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Abstract

We study the investor behavior on a leading peer-to-business lending platform and find evidence of two new investment biases—a default shock bias and a deep market bias. First, we find investors to stop investing in new loans and to cease from diversifying their portfolio after experiencing a loan default. This default shock significantly worsens the risk-return profile of investors' loan portfolios. Second, investors are unable to cope with a glut of loan campaigns. Similar to the default shock bias, investors cease from investing in new loans and consequently underdiversify their portfolios as more loans become available on the platform. Deeper markets also result in a deterioration of investors' risk-return profiles. Third, investment experience on the platform reduces the effect of the deep market bias.

JEL-Codes: G110, G400.

Keywords: behavioral finance, investment bias, peer-to-business lending, crowdlending, RAROC, diversification.

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1. Introduction

In this paper, we analyze two new investment mistakes: a *default shock bias* and a *deep market bias*. We refer to a *default shock bias* when investors cease to diversify their portfolio after experiencing a default in their existing portfolio. A *deep market bias* refers to an investment bias that causes investors to underinvest in their portfolios because too many investment opportunities are currently available on the market. Our research aptly provides two novel explanations concerning why investors underdiversify their portfolios. By using data from peer-to-business lending, we study whether experience of a loan default and the availability of many investment opportunities affects the investment behavior of retail investors and consequently deteriorates the risk-return profile of their investment portfolios.

A natural benchmark for the two investment mistakes under scrutiny constitutes sophisticated lenders such as banks. The literature on credit risk modeling and bank management evidences that banks build portfolios based on the principle of diversification and that they use quantitative credit risk models to steer their loan portfolios (Hull, 2015). Such models explicitly consider default probabilities and losses given default of loans as well as their contribution to the portfolio risk and their profitability. Moreover, banks do not usually adopt their investment strategies at all after experiencing a loan default, as defaults are a well-anticipated part of their business model.

Although in sum retail investors behave in line with what has been referred to as ‘the wisdom of the crowd’ (Kelley and Tetlock, 2013), on an individual level they have been shown to make several investment mistakes (Calvet et al., 2009). In addition, their returns are often driven by sentiments (Kumar and Lee, 2006; Bollen et al., 2011). Furthermore, the 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 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 and a deep market bias. The digitalization of financial services and the recent advent of new financial technologies (fintechs) could principally render investment mistakes less likely. Digital innovations have the potential to support retail investors in their investment decisions. However, up to now, many new investment tools still had to prove their value. Through investigating a robo-advice tool from India, D’Acunto et al. (2018) show that ex ante well-diversified investors possess smaller portfolios, once they use the robo-advicing tool. In crowdfunding markets, evidence on the performance of retail investors is mixed. While in the peer-to-peer lending context Lin and Viswanathan (2016) evidence that investors suffer from a home bias, investors in equity crowdfunding appear to generate comparatively high returns

(Signori and Vismara, 2017). By 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.

Peer-to-business lending is peculiar in many respects. First, unlike in peer-to-peer lending, where borrowers seek to refinance their personal debt or capital needs for consumption purposes, peer-to-business lending involves the financing of corporations. In order to make this type of business model sustainable, borrowers must provide sophisticated information upon their current financial situation. While anyone can provide capital for these loan projects, it requires at least some degree of financial literacy to understand the projects that seek funding. Second, investments in peer-to-business lending are possible with sums as small as 100 EUR. This makes losses relatively easy to digest. Consequently, investors should continue making investments and improve the diversification of their portfolio independent of a default in their portfolio and the number of available investment opportunities.

Furthermore, we address the question of whether the *default shock bias* and the *deep market bias* are reduced by the experience of the investors. Through the use of Swedish data, Calvet et al. (2007, 2009) have shown that financially more sophisticated and better educated investors are less likely to underdiversify their portfolios of stocks and mutual funds as well as to suffer 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 have to actively identify and choose investment projects on these markets, we expect more experienced investors to have a better risk-return profile and suffer from both biases to a lesser extent.

We start with deriving our three hypotheses concerning why investors may suffer from the investment biases outlined above and why more experienced investors may suffer less from them. Thereafter, we describe our data and outline the methods we apply. We then commence with a series of tests of whether the default shock bias and a deep market bias exist. Our findings are robust to different model specifications and dependent variables. In particular, we test whether the loan defaults and a glut of investment opportunities reduce the probability of an investment taking place at all, the number of new investments, the amount of new investments, and the amount of new investments relative to the investor's existing portfolio. If investors indeed suffer from a default shock bias and a deep market bias, we expect all of these measures to decrease and the risk-return relationship of the overall portfolio to worsen if a loan in the portfolio is defaulted or the available investment opportunities are comparatively large. This is confirmed by various tests. To measure the risk-return profile, we construct Value at Risk (VaR) measures and determine the risk-adjusted return on capital (RAROC). We then further examine whether the risk-return profiles improve as investors gain more experience and suffer less from these biases. Our data supports the conjecture that experienced investors are less prone to the deep market bias. Our results are robust to different RAROCs based on different VaR estimates.

Our paper is among the first to investigate investor behavior in peer-to-business lending. It attempts to identify some of the mistakes especially less experienced investors make. Given that the market leader Funding Circle has recently passed the mark of 5 bn USD lent worldwide, this is a relevant market segment of crowdlending that is largely underresearched. Our paper does not only help to understand existing investment biases better, but also informs policy makers and regulatory initiatives like the 'FinTech Action plan' that was recently proposed by the European Commission (2018).

2. Theory and hypotheses

Peer-to-business lending represents a new asset class for retail investors. Before the rise of peer-to-business lending platforms, investing in small corporate loans was almost exclusively available to institutional investors. Investors on online lending platforms cannot immediately obtain a diversified portfolio. They have to invest continuously in new loan projects over time in order to benefit from diversification. Furthermore, many retail investors have no experience in corporate loan investments and do not receive professional investment advice. Before we outline our hypotheses on possible behavioral biases, we provide a theory on how investors should rationally build a loan portfolio in peer-to-business lending.

2.1. A short theory of rational loan portfolio formation

Due to the nature of their business, banks can be regarded as being professional investors in loan portfolios. They use credit risk models and further tools based on these models to control risks and the risk-return relationship in their loan portfolios (Hull, 2015). Besides the purely 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).[1] While the numerator of the RAROC is

[1] It should be noted that the concept exists in several variants, some of which are also called RORAC (return on risk-adjusted capital).

based on the expected profit of the portfolio, that is the interest charged minus the refinancing costs and expected loan losses, the denominator is essentially based on the VaR.[2] It can also be employed for the decision on expanding or reducing 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 is concerned with the question of how to allocate the overall risk capital to the existing business lines in order 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 that 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 (as quantity relative to the portfolio size) remains roughly the same if we were to add or remove 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 is therefore advisable to diversify into new loans, as the expected return does not change if the loan has an average interest margin, but the RAROC will increase due to a smaller VaR.

