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Investor returns and "re-intermediation": A case of PPDai.com

Pengzhi Zeng*, Geng Peng, Yin Liu and Benfu Lv

School of Economics and Management, University of Chinese Academy of Sciences, Zhongguancun Road East 80, Haidian District, Beijing, China.

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Online peer-to-peer (P2P) lending is a nascent but burgeoning marketplace that is expected to transform the landscape of the finance industry. Although, this topic is crucial, studies on the performance of individual investors in the P2P lending marketplace are few. The majority of P2P lending platforms add more intermediation or platform-based investment to improve product offerings and market efficiency. However, research on the performance of those different types of "re-intermediation" is limited. A unique and complete dataset from PPDai.com indicates that almost 95% of individual investors on the online peer-to-peer lending market generally do not obtain returns commensurate to the amount of systematic risks they assume. The performance of the different types of "re-intermediation", such as portfolio tools and financial products, is not statistically distinguishable from that of the market. Nevertheless, the returns of these "re-intermediation" are less volatile, which shows most individuals can benefit from these types of "re-intermediation".

Key words: Peer-to-peer lending, performance, individual investor, re-intermediation.

INTRODUCTION

Online peer-to-peer lending (P2P lending) recently emerged as an appealing new financing channel different from traditional financial intermediaries, which facilitate individuals with limited institutional mediation (Michels, 2012; Duarte et al., 2012; Rigbi, 2013; Lin et al., 2013; Chishti, 2016). P2P lending is generally regarded as the household credit implementation of crowdfunding or simply called debt-based crowdfunding and with close relationship with consumer finance (Feinberg, 2003; Holmes et al., 2007; Dobbie and Skiba, 2013). This emerging online credit marketplace was virtually nonexistent before 2005. However, in 2014, P2P lending in the United States generated over $8.9 billion in loans with $1.32 billion in venture capital investments (Wei and Lin, 2016). Meanwhile, the banking regulator-estimated loan balance of online P2P lending platforms in China reached a total of RMB 621.3 billion (Financial Times, 2016[1]) in July 2016.

Despite the global expansion of this industry, little systematic research has been conducted on the fundamental topic of the return performance of individual investors (Morse, 2015). Disintermediation is one of the most significant characteristics of P2P lending. However, disintermediation seems to benefit from more intermediation (Morse, 2015). At the same time, P2P lending platforms all over the world are adding or have added more intermediation to improve product offerings and enhance market efficiency. For instance, PPDai.com[2] offers portfolio tools that can bid on loan listings automatically as well financial products that fund loan

[1] http://www.ftchinese.com/story/001069068
[2] http://www.ppdai.com

listings independent of the individuals. These platform-based investments are considered as different types of “re-intermediation” in this paper. However, research on the performance of re-intermediation is limited, since if the performance of the different types of “re-intermediation” is inferior to the performance of the most individual investors or the market return, then the platform should not offer those portfolio tools and financial products to individuals. In the current study, an analysis of a dataset is conducted to investigate the performance of individual investors and re-intermediation for the first time.

A unique and complete dataset from PPDai.com is used in the study. The dataset contains more than 1 million loans and the investment track records of more than 0.14 million individual investors over a four-year interval (2011 and 2015). The internal return rate (IRR) of each loan was first calculated based on Freedman and Jin (2014). The dataset allows us to identify the investment choices made by individuals or the re-intermediation. Thus, the rate-of-return series of individuals and the platform-based investment (re-intermediation) was calculated. The individual investors were divided into different groups and then construct a portfolio from the investment track records of each group. The weekly rate-of-return series of the portfolios during the four-year interval was studied and computed: (*a*) The rate-of-return series of the “market” portfolio; (b) Rate-of-return series of individual portfolios (the investors were classified into 10 subsets according to their total investment size or investing experience, which is measured by the number of weeks an investor bids on loan listings in the platform). Ten portfolios according to the investment size or experience of individual-related investors were obtained; (c) Rate-of-return series of the re-intermediation-related portfolios (these portfolios consist of investment records made by the re-intermediation, portfolio tools or financial products). This paper uses the time-series regression approach of Black et al. (1972) to verify whether a particular portfolio can obtain an “excess return” or outperform the market under different asset pricing models. Hence, the performance returns between the portfolios and the “market” benchmarks are compared.

