an investor newly undertook (negative binomial, specification (3)). All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. Coefficients reported are average marginal effects for the logit model and incidence rate ratios for the negative binomial model. In the last specification, we include an interaction between Insolvency_{t-1} and $\#\text{Investments}_{t-1}$. Investors who could rationally conclude that the probabilities of default are higher than would have been expected from a binomial test (significance level of 5%) are excluded from the analysis. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

Table A4 Regression results explaining the investment behavior inpeer-to-business lending including the cumulated loan repayments as explanatory variable

Dependent Variable	(1) ln(NewInvAmount)	(2) NewInvestment	(3) #NewInvestments	(4) ln(NewInvAmount)
$Insolvency_{t-1}$	−1.1284***	−0.2375***	0.5398***	0.4050**
	(0.1488)	(0.0330)	(0.0650)	(0.1640)
$\#Investments_{t-1}$	0.0738***	0.0152***	1.0726***	0.0962***
	(0.0063)	(0.0007)	(0.0037)	(0.0061)
Loan Repayments	−0.0905***	−0.0248***	0.8682***	−0.1255***
	(0.0195)	(0.0025)	(0.0119)	(0.0181)
ln(Distance)	−0.1016	−0.0155	0.9709	−0.0736
	(0.1809)	(0.0226)	(0.0954)	(0.1690)
ToP	−0.0839***	−0.0127***	0.9244***	−0.0783***
	(0.0096)	(0.0016)	(0.0081)	(0.0093)
Gender	−0.5548***	−0.0743***	0.7238***	−0.5008***
	(0.1061)	(0.0179)	(0.0697)	(0.1000)
Age	0.0292***	0.0030***	1.0135***	0.0283***
	(0.0034)	(0.0004)	(0.0019)	(0.0032)
$\#Investments_{t-1}$ ·				−0.0596***
$Insolvency_{t-1}$				(0.0051)
Constant	3.3668***		0.9089	3.2051***
	(1.1231)		(0.5335)	(1.0657)
Time FE	Yes	Yes	Yes	Yes
N	17,930	17,930	17,930	17,930
Pseudo-/ Adj. R^2	0.1801	0.1707	0.0843	0.2001

The dependent variable is the natural logarithm of the amount an investor newly invested (OLS, specification (1) and (4)), a dummy variable indicating whether the investor carried out at least one new investment (logit, specification (2)), and the number of investments an investor newly undertook (negative binomial, specification (3)). All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. Coefficients reported are average marginal effects for the logit model and incidence rate ratios for the negative binomial model. In the last specification, we include an interaction between $Insolvency_{t-1}$ and $\#Investments_{t-1}$. Investors who could rationally conclude that the probabilities of default are higher than would have been expected from a binomial test (significance level of 5%) are excluded from the analysis. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

Table A5 Results of the baseline regressions, as specified in Sect. 4 with $\text{Insolvency}_{t-1} \cdot \text{RatingB}$

Dependent Variable	(1) ln(NewInvAmount)	(2) NewInvestment	(3) #NewInvestments
Insolvency_{t-1}	−0.7157***	−0.1860**	0.7044
	(0.2746)	(0.0744)	(0.2506)
$\text{Insolvency}_{t-1} \cdot \text{RatingB}$	−1.8646***	−0.1644**	0.4250**
	(0.3235)	(0.0799)	(0.1581)
RatingB	1.7101***	0.1618***	2.1271***
	(0.1575)	(0.0163)	(0.1366)
$\#\text{Investments}_{t-1}$	0.0639***	0.0129***	1.0604***
	(0.0057)	(0.0007)	(0.0036)
ln(Distance)	−0.0424	−0.0097	1.0165
	(0.1819)	(0.0227)	(0.1076)
ToP	−0.1178***	−0.0220***	0.8769***
	(0.0078)	(0.0013)	(0.0067)
Gender	−0.5490***	−0.0768***	0.7092***
	(0.1028)	(0.0175)	(0.0677)
Age	0.0260***	0.0025***	1.0110***
	(0.0034)	(0.0004)	(0.0019)
Constant	2.8988***		
	(1.1143)		
Time FE	Yes	Yes	Yes
N	17,930	17,930	17,930
Pseudo-/ Adj. R^2	0.2008	0.1729	0.0840

The dependent variable is the natural logarithm of the amount an investor newly invested (OLS, specification (1)), a dummy variable indicating whether the investor carried out at least one new investment (logit, specification (2)), and the number of investments an investor newly undertook (negative binomial, specification (3)). We also include an interaction between Insolvency and RatingB, which is a dummy indicating whether the defaulted loan was B-rated. All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. Coefficients reported are average marginal effects for the logit model and incidence rate ratios for the negative binomial model. Investors who could rationally conclude that the probabilities of default are higher than would have been expected from a binomial test (significance level of 5%) are excluded from the analysis. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

Table A6 Results of the baseline regressions, as specified in Sect. 4 with $\#Defaults_{t-1}$ instead of Insolvency

Dependent Variable	(1) ln(NewInvAmount)	(2) NewInvestment	(3) #NewInvestments
$\#Defaults_{t-1}$	−1.2060***	−0.2263***	0.5262***
	(0.1390)	(0.0323)	(0.0647)
$\#Investments_{t-1}$	0.0724***	0.0143***	1.0665***
	(0.0057)	(0.0006)	(0.0034)
ln(Distance)	−0.1075	−0.0173	0.9742
	(0.1819)	(0.0227)	(0.1076)
ToP	−0.1145***	−0.0225***	0.8779***
	(0.0079)	(0.0013)	(0.0066)
Gender	−0.5654***	−0.0779***	0.6972***
	(0.1046)	(0.0178)	(0.0651)
Age	0.0274***	0.0026***	1.0115***
	(0.0034)	(0.0004)	(0.0019)
Constant	3.5193***		
	(1.1169)		
Time FE	Yes	Yes	Yes
N	17,930	17,930	17,930
Pseudo-/ Adj. R^2	0.1784	0.1616	0.0790

The dependent variable is the natural logarithm of the amount an investor newly invested (OLS, specification (1)), a dummy variable indicating whether the investor carried out at least one new investment (logit, specification (2)), and the number of investments an investor newly undertook (negative binomial, specification (3)). Instead of $Insolvency_{t-1}$, we include the variable #Defaults,which measures the number of defaults a specific investor has experienced. All variables are defined in Table 1. Standard errors are clustered on the investor level and reported in parentheses. Coefficients reported are average marginal effects for the logit model and incidence rate ratios for the negative binomial model. Investors who could rationally conclude that the probabilities of default are higher than would have been expected from a binomial test (significance level of 5%) are excluded from the analysis. *$p < 10\%$, **$p < 5\%$, and ***$p < 1\%$

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