For banks, loan losses—even if the vast majority of loans reveals no defaults—are everyday business and are considered ex ante in the numerator and the denominator of the RAROC. It is also part of their regular business to extend new loans independent of whether old loans are paid back or default (Roy, 2016). If the number of defaults is higher than anticipated in the calculations leading to the RAROC, the bank will not usually cease to extend loans but instead update its credit risk model.

2.2. Hypotheses

Personal experience affects future investment decisions and helps to explain the heterogeneity in portfolio choices. Consistent with reinforcement learning theory (see e.g. Cross, 1973; Kaustia and Knüpfer, 2008), investors tend to repeat investment strategies that have resulted in favorable outcomes and tend to avoid investment strategies that have resulted in less favorable outcomes. Investment decisions can be affected by both the personal investment experience (see e.g. Kaustia and Knüpfer, 2008; Choi et al., 2009; Chiang et al., 2011; Andersen et al., 2018) and broader economic circumstances an investor has experienced such as a recession or particular labor market conditions (see e.g. Malmendier and Nagel, 2011; Knüpfer et al., 2017; Laudenbach et al., 2017). Andersen et al. (2018) highlight that stock investors who have suffered losses from defaults in the financial crisis subsequently change their risk-taking behavior. We conjecture that even in

[2] Typically, the unexpected loss is used, which is defined as the portfolio VaR at a 99.5 % or a 99.9 % level minus the expected loss.

comparatively good economic conditions a default in the crowdlending portfolio may be a reason to alter the investment behavior. Investors, who experience a loan default may draw the conclusion from this event that they have made a mistake in trusting the platform and the lender. Consequently, they may reduce their exposure or stop participating in the new crowdlending market altogether. As diversification has to be achieved over time in this new asset class, investors tend to have small portfolios and may therefore be more greatly affected by a default in their loan portfolio compared with investors of well diversified stock portfolios. However, such behavior may well be irrational and constitute a bias if refraining from investing deteriorates the risk-return profile of the crowdlending portfolio. We therefore conjecture:

Hypothesis 1: Investors suffer from a *default shock bias* that decreases their readiness to further diversify their portfolio and thereby deteriorates their risk-return profile.

It has often been shown that human decision making capacity deteriorates if individuals receive too much information. This phenomenon has been referred to as information overload and has been found in various domains such as organization science, marketing, accounting, and management information systems (see Eppler and Mengis (2004) for an excellent review of the literature). By using an experimental setting, Tuttle and Burton (1999) show that information overload also exists if individuals analyze investments. In particular, they show that the human capacity to process information limits on the amount of information that can be processed per unit of time. Moreover, there is also extensive evidence of the fact that consumers suffer from choice overload (Iyengar and Lepper, 2000; Iyengar et al., 2004; Dhar, 1997; Shafir et al., 1993), which results in a type of behavior in which individuals either choose the default option or no option at all if confronted with too many prospects.

In the realm of crowdfunding, investors can inform themselves about active projects on the respective Internet platform. Being aware of the fact that investors may be overstrained in searching the entirety of active projects that suit their portfolio, many platforms have implemented filters that enable them to search, for example, for specific business segments or project volumes. Nevertheless, investors still confront the task to identify the relevant filters to place and which projects to look for. Empirical research on crowdfunding evidences that the number of projects that is active on a particular day impacts crowd support. This result has been shown to be relatively robust and holds for reward-based crowdfunding (Kuppuswamy and Bayus, 2017), equity-crowdfunding (Hornuf and Schwienbacher, 2017), and peer-to-business lending (Cumming and Hornuf, 2018). Crowd support can deteriorate for two reasons—either because potentially new investors do not join the community or existing investors amend their investment behavior. In our empirical analysis, we test whether changes in the behavior of existing investors affect crowd support and conjecture that the more loan campaigns become available, the less likely it is that investors invest in a loan. We refer to markets with many investment opportunities as deep markets and hypothesize:

Hypothesis 2: Investors suffer from a *deep market bias* that decreases their readiness to further diversify their portfolio and thereby deteriorates their risk-return profile.

Investors tend to make better investment decisions as they gain more experience (Korniotis and Kumar, 2011; Nicolosi et al., 2009). Moreover, experienced investors are less prone to behavioral biases. Feng and Seasholes (2005) and Dhar and Zhu (2006) show that the disposition effect, which describes 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. Moreover, in an earlier paper, Calvet et al. (2007) evidence that more sophisticated households incur higher returns because they invest more efficiently and more aggressively. We study whether experience affects the investment performance in general, as well as the magnitude of the default shock bias and the deep market bias in particular. We thus hypothesize:

Hypothesis 3a: Investors with more experience tend to improve their risk-return profile.

Hypothesis 3b: Investors with more experience suffer less from the *default shock bias* and the *deep market bias.*

3. Data

3.1. Summary statistics of loan data

For the following analysis, we use data from Zencap, which is the first and the largest German peer-to-business lending platform. We obtain 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 been the world's leading crowdlending platform for corporate loans.

The platform facilitates loans for small and medium-sized corporations. These corporations post their loan projects with the requested principal amount as well as several firm characteristics and financial information on the platform. Corresponding to the estimated default risk, the platform assigns a rating ranging from A (best) to E (worst) as well as a corresponding interest rate. The investors can invest in the loan campaign within a pre-defined funding period.[3] If the invested amount reaches the principal amount at the end of the funding period, a loan campaign is successful and the loan is funded. After receiving the funds, the borrowers re-pay their loans in the form of fixed monthly annuities, due at the middle of each month.

In the observation period, 414 borrowers applied for a loan via the platform. Tables 2 and 3 show the descriptive statistics of these corporations and of the investors backing the loans. On average, the platform assigned a nominal interest rate of 7.38 % to these corporations. Not all of the corporations were profitable. The net income ranges between a minimum of −346,300 EUR and a maximum of over 1 m EUR. In total, 367 loan applications were successful. 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 made use of the forum P2P-kredite.com (http://www.p2p-kredite.com) to research which loans defaulted within the observation period. We observe five borrowers who declared insolvency before November 2015, equaling 1.36 % of all successfully funded corporations. However, we do not consider the defaults of successfully funded corporations which declared insolvency after the end of the observation period. In total, 2,129 investors backed the loans on the platform. Overall, 89 % of the investors are male. Moreover, the average investor is 41 years old.

[Table 1, 2, and 3 about here.]