This empirical analysis clearly demonstrates the performance returns of the individuals and the re-intermediation. The empirical results show that investors with a large investment or long investment experience will likely obtain an “excess return.” Almost 95% of the investors do not obtain returns commensurate to the amount of systematic risk they assume. Moreover, the re-intermediation can only achieve returns that are not statistically distinguishable from market returns but are significantly stable.

This study is one of the first to systematically analyze investor returns in the P2P lending market and the performance of re-intermediation using a comprehensive and large-scale dataset. Thus, the study contributes to the extensive and growing literature on online P2P lending and crowdfunding. Recent works include those of Hosanagar et al. (2010), Herzenstein et al. (2011), Pope and Sydnor (2011), Michels (2012), Duarte et al. (2012), Zhang and Liu (2012), Burtch et al. (2013), Lin et al. (2013), Rigbi (2013), Tomczak and Brem (2013), Barasinska and Schäfer (2014), Freedman and Jin (2014), Agrawal et al. (2015), Liu et al. (2015), Lin and Viswanathan (2015), Iyer et al. (2015), Zheng et al. (2015a, b), Hildebr et al. (2016), Wei and Lin (2016) and Kang et al. (2016), most part of them have been summarized by Morse (2015). Given the global expansion of this industry, the present study has important and timely implications for investors and P2P platforms, as well as policy makers and regulators, particularly in China, where investors in the market may have limited professional financial skills. This study also contributes to the literature on the performance of individual investors in the financial market (Schlarbaum et al., 1978a, b; Odean, 1999; Barber and Odean, 2001; Grinblatt and Keloharju, 2000; Linnainmaa, 2003). However, the recent literature documented that some individual investors systematically outperform the market (Ivković and Weisbenner, 2004; Coval et al., 2005), which is also consistent with these findings.

PPDai.com

PPDai.com is one of the largest online P2P lending platforms in China. This platform, which was launched in 2007, facilitates the transactions of numerous individuals to borrow and lend money without financial institutions acting as intermediaries. The website says that PPDai.com has more than 35 million registered members with a total of more than RMB 31.6 billion of transaction volume[3].

After a potential borrower places a request for a short-term, unsecured, and fixed-rate loan, which also includes the amount he or she wants to borrow and the interest rate to pay, he or she also has to submit personal information, which includes national identification card, cell phone number, and online video, verification of diplomas, age, income, job status, copies of pay checks and bank statements. The platform uses this information to verify the identity of a user and assess his or her creditworthiness. Part of the information is standardized and mandatory, such as national identification card and cell phone number. In the United States, P2P platforms can easily obtain the credit reports of potential borrowers from a major credit-reporting agency, such as Experian. However, well-established credit rating agencies do not exist in China. Hence, PPDai.com assigns each listing, a credit grade that reflects the risk of default to investors or lenders according to their personal information and

[3] http://map.invest.ppdai.com

borrowing request. Credit grades in the platform range from AAA, which signifies that the loan listing is extremely low risk, through AA, A, B, C, D, and E to F, which indicates the highest risk by default.

After a loan listing is posted and becomes active, potential investors or lenders can browse through the website to decide whether or not to fund and the amount to contribute, which in most situations will be a minimum of RMB 50. A loan listing is successfully funded if and only if it receives sufficient bids that cover the requested amount. The loan listings in the PPDai.com are auto-funding listings, which means the loan listing is closed as soon as the requested amount is met by investors. This operating model is one of the most commonly used by the majority of P2P lending websites in the United States (Herzenstein et al., 2011; Michels, 2012; Duarte et al., 2012; Zhang and Liu, 2012).

Data-driven models are necessary to assess and price credit risks in microfinance (Einav et al., 2013). These models can also be employed to make investment choices in the P2P lending market because online P2P lending is also a typical representation of microfinance, and the platforms always have advantages in terms of information access and computational ability unlike individual investors. As a result, P2P lending platforms all over the world add more intermediation to improve product offerings.

In 2014, PPDai.com offered new portfolio tools and financial products, collectively called "re-intermediation" in this paper, to individual investors to enhance market efficiency. Portfolio tools, such as "kuaituo" and "auto-bid," can be used to bid automatically. Investors only need to set the filter criteria, which mainly include the average amount of each bid and the risk preferences. The investment tools will bid automatically on the listings that fit the requirements. The platform also offers financial products to individual investors. Unlike investment tools, individual investors only need to choose the investment size and investment horizon. The platform makes investment decisions independent of investors. However, individuals need to pay a fee to join a financial product, whereas portfolio tools are free.