3.2. Construction and summary statistics of portfolio data

Because we are interested in investor specific VaRs and RAROCs and loan repayments only take place once per month, we create 20 valuation dates in the middle of each month starting from 15th April 2014 and ending 15th November 2015. We set the valuation dates immediately after the repayment dates. In a first step, we determine how much investors have invested in each loan at each valuation date, also considering the payback from the monthly annuities. Thus, we derive a loan portfolio for each investor on each valuation date and construct a monthly panel data set with valuation dates forming the time dimension and the investor as a cross-sectional dimension. In a next step, we use this monthly panel data to calculate aggregated portfolio

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

variables. All portfolio variables are weighted with the amount invested in each loan on each valuation date. Furthermore, we observe the new investment decisions the investors make on each valuation date.

Table 4 shows the descriptive statistics of the portfolio variables. The investment behavior varies greatly within the group of investors and the valuation dates. On 36 % of the valuation dates, investors decide to invest in at least one new project. The mean amount the investors invest equals 559 EUR and is well above the minimum investment of 100 EUR even though we have many observations with zero investments. The number of new investments in loan projects ranges from 0 to 41. On average, investors hold portfolios consisting of 10 different loans. Within the observation period, 99 % of all investors hold 78 loans or less. However, in order to achieve a well-diversified portfolio, that is one in which the portfolio risk scales linearly with portfolio size, a portfolio of several hundred loans would be necessary.[4]

[Table 4 about here.]

We measure the effect of the investment decisions on the risk and the 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 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 mentioned two measures and obtain the RAROC. The RAROC is calculated as the expected return of a portfolio over the VaR. A detailed explanation of the VaR determination of the portfolios and the calculation of the RAROC can be found in the Appendix. To analyze the risk-return profile over time, we observe changes in the RAROC ($\Delta RAROC$). An increase of the RAROC indicates an improvement of the risk-return profile. By contrast, a decrease implies a deterioration of the risk-return profile.

As described in Table 8, the change of the RAROC is, on average, positive when investors choose new investments, yet, in approximately 17 % of the cases new investments result in a negative change of the RAROC. Not investing in new loans can also have a positive, negative or zero effect on the risk-return profile.

[Table 8 about here.]

Furthermore, we determine the experience of each investor on the platform on each valuation date. Therefore, we calculate the difference between the valuation date and the date of the account creation for each investor. Moreover, the descriptive analysis suggests that on 1 % of the valuation dates, an investor has

[4] Dorfleitner and Pfister (2014) show that in order to have constant per unit risk, which can be interpreted as having a well diversified portfolio, the minimum number of loans ranges from roughly 200 (VaR at 95 % level and loan default probability of 0,5 %) to more than 500 (VaR at 99.9 % level and loan default probability of 10 %).

already experienced at least one of the five insolvencies that occurred on the platform. We also investigate the competitive environment of the campaigns. On average, 34 loan campaigns were active on a given day. 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. Methodology

To examine which factors impact on the investment behavior, we estimate the effects of several covariates on the investment decision of each investor i at each valuation date t. We specify the following regression equation:

$$
\begin{aligned}
InvestmentDecision_{i,t} = & \alpha + \beta_1 \cdot InsolvDummy_{i,t} + \beta_2 \cdot \#Campaigns_{i,t} + \beta_3 \cdot Distance_{i,t} \\
& + \beta_4 \cdot Experience_{i,t} + \beta_5 \cdot (Experience_{i,t})^2 + \beta_6 \cdot \#Inv_{i,t-1} \\
& + \beta_7 \cdot Gender_i + \beta_8 \cdot Age_{i,t} + \beta_9 \cdot TimeFE + \epsilon_{i,t}
\end{aligned}
\quad (1)
$$

where *Investment Decision* represents one of four different dependent variables, namely *NewInvDummy*, *log(NewInvAmount)*, *#NewInv* and *NewInvRel*. *NewInvDummy* is a binary variable equaling one if the investor makes at least one new investment by the next valuation date. Therefore, we apply a logit regression for this specification. For the natural logarithm of the newly invested capital (*NewInvAmount*) as well as the newly invested capital related to the total portfolio value of the previous valuation date (*NewInvRel*), we estimate OLS regressions. Finally, since the number of new investments is a count variable and our data suffers from overdispersion, we use a negative binomial model to examine the effect of the covariates on *#NewInv*.

To test our hypotheses we include the explanatory variables $InsolvDummy_{i,t}$, $\#Campaigns_{i,t}$, as well as $Experience_{i,t}$. To account for potential non-linear effects of experience, we also add the squared term of experience. Prior research indicates that crowdfunding investors suffer from a local bias (Lin and Viswanathan, 2016). Therefore, we include the average distance between the investors and the active loan campaigns at each valuation date ($Distance_{i,t}$) as a control variable. Furthermore, the size of the portfolio is shown to be related to the investment behavior (Kaustia and Knüpfer, 2008; Goetzmann et al., 2015; Laudenbach et al., 2017). We thus add the number of loans in the portfolio at the last valuation date ($\#Inv_{i,t-1}$). Moreover, we control for the age and the gender of the investor, who have been shown to influence risk taking and the investment behavior (see e.g. Barber and Odean, 2001; Agnew et al., 2003; Bajtelsmit et al., 1999). In all models, we cluster the standard errors at investor level. Furthermore, we include time fixed effects (*Time FE*).

In a next step, we analyze the determinants of changes of the risk-return profile of the portfolios. We use our monthly panel data to investigate the changes of the RAROC for the investor i on the valuation date t. To address potential endogeneity concerns resulting from the simultaneous determination of the investment decision and the change of the RAROC, we implement an instrumental variable approach. We estimate a two-stage least squares (2SLS) model. In the first stage, we predict the *Investment Decision* using equation (1). In this context, the hypothesis-related variables *InsolvDummy*, *#Campaigns*, and the control variable *Distance* serve as instruments. In the second stage, we use the predicted value of the investment decision ($\widehat{InvestmentDecision}_{i,t}$) instead of the investment decision and estimate the following regression equation:

$$\begin{aligned}\Delta RAROC_{i,t} = & \alpha + \beta_1 \cdot \widehat{InvestmentDecision}_{i,t} + \beta_2 \cdot Experience_{i,t} + \beta_3 \cdot (Experience_{i,t})^2 \\ & + \beta_4 \cdot \#Inv_{i,t-1} + \beta_5 \cdot Gender_i + \beta_6 \cdot Age_{i,t} + \beta_7 \cdot TimeFE + \epsilon_{i,t}\end{aligned} \tag{2}$$

We control for the relevance of our instruments by ensuring that the F-statistic of the first stage is above a value of 10 (Bascle, 2008; Staiger and Stock, 1997). Furthermore, we test the exogeneity condition of the instruments with the use of a test of overidentifying restrictions (Bascle, 2008).