METHODOLOGY

The data

The main data source is a collection of loan-listing web pages from PPDai.com. The data were obtained by downloading all the loan-listing web pages since the platform's official inception (June 2007 to October, 2015). Next, a pattern-matching algorithm was listings submitted by more 3.9 million potential borrowers, among which 98,1629 loan listings were funded, and investment track records of more than 140,000 individual investors. Items with nonstandard or missing data were disregarded, and earlier and later data were discarded to avoid the initial launch period and truncation on loan repayments. The period studied is from November 2011 to October 2015, which comprise a four-year interval.

The IRR of the defaulted loans was calculated using the approach of Freedman and Jin (2014). If a loan is not defaulted, then the IRR is equal to the interest rate of the loan, because loans with truncation on loan repayments were disregarded in the interval studied. The detailed algorithm is as follows:

a) Loan size ($LoanSize$), interest rate of a loan ($InterestRate$), term to amortize ($Term$), and number of months during which the payments have been made ($PayTerm$) were determined.
b) The amortized monthly payment ($MonthlyPay$) is calculated as follows:

$$MonthlyPay = \frac{\left[LoanSize*\left(\frac{InterestRate}{12}\right)*\left(1+\frac{InterestRate}{12}\right)^{Term}\right]}{\left[\left(1+\frac{InterestRate}{12}\right)^{Term}-1\right]} \quad (1).$$

c) Solve for the IRR that equalizes $LoanSize$ to the sum of the present value of $MonthlyPay$ from one to $PayTerm$ using the IRR as the discount factor. The equation was defined as follows:

$$LoanSize = \sum_{1}^{Term}\left[\frac{MonthlyPay}{\left(1+\frac{IRR}{12}\right)^{Term}}\right] \quad (2)$$

Given a loan without any payment or defaulted at the first month, we set the IRR = -12, and $PayTerm$ = 1, which means that the monthly discounter factor is -1. The dataset allows us identify the investment decisions made by individual investors or the platform. The rates of return of individual investors and platform was calculated independently. We can calculate the rates of returns on a portfolio in week t given a portfolio that contains n bids in week t because the IRR, $PayTerm$, and $BidAmount$ (amount of bid) for each bid is known. The rates of returns are calculated as follows:

$$ReturnRate_t = \left(\sum_{1}^{n} IRR_n * BidAmount_n * PayTerm_n\right) / \left(\sum_{1}^{n} BidAmount_n * PayTerm_n\right) \quad (3)$$

Five additional rate-of-return series are calculated as representations of the investment performance of the benchmark "market" collections of loans. According to PPDai.com, the loans are aggregated into the following types: loans with low risk by default (loans assigned with credit grade "AAA" or "AA"), loans with middle risk by default (if credit grade of the loan is "A", "B" or "C"), and loans with high risk by default (which are graded into "E" or "F"). A type for loans that have the lowest risk by default (loans graded into "AAA") was added. These types ("low risk," "middle risk," "high risk" and "safe risk") and the four portfolios (low risk, middle risk, high risk and safe risk) are constructed from the four types of loans. Based on Expression (3), the rate-of-return series of all these portfolios are obtained. The November 2011 to October 2015 weekly rates of return correspond to the low-risk portfolio, middle-

Corresponding author. zengpengzhiu@163.com. Tel: +86 15600616586.

Table 1. Summary statistics.

Quantile (%)	Investment size	Investment experience
50	1400.0	3
60	2000.0	5
70	6285.0	10
80	14249.8	18
90	41764.9	36
95	99153.4	57
99	525597.4	110
99.73	1740830.0	157
99.9*	3858430.0	195

* It is believed that the empirical results are robust to other breakpoints.

risk portfolio, high-risk portfolio, safe-risk portfolio and market implemented to take the variables of interest from the web page HTML code. The resulting dataset consists of more than 5 million portfolio. Given that one of the objectives of this study is to examine the investment performance of individual investors, we do more than just measure the average return of individual investors. Moreover, the proportions of investors who outperform the market and underperform the market must be determined. This information can be obtained from two aspects, namely, total investment size and investment experience. Investment experience is measured by the number of weeks an investor bids on some loan listings. For example, if an investor funds loan listings in two distinct weeks, the investment experience of the investor is equal to two. These two criteria were chosen mainly because of the following reasons. A less-sophisticated investor tends to obtain a low or negative return and is more likely to withdraw from the market. As a result, less skilled investors are inclined to have a small total investment size and to be less experienced from an ex post perspective. Thus, a feasible method may be employed to distinguish investors with investment skills from those with less skills. This approach involves dividing the investors into different groups according to their total investment size or investment experience. The overall performance of these groups was assessed.