5. Results

5.1. What are the determinants of new investment decisions?

In the first part of our analysis, we investigate which factors drive investors towards making new investment decisions. Table 6 displays the results. Moreover, we test for the influence of experience in more detail in Table 7.

For the first three specifications, we find that *InsolvDummy* is significantly negatively related to new investment decisions. This suggests that investors indeed tend to recoil from new investments after experiencing a default. The economic significance is large as well. All else equal, the second specification suggests that investors who have experienced a default invest approximately 93 % less[5] than investors who have never encountered such a negative event. This result provides strong evidence in favor of our first hypothesis, being that investors inherit a default shock bias and tend to stop investing in an asset class after experiencing a

[5]Calculated as $e^{-2.71} - 1 = -93.35\%$.

default within this asset class. Unlike banks, investors appear to be surprised that loans can default and thus, they irrationally change their investment behavior after experiencing such an insolvency.

Furthermore, our results show that the number of simultaneously active loan campaigns is significantly negatively related to new investment decisions in all four specifications. This indicates that investors invest less when they have a great number of investment possibilities. In the data, one additional active loan project decreases the invested capital by almost 24 %.[6] This result is consistent with our second hypothesis.

Moreover, we find that the effect of experience is U-shaped. Initially, experience is negatively associated with new investment decisions in all four specifications. In particular, investors appear to invest more when they are relatively new on the platform, which contradicts the hypothesis 3a. However, the squared term of experience indicates a reversal point, given the significantly positive coefficient of the squared term. This result suggests that experience has a negative influence on new investment decisions but the effect diminishes with more experience. At a certain tipping point the relationship reverses. As the squared terms in non-linear models cannot intuitively be interpreted, we plot the predictive margins for different levels of experience for the logit and the negative binomial models and find that the negative effect of experience weakens for more experienced investors. There are several plausible explanations for this type of investment behavior. On the one hand, investors could start using the platform by investing a certain amount of capital in several loan projects. Subsequently, they observe how their investments develop without investing further capital. If they are satisfied with their investments, they start investing again. This point could mark the reversal point in our analysis. On the other hand, the investment behavior could be driven by liquidity. Again, investors commence by investing a certain amount of capital. Then they wait until they receive sufficient repayments from their loan investments before they invest again. However, we test for the influence of the aggregated cash repayments and do not find evidence of a relationship between aggregated liquidity and the investment behavior.[7]

Turning to control variables, we find several interesting effects as well. The number of previously invested loan projects is significantly positively related to new investment decisions for the first three specifications, suggesting that investors who already have invested in more loans are more likely to invest again. Furthermore, the data suggests that women and young people have a lower propensity to undertake new investments. The first relationship could be explained by the fact that women generally tend to trade less and are more risk averse than men (see e.g. Barber and Odean, 2001; Agnew et al., 2003; Dwyer et al., 2002). That younger people have a lower propensity to invest is in line with the literature, which shows that older

[6]Calculated as $e^{-0.27} - 1 = -23.82\%$.

[7]Results can be provided upon request.

people tend to trade more (see e.g. Agnew et al., 2003). Additionally, age may serve as a proxy for wealth, indicating that wealthier individuals invest more (see e.g. Bajtelsmit et al., 1999). The coefficient of the mean distance of the active loan projects, however, is not significantly different to zero. This holds true for all four dependent variables. Thus, we do not find evidence of the fact that the geographical distance plays a role in peer-to-business lending.

[Table 6 about here.]

To test hypothesis 3b, we divide our data set into two subsamples based on the mean experience of the investors: the first subsample contains all observations of investors with little experience on the platform (experience of less than 200 days), and the second subsample includes all observations with experienced investors (experience of 200 days or more). Table 7 provides the results. In the section concerning robustness checks, we repeat the analysis using different levels of experience to create our subsamles.

We find that the influence of the default shock bias persists not only for new investors but also for investors with longer experience. The coefficient of *InsolvDummy* is negative and highly significant in all specifications. Moreover, the results show a different impact of the simultaneously active loan campaigns on the investment decision depending on the level of experience. While new investors tend to invest less when they have more investment opportunities, experienced investors appear to act more rationally and invest more when they have greater investment choices. To examine the effect of experience on the deep market bias in more detail, we include an interaction term between the number of active campaigns and experience in our main model. Results are shown in the last column of Table 6. The significant positive sign of the coefficient of the interaction term suggests that experienced investors suffer from the deep market bias to a lesser extent. Overall, the results provide evidence for hypothesis 3b.

[Table 7 about here.]

5.2. What drives changes in the risk-return profile of the portfolios?

In addition to the analysis of the investment behavior, we examine how these investment decisions, as well as experience and further controls, impact the risk-return profile of the investors. Note that new investment decisions also include the decision not to make a new investment on a valuation date. We estimate three different models. The first model includes all hypothesis-related variables, but not the new investment decision. In the second model, we add the investment decision. In the third model, which we regard as being our main model, we estimate a 2SLS model, considering potential endogeneity concerns due to simultaneous determination of the investment decision and the change in the RAROC. Table 8 provides the results.

The first model indicates that *InsolvDummy* and *#Campaigns* have a significant negative impact on the change of the RAROC. However, this effect vanishes if we include the new investment decision in the second and the third model. Therefore, we conclude that the first model suffers from an omitted variable bias and *#Campaigns* as well as *InsolvDummy* only capture the significant effect of the investment behavior in the first model. In both the second and the third model, the investment behavior is highly significantly associated with the change of the RAROC. In particular, the 2SLS model, indicates that *InsolvDummy* and *#Campaigns* significantly affect the investment decision. The investment decision, in turn, is significantly related to the change of the RAROC. The evidence suggests a positive relationship between a high amount of newly invested capital and improvements of the risk-return profile of the investors.

Furthermore, we find that the coefficient of *Experience* is significantly negative indicating that experience deteriorates the risk-return profile. However, the coefficient of the squared experience is significantly different to zero with a positive sign. Together with the effect of experience throughout the first stage, this indicates a reversal point subsequent to approximately 340 days, after which more experience is associated with an improvement of the RAROC.[8]

[Table 8 about here.]

With subsample regressions, we examine the effect of covariates on the change of the RAROC depending on the level of experience. Similar to the analysis of the investment behavior, we separate the observations with respect to less experienced investors (experience less than 200 days) and experienced investors (experience of 200 days or more). Table 9 shows the results for the 2SLS estimation.

In both subsamples, the investment decision is significantly positively associated with a change in the RAROC. This is consistent with the results from our main models. However, we find interesting effects regarding gender and age. The data suggest that experienced women tend to enhance their risk-return profile compared with experienced men. Moreover, for inexperienced investors we find a negative association between age and the change of the RAROC.

[Table 9 about here.]

Overall, we find strong evidence in favor of our first two hypotheses. Analyzing both the investment behavior and changes in the risk-return profile suggests that investors suffer from a default shock bias.

[8] A value of $x = 340$ marks the minimum of the term $(\beta_{Exp.;2ndStage} + \beta_{Exp.1stStage} \cdot \beta_{NewInvAmount}) \cdot x + (\beta_{Exp.^2;2ndStage} + \beta_{Exp.^2;1ndStage} \cdot \beta_{NewInvAmount}) \cdot x^2$, where x represents the experience in days.

Investors tend to recoil from new investments after having experienced a loan default in their portfolio. This behavior, in turn, is associated with a deterioration of the risk-return profile of the portfolio. Moreover, investors appear to suffer from a deep market bias and invest less when they have a broad selection of loan campaigns in which to invest. Again, this investment behavior appears to be irrational as it is related to a worsening of the risk-return profile.

In order to examine hypotheses 3a and b, we investigate the effect of experience on both the investment behavior and the risk-return profile. Our results suggest that the association between the investment behavior and experience is U-shaped. Investors appear to invest less with increasing experience up to a certain tipping point. After this, the relationship reverses. We observe the same pattern for the relationship between experience and the risk-return profile. Regarding hypothesis 3b, we obtain some evidence suggesting that the effects of the biases are weakened with increased experience. Experienced investors invest significantly more when they have greater investment choices. This investment behavior is related to an improvement of the risk-return profile.

5.3. Robustness Checks

We perform several tests and estimate further specifications in order to ensure the robustness of our results. To this end, we repeat all subsample regressions with different levels of experience for both the analysis of the investment behavior and the change within the risk-return profile. The results remain largely unchanged, defining less experienced investors as being investors with less than 250 days and less than 180 days of experience, respectively.[9] In the analysis of the investment behavior, we note small differences for experienced investors in the last specification. In particular, the significance of the coefficient of *#Campaigns* decreases from a 1% significance level in our main model to a 5% level for investors with more than 250 days experience. Furthermore, the coefficient of $\#Inv_{i,t-1}$ is negatively significant at a 10 % level for investors with more than 180 days experience. With regard to the investigation of changes in the RAROC, we find that the coefficient of age, which is not significant in our main model, becomes negatively significant at a 10 % level when defining experienced investors as being investors with more than 250 days of experience.

Moreover, we calculate the change of the RAROC based on different VaR levels. Table 10 presents the results using a 95 %, a 97 % and a 99 % VaR, respectively. As the probability of default for A-rated bonds equals 0.6 % according to the platform, the VaR of an investor's portfolio can amount to zero for these VaRs. As we cannot calculate the RAROC for a VaR of zero, the number of observations decreases with a lower

[9]Results can be provided upon request.

probability threshold of the VaRs. We find that the results remain robust when using the different RAROCs. In particular, we find a positive influence of new investment decisions in all specifications. Additionally, experience retains its previously exhibited relationship with the change of the RAROC.

[Table 10 about here.]

As another robustness check for the results of the 2SLS model, we use other measures for the investment behavior as dependent variables in the first stage. The results of the second stage are displayed in Table 11. Our findings hardly change when we use different endogenous variables to measure the investment behavior. The predicted values of *NewInvDummy*, *#NewInv* and *NewInvRel* are all significantly positively related to the $\Delta RAROC$. Moreover, the effect of experience is similar to the effect found in the main model. We find evidence that the change of the RAROC first decreases with longer experience, but this relationship reverses after a tipping point is reached. However, the exogeneity condition is not valid for the instruments in the case of *NewInvRel*. Hence, the estimator could be inconsistent using this endogenous variable.

[Table 11 about here.]

Furthermore, we use different instruments for our 2SLS model. First, we reduce the number of instruments and only use one of the variables *InsolvDummy*, *#Campaigns* and *Distance* as an instrument. The results remain robust. The hypothesis-related variables are significantly related to the investment decision in the first stage, but not significantly related to the change of the RAROC in the second stage. Second, we use the age and the gender as instruments and include all previous instruments in the second stage. Again, *InsolvDummy*, *#Campaigns* and *Distance* are not significantly associated with the $\Delta RAROC$ in the second stage. The effect of the other variables remains unchanged as well. In particular, both the impact of experience and the squared term of experience remain largely unchanged in all models.

6. Conclusion

We find evidence to support the fact that investors suffer from two new investment biases—the default shock bias and the deep market bias. Furthermore, we show that experienced investors are less prone to making these investment mistakes. We use data from a peer-to-business lending platform, which allows retail investors to invest in corporate loans. Before the rise of crowdfunding, this asset class was virtually exclusively available to banks and other institutional investors. Hence, the retail investors who are active on such platforms can be assumed to have only limited experience concerning this asset class.

Rational investors should strive to diversify their loan portfolio as much as possible in order to achieve the best possible risk-return profile of their portfolio. In contrast to the stock market, on which investors can invest in exchange traded funds and have a huge universe of stocks to choose from, it is not possible to immediately obtain a diversified loan portfolio in peer-to-business lending. Investors have to invest continuously in several subsequent loan campaigns that are posted on the platform over time. We show that investors are paralyzed by the shock they appear to suffer from experiencing a default of a loan in their portfolio. Thereafter they invest in less new loans and thus stop to diversify their portfolio. This default shock bias results in a deterioration of the risk-return profile of their portfolio. Moreover, a glut of simultaneously active loan campaigns is negatively related to new loan investments. Investors appear to be unable to cope with the information provided if many campaigns are simultaneously active and tend to invest less. The deep market bias also results in a worsening of the risk-return profile of the portfolio. Furthermore, we find that experienced investors suffer from the deep market bias to a lesser extent. However, increased experience is not directly associated with improvements in the risk-return profile. By contrast, our results suggest that this relationship is U-shaped. Investors deteriorate their risk-return profile up to a certain level of experience until this relationship reverses.

One could argue that the default shock bias could also represent a rational investor behavior. In the case that investors gain additional information through experiencing a loan default, the new investment behavior could well be rational. In particular, investors might realize that the true default probability is higher than the expected default probability. Alternatively, investors may suspect that the borrower or the platform are engaging in fraudulent behavior. However, we see no reason to conclude that investors indeed gain such superior information through experiencing a loan default. Analyzing the rating classes of the loans and the average default probability provided from the platform indicates that approximately eight defaults can be expected from the 367 successfully funded loans, while only as few as five were observed during our investigation period. Furthermore, we do not find any indication of fraudulent behavior.