The investors must be divided into different groups to examine their performances. However, the total investment size of individual investors is heavily skewed in the dataset, as shown in Table 1. Investors below the 50th percentile have a total investment size less than RMB 1400, whereas investors in the 99.9th percentile invested more than RMB 3.8 million in the market. To avoid possible biases, we classify the investors into 10 groups and a portfolio is constructed based on each group. According to Expression (3), a rate-of-return series is calculated for each portfolio. 10 groups of investors were obtained according to the following breakpoints: bottom 50, 50-60, 60–70, 70–80, 80–90, 90–95, 95–99, 99.73–99.9 and top 99.9–100%. The same breakpoints were also set when we divided the investors according to the investment experience. The investment experience is also heavily skewed. The summary statistics are shown in Table 1. The table shows that 50% of the investors in the dataset have an investment experience not longer than a month, whereas investors in the 99.9th percentile bid on some loan listings almost throughout the four-year interval.

The attributes of the rate-of-return series of different portfolios are summarized in Table 2. Panel A shows the details of the rate-of-return series of the portfolios, which are constructed from different investment track records of various groups of investors. The arithmetic mean annualized weekly return on the portfolio of the investors below the 50th percentile during the four years is estimated to be 0.074, whereas the return on the portfolio of individual investors in the 99.9th percentile is estimated to be 0.118. A negative relation exists between the investment size of investors included in the portfolio and the standard deviation of the returns on the portfolio. A stronger positive relation exists between the total investment size of investors and the average return on the portfolio. These findings indicate that investors with a large total investment size will likely obtain high and steady returns. This phenomenon is also discovered when the performance of investors is analyzed according to their investment experience. Investors with a short investment experience will likely have low returns with a high standard deviation. This preliminary examination indicates that some individual investors outperform other investors systematically.

Panel B shows the details of the rate-of-return series of the benchmarks. The average return on the market portfolio is 0.108 with a standard deviation of 0.03. The average return on the safe-risk portfolio is 0.086, whereas the figure of the standard deviation is 0.005, which is significantly smaller than that of the market portfolio at 0.03. The unreported results indicate that when the weekly returns on the safe-risk portfolio are regressed on the returns of the market portfolio by OLS, the R^2 statistic of the linear regression model is close to zero, which indicates that the returns on the market portfolio slightly affect the returns on the safe-risk portfolio. The returns on the safe-risk portfolio are independent from the returns on the market portfolio. Thus, the portfolio is almost a zero-beta portfolio (Blume and Friend, 1973), which will be used in one of the empirical models.

Panel B indicates that significant differences exist in the rate-of-return series on the three portfolios consisting of loans with different risk grades (low risk, middle risk, and high risk). The average returns of the portfolios range from 0.107 for the low-risk portfolio to 0.120 and 0.092 for the high-risk portfolio with a standard deviation of 0.016, 0.067, and 0.040, respectively. The attributes of rate-of-return series of the three portfolios vary significantly. Based on the concept of Fama and French (1993), the high returns on some portfolios may incur high-risk factors. Some individual investors obtain low returns simply because of their risk preferences. For example, when an investor only bids on the loan listings with risk grade “AAA” on the average, he or she can expect a return rate of 0.086. Another investor can expect a return of 0.107 if he or she also bids on loan listings with risk grade “AA” or “A”. Thus, we should employ an asset-pricing model to cover the differences of returns resulting from risk preferences. The average return on the high-risk portfolio is less than that on the middle-risk portfolio and even on the low-risk portfolio. This condition can result from the high default rate of high-risk loans. As a result, only few of the high-risk loan listings are successfully funded. The return rate of the low-risk portfolio is almost equal to the return rate of the market (0.108)

Table 2. Summary statistics.