In the stock market, investors are confronted with a huge universe of different stocks. However, there is only little evidence to suggest that investors suffer from a deep market bias in this context. In fact, to the contrary, stocks are a common and popular asset class. Solely Iyengar et al. (2004) show that the participation rate in 401(k) retirement plans tends to decrease along with a high number of investment possibilities. A potential explanation why investors generally remain unfazed by the great amount stocks could be the wide range of investment advice for stock investments. Both the information and the choice overload could be reduced, for example, with the aid of either investment advisers or investment journals. Furthermore, the investment opportunities are less dynamic in a stock market and, therefore, investors usually have no time pressure under which to decide which stocks to buy. In peer-to-business lending, investors can only invest within the funding period. Thereafter the investment opportunity typically ceases to exist.

Both the default shock bias and the deep market bias result in fewer investments in peer-to-business lending. In particular, the platforms providing this form of investment should be concerned with trying to diminish the effects of these investment biases. A credit risk tool provided by the platform could help investors to better understand risk of defaults and also to filter relevant information in order to decrease the information load for investors. Furthermore, such a tool could help investors to invest in a way that optimizes the risk-return profile of their portfolio.

Our paper has several limitations. First, our observation period is rather short. A longer period would lead to more loan observations and enable a greater insight into the learning effects over time. Furthermore, more demographic information on the investors such as the income could help to examine the effect of the behavioral biases and experience in more detail. Moreover, an analysis of the question of whether investors suffer from these investment biases when investing in other asset classes that are predominated by institutional investors appears to be promising. Equity crowdfunding, which enables retail investors to have the opportunity to provide equity to start-ups, could be a relevant setting in this context.

Table 1: Definition of variables.

	Borrower Variables
EBIT	EBIT of the corporation running the loan project, in EUR.
Employees	Number of employees in the corporation running the loan project.
Equity	Equity of the corporation running the loan project, in EUR.
Foundation Year	Foundation year of the corporation running the loan project.
Lenders	Total number of lenders backing a loan project.
Loan Duration	Duration of the loan in month.
Net Income	Net income of the corporation running the loan campaign.
Rating Class	Rating class of the campaign as assigned by the platform. Ranging from A+ to C−.
	Investor Variables
Age	Age of the investor.
Gender	Gender of the investor (1 = female).
	Portfolio Variables
#Campaigns	Number of simultaneously active loan projects on the platform on each valuation date.
Distance	Mean distance of all the active loan projects on the valuation date and the investor in km.
ExpReturn	Expected Return of the portfolio calculated as the weighed average of the expected returns of the loan projects the investor invested in on each valuation date. 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.
Experience	Experience of the investor on the platform in months. Calculated as the date on valuation date minus the account creation date.
InsolvDummy	Dummy Variable indicating whether the borrower declared insolvency previous to the valuation date (1 = insolvency).
#Inv	Total number of investments and investor invested in until the valuation date.
Min Distance	Minimal distance of all the active loan projects on the valuation date and the investor in km.
NewInvAmount	Amount the investor newly invested on each valuation date, in EUR.
NewInvDummy	Dummy variable indicating whether the investor made at least one new investment on the valuation date.
#NewInv	Number of investments an investor newly invested on the valuation date.
NewInvRel	Amount newly invested over the portfolio value of the previous valuation date.
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 (RAROC). Calculated as the expected return of the portfolio divided by the value at risk of the portfolio.
Success Dummy	Dummy Variable indicating whether the campaign was successful (1 = successful).
VaR	Value at Risk (VaR) of the portfolio. The VaR is a relative measure and is calculated as the risk capital over the total invested amount on each valuation date. The 99.5 % VaR is used if not stated otherwise. For a detailed calculation of the VaR, see the Appendix.

Table 2: Descriptive statistics of the metric variables of the corporations and the investors. The variables are defined in Table 1.

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

Table 3: Descriptive statistics of the categorical variables of the corporations and the investors. In general, borrower variables have 414 observations. For *InsolvDummy*, only the 367 successfully funded corporations are considered. Investor variables have 2,129 observations. The variables are defined in Table 1.

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

Table 4: Descriptive statistics of the portfolios. Monthly panel data for 2,219 investors and 20 valuation dates. The variables are defined in Table 1. As many investors created their accounts after the beginning observation period, several portfolio variables are not available for all investors on all valuation dates.

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
Min Distance	42,580	55.31	259.53	0	7703.35
Experience	22,087	6.7015	4.82	0	19.87
NewInvAmount	22,087	558.50	2014.29	0	130,000
NewInvDummy	22,087	0.36	0.48	0	1
#NewInv	22,087	1.31	2.99	0	41
NewInvRel	18,405	0.22	1.31	0	74.00
#Inv	20,398	10.32	17.18	1	315
ExpReturn	20,398	0.06	0.01	0.03	0.13
VaR	20,398	0.42	0.32	0.04	1
RAROC	20,398	0.23	0.17	0.03	1.24
ΔRAROC	18,265	0.02	0.05	-0.27	0.43
InsolvDummy	20,398	0.01	0.04	0	1

Table 5: Descriptive statistics of the change of the RAROC.

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

Table 6: Regression Results for the Investment behavior using logit (dep. variable: *NewInvDummy.*), ordinary least squares (dep. variable: log(*NewInvAmount*), and *NewInvRel*) and negative binomial model (dep. variable: *#NewInv*). Standard errors are clustered on investor level and shown in parentheses. For the logit and the negative binomial model, marginal effects at means are displayed instead of coefficients. In the last specification, we additionally include an interaction term between #Campaigns and experience (Experience·#Campaigns). The symbols *, **, and *** express significance at the 10 %, 5 %, and 1 % level, respectively. The variables are defined in Table 1.

Dependent Variable	NewInvDummy	log(NewInvAmount)	#NewInv	NewInvRel	log(NewInvAmount)
InsolvDummy	−3.4795***	−2.7129***	−7.4936***	−0.0394	−1.114***
	(0.6550)	(0.6898)	(1.3640)	(0.0405)	(0.1336)
#Campaigns	−0.0400***	−0.2721***	−0.0808***	−0.2135***	−0.2474***
	(0.0077)	(0.0614)	(0.0157)	(0.0751)	(0.0623)
log(Distance)	−0.0199	−0.0908	−0.0135	0.0018	−0.1091
	(0.0267)	(0.1803)	(0.0676)	(0.0371)	(0.1784)
Experience	−0.0457***	−0.2736***	−0.1776***	−0.1477***	−0.3321***
	(0.0046)	(0.0285)	(0.0135)	(0.0144)	(0.0405)
$(\text{Experience})^2$	0.0012***	0.0084***	0.0056***	0.0066***	0.0099***
	(0.0003)	(0.0014)	(0.0008)	(0.0007)	(0.0016)
$\#\text{Inv}_{t-1}$	0.0154***	0.0671***	0.0413***	−0.0006**	0.0724***
	(0.0009)	(0.0056)	(0.0018)	(0.0003)	(0.0061)
Gender	−0.0899***	−0.5629***	−0.2327***	−0.0508	−0.5654***
	(0.0207)	(0.1042)	(0.0614)	(0.0362)	(0.1036)
Age	0.0031***	0.0272***	0.0076***	0.0025***	0.0278***
	(0.0005)	(0.0033)	(0.0012)	(0.0007)	(0.0033)
Time FE	yes	yes	yes	yes	yes
Experience · #Campaigns					0.0099***
					(0.0016)
Constant		6.6454***		4.6493***	6.5136***
		(1.5027)		(1.4550)	(1.4953)
N	18,315	18,315	18,315	18,315	18,315
Pseudo-/ Adj. R^2	0.1606	0.1754	0.0820	0.0370	0.1816

Table 7: Subsample-Regression Results for the investment behavior using logit (dep. variable: *NewInvDummy.*), ordinary least squares (dep. variable: log(*NewInvAmount*), and *NewInvRel*) and negative binomial model (dep. variable: *#NewInv*). Standard errors are clustered on investor level and shown in parentheses. For the logit and the negative binomial model, marginal effects at means are displayed instead of coefficients. The symbols *, **, and *** express significance at the 10 %, 5 %, and 1 % level, respectively. The variables are defined in Table 1.

	Experience < 200 days				Experience ≥ 200 days			
	NewInvDummy	log(NewInvAmount)	#NewInv	NewInvRel	NewInvDummy	log(NewInvAmount)	#NewInv	NewInvRel
InsolvDummy	−3.4298***	−3.4769***	−20.0320***	−0.9532***	−2.7082***	−2.6925***	−5.4842***	−0.1879***
	(0.8596)	(1.1408)	(7.6326)	(0.1398)	(0.5020)	(0.6788)	(0.9784)	(0.0452)
#Campaigns	−0.0468***	−0.3531***	−0.1844***	−0.2422***	0.0172***	0.0242***	0.0458***	0.0013***
	(0.0089)	(0.0618)	(0.0288)	(0.0742)	(0.0048)	(0.0025)	(0.0118)	(0.0004)
log(Distance)	0.0074	0.1267	0.1328	0.0309	−0.0331	−0.2795	−0.0691	−0.0558
	(0.0360)	(0.2551)	(0.1681)	(0.0601)	(0.0366)	(0.2215)	(0.0847)	(0.0399)
$\#\text{Inv}_{t-1}$	0.0562***	0.4960***	0.3562***	−0.1550***	0.0108***	0.0559***	0.0248***	−0.0003
	(0.0056)	(0.0361)	(0.0286)	(0.0191)	(0.0008)	(0.0048)	(0.0015)	(0.0002)
Gender	−0.1190***	−0.7121***	−0.5198***	−0.0705	−0.0864***	−0.4957***	−0.1708**	−0.0404***
	(0.0265)	(0.1390)	(0.1380)	(0.0701)	(0.0300)	(0.1396)	(0.0772)	(0.0123)
Age	0.0024***	0.0202***	0.0109***	0.0099***	0.0026***	0.0223***	0.0048***	0.0001
	(0.0007)	(0.0043)	(0.0032)	(0.0015)	(0.0006)	(0.0043)	(0.0014)	(0.0005)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Constant		3.4067*		5.2040***		0.4696		0.3406
		(1.8247)		(1.4906)		(1.2900)		(0.2461)
N	9094	9094	9094	9094	9221	9221	9221	9221
Pseudo-/ Adj. R^2	0.0396	0.0821	0.023	0.0299	0.1926	0.2049	0.0950	0.0041

Table 8: Regression Results for the change of the RAROC. Standard errors are clustered on investor level and shown in parentheses. The last two columns show a two-stage-least-squares (2SLS) estimation with log(*NewInvAmount*) being the dependent variable of the first stage and $\Delta RAROC$ the dependent variable of the second stage. The symbols *, **, and *** express significance at the 10 %, 5 %, and 1 % level, respectively. The variables are defined in Table 1.

			2 SLS	
Dependent Variable	ΔRAROC	ΔRAROC	log(NewInvAmount)	ΔRAROC
log(NewInvAmount)		0.0067***		0.0084***
		(0.0001)		(0.0017)
InsolvDummy	−0.0197***	−0.0005	−2.8556***	
	(0.0069)	(0.0036)	(0.7578)	
#Campaigns	−0.0028***	−0.0010	−0.2725***	
	(0.0010)	(0.0009)	(0.0614)	
log(Distance)	−0.0007	−0.0001	−0.0909	
	(0.0017)	(0.0012)	(0.1806)	
Experience	−0.0085***	−0.0066***	−0.2720***	−0.0062***
	(0.0004)	(0.0003)	(0.0286)	(0.0006)
$(\text{Experience})^2$	0.0003***	0.0003***	0.0084***	0.0003***
	(0.0000)	(0.0000)	(0.0014)	(0.0000)
$\#\text{Inv}_{t-1}$	0.0003***	−0.0001***	0.0671***	−0.0002*
	(0.0000)	(0.0000)	(0.0056)	(0.0001)
Gender	−0.0044***	−0.0006	−0.5652***	0.0004
	(0.0010)	(0.0007)	(0.1046)	(0.0012)
Age	0.0002***	−0.0000	0.0272***	−0.0001
	(0.0000)	(0.0000)	(0.0033)	(0.0001)
Time FE	yes	yes	yes	yes
Constant	0.0938***	0.0492***	6.6492***	0.0291***
	(0.0206)	(0.0181)	(1.5036)	(0.0024)
N	18,265	18,265	18,265	18,265
Adj.R^2	0.0809	0.2279	0.1747	0.2183

Table 9: Subsample-Regression Results for the change of the RAROC. Standard errors are clustered on investor level and shown in parentheses. We apply two-stage-least-squares (2SLS) estimation with log(*NewInvAmount*) being the dependent variable of the first stage and $\Delta RAROC$ the dependent variable of the second stage. The symbols *, **, and *** express significance at the 10 %, 5 %, and 1 % level, respectively. The variables are defined in Table 1.