Panel A: Weekly return rate series of different portfolios: November 2011 to October 2015												
Quantile		**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**Obs.**
Invest amount	$\overline{R_{jt}}$	0.074	0.083	0.088	0.091	0.097	0.102	0.108	0.113	0.117	0.118	211
	$\sigma(R_{jt})$	0.056	0.059	0.042	0.043	0.039	0.037	0.033	0.029	0.033	0.038	211
Invest experience	$\overline{R_{jt}}$	0.076	0.091	0.089	0.095	0.100	0.105	0.112	0.115	0.114	0.116	211
	$\sigma(R_{jt})$	0.087	0.055	0.052	0.042	0.039	0.038	0.031	0.030	0.030	0.028	211
Panel B weekly return rate series of different market portfolios												
Market return	$\overline{R_{jt}}$						0.108					211
	$\sigma(R_{jt})$						0.031					
Safe return	$\overline{R_{jt}}$						0.086					211
	$\sigma(R_{zt})$						0.005					
Low-risk return	$\overline{R_{jt}}$						0.107					211
	$\sigma(R_{jt})$						0.016					
Middle-risk return	$\overline{R_{jt}}$						0.120					211
	$\sigma(R_{jt})$						0.067					
High-risk return	$\overline{R_{jt}}$						0.092					211
	$\sigma(R_{jt})$						0.040					
Tools return	$\overline{R_{jt}}$						0.113					31
	$\sigma(R_{jt})$						0.008					
Product return	$\overline{R_{t}}$						0.116					54
	$\sigma(R_{jt})$						0.013					

but with a substantially small standard deviation. This descriptive statistical analysis indicates that funding the low-risk loans is a good choice.

The rates of returns on the portfolios of different types of re-intermediation are also presented in Panel B. The average returns on the portfolios of investment tools and financial products are 0.113 and 0.116, respectively, and the standard deviations are 0.008 and 0.013, respectively. Meanwhile, during the same period, the average returns of the market are 0.1156 and 0.1153, and the standard deviations are 0.0074 and 0.0075, respectively. The difference between the rate-of-return series is almost negligible. Hence, the re-intermediation, such as investment tools and financial products, can hardly outperform that of the market. Nevertheless, these types of "re-intermediation" can help individual investors obtain a return rate that is not lower than that of the market.

Risk-adjust performance criteria

However, a rigorous and complete appraisal of performance results requires that the differences in investment risk preferences be considered as well and additional benchmarks be constructed. The asset pricing models of Sharpe (1964), Black et al. (1972), Merton (1973) and Fama and French (1993) can be used to organize ideas. A new asset pricing model was not proposed but employ asset pricing models to compare the rate-of-return series of different portfolios constructed in the previous section. To ensure the robustness and comprehensiveness of the empirical results, we run the regressions by choosing different asset-pricing models. The estimating equations have the following forms:

$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + e_{jt} \quad (4)$$

$$R_{jt} - R_{zt} = a_j + b_j(R_{jt} - R_{zt}) + e_{jt} \quad (5)$$

$$R_{jt} - R_{ft} = a_j + b_j\left(R_{mt} - R_{ft}\right) + m_j MML_t + h_j HML_t + e_{jt} \quad (6)$$

Where R_{jt} is the return on an individual-related or re-intermediation-related portfolio in week t. R_{ft} is the "risk-free" rate. The one-year deposit rate of China is used as the "risk-free" rate in place of the rate of Treasury bills observed at the beginning of week t. R_{zt} is the return on the safe-risk portfolio (consisting of loans with risk grade AAA) in week t, and MML_t (middle minus low) is the difference in each week between the return on the middle-risk portfolio (consisting of loans with a middle risk grade) and the return on the low-risk portfolio (consisting of loans with low-risk grade). HML_t (high minus low) is the difference of each week between the return on the high-risk portfolio (consisting of loans in the high-risk grade) and return on the low-risk portfolio. e_{jt} is the error term and the regression yield parameter a_j, b_j, m_j, h_j. The estimate of intercept a_j provides a measure of portfolio j's risk-adjusted performance over a concerned period and a measure of the volatility on coefficient b_j. If estimate a_j is statistically and significantly positive, the portfolio obtains a positive excess return and outperforms the benchmark. If estimate b_j is statistically significant and larger than 1, the volatility of the portfolio is higher than that of the market or vice versa. The return performance of different portfolios of interest is assessed through the following steps. Equation 1 was examined by using the excess return of market, $R_{mt} - R_{ft}$ to explain the excess returns of the portfolios of interest. Equation 2 uses $R_{mt} - R_{zt}$ as an explanatory variable, and we utilize R_{zt} as the "risk-free" rate. Equation (3) uses $R_{mt} - R_{ft}$, MML_t, HML_t to explain the excess returns on an individual-related or re-intermediation