	Experience $<$ 200 days		Experience $\geq$ 200 days	
Dependent Variable	log(NewInvAmount)	ΔRAROC	log(NewInvAmount)	ΔRAROC
log(NewInvAmount)		0.0142***		0.0047***
		(0.0024)		(0.0009)
InsolvDummy	−3.6777***		−2.8923***	
	(0.9218)		(0.7786)	
#Campaigns	−0.3759***		0.0453***	
	(0.0608)		(0.0041)	
log(Distance)	0.0274		−0.2789	
	(0.1887)		(0.2221)	
$\#\text{Inv}_{t-1}$	0.1208***	−0.0012***	0.0558***	−0.0000
	(0.0059)	(0.0003)	(0.0048)	(0.0001)
Gender	−0.5302***	0.0005	−0.4992***	0.0018*
	(0.1222)	(0.0018)	(0.1406)	(0.0010)
Age	0.0312***	−0.0002**	0.0222***	−0.0000
	(0.0038)	(0.0001)	(0.0043)	(0.0000)
Time FE	yes	yes	yes	yes
Constant	6.5068***	0.0072***	0.0767	−0.0003
	(1.5346)	(0.0025)	(1.2957)	(0.0012)
N	9,094	9,094	9,171	9,171
Adj.R^2	0.144	0.151	0.204	0.139

Table 10: Robustness Test for RAROC. The RAROC is calculated on the basis of different VaRs (95 %, 97 % and 99 %). Standard errors are clustered on investor level and shown in parentheses. We apply two-stage-least-squares (2SLS) estimation with log(*NewInvAmount*) being the dependent variable of the first stage and $\Delta RAROC$ the dependent variable of the second stage. The symbols *, **, and *** express significance at the 10 %, 5 %, and 1 % level, respectively. The variables are defined in Table 1.

	RAROC with 95 % VaR		RAROC with 97 % VaR		RAROC with 99 % VaR	
	log(NewInvAmount)	ΔRAROC	log(NewInvAmount)	ΔRAROC	log(NewInvAmount)	ΔRAROC
log(NewInvAmount)		0.0098***		0.0096***		0.0102***
		(0.0015)		(0.0014)		(0.0018)
InsolvDummy	−8.5361***		−6.6425***		−3.1251***	
	(0.9055)		(0.8637)		(0.8737)	
#Campaigns	−0.2849***		−0.2876***		−0.3244***	
	(0.0688)		(0.0686)		(0.0680)	
log(Distance)	−0.0015		0.0335		−0.0859	
	(0.2415)		(0.2119)		(0.1873)	
Experience	−0.2564***	−0.0158***	−0.2856***	−0.0124***	−0.2830***	−0.0081***
	(0.0380)	(0.0010)	(0.0349)	(0.0008)	(0.0299)	(0.0007)
$(\text{Experience})^2$	0.0068***	0.0007***	0.0081***	0.0005***	0.0087***	0.0004***
	(0.0019)	(0.0000)	(0.0017)	(0.0000)	(0.0015)	(0.0000)
$\#\text{Inv}_{t-1}$	0.0554***	−0.0004***	0.0587***	−0.0003***	0.0654***	−0.0003***
	(0.0048)	(0.0001)	(0.0050)	(0.0001)	(0.0055)	(0.0001)
Gender	−0.5312***	−0.0007	−0.5213***	0.0015	−0.5619***	−0.0000
	(0.1511)	(0.0023)	(0.1395)	(0.0018)	(0.1125)	(0.0013)
Age	0.0309***	−0.0000	0.0298***	−0.0000	0.0274***	−0.0001**
	(0.0044)	(0.0001)	(0.0040)	(0.0001)	(0.0035)	(0.0001)
Time FE	yes	yes	yes	yes	yes	yes
Constant	6.6353***	0.0805***	6.5440***	0.0625***	7.7218***	0.0407***
	(1.8416)	(0.0049)	(1.7133)	(0.0040)	(1.6197)	(0.0029)
N	11,673	11,673	13,397	13,397	16,981	16,981
Adj.R^2	0.1678	0.1679	0.1688	0.1743	0.1734	0.1949

Table 11: Robustness Test for RAROC. The first stage is estimated using different measures of the investment behavior as dependent variable. The endogenous variables are *NewInvDummy* in specification (1), *NewInvRel* in specification (2), and *#NewInv* in specification (3). Standard errors are clustered on investor level and shown in parentheses. We apply two-stage-least-squares (2SLS) estimation with $\Delta RAROC$ as the dependent variable of the second stage. The symbols *, **, and *** express significance at the 10 %, 5 %, and 1 % level, respectively. The variables are defined in Table 1.

	(1)	(2)	(3)
Dependent Variable	ΔRAROC	ΔRAROC	ΔRAROC
Investment Behavior	0.0557***	0.0133**	0.0118***
	(0.0107)	(0.0056)	(0.0038)
Experience	−0.0062***	−0.0065***	−0.0054***
	(0.0006)	(0.0009)	(0.0011)
(Experience)^2	0.0003***	0.0003***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
#Inv$_{t-1}$	−0.0002*	0.0003***	−0.0006**
	(0.0001)	(0.0000)	(0.0003)
Gender	0.0002	−0.0037***	−0.0014
	(0.0011)	(0.0010)	(0.0012)
Age	−0.0000	0.0001***	0.0000
	(0.0000)	(0.0000)	(0.0000)
Time FE	yes	yes	yes
Constant	0.0250***	0.0288***	0.0302***
	(0.0029)	(0.0040)	(0.0031)
N	18,265	18,265	18,265
Adj.R^2	0.1978	0.1241	0.1840

Appendix

Calculation of the RAROC

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

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

To estimate the RAROC, we calculate the value at risk 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 SMEs and empirically estimate their asset correlation depending on the size of the corporation and the probability of default (PD). By using a Maximum-Likelihood-Estimator, they obtain asset correlations for small corporations between 0.009 and 0.04. Our data set mainly contains small corporations. Therefore, we generally assume an asset correlation of 0.025 for corporations in different industries. As the asset correlation of corporations within 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 12).

Table 12: Probability of Default of the loans. The values of the average expected PD are derived from the peer-to-business lending platform. Note: 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.

Rating Class	A+	A	B	C	C−
Expected PD in %	0.6	1.5	2.3	3	4

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

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

with c_i being the $\Phi^{-1}(PD_i)$. 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 default probabilities of each loan, according to their rating classes.

As most portfolios comprise 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 the 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 out 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 basis of the average PD of each portfolio. We obtain the value at risk of a homogenous 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 homogenous 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 fact that investors hold heterogeneous portfolios and for benefits through diversification. We divide the VaR of the portfolio by the total amount invested on each valuation date in order to measure the portfolio risk relative to the portfolio value.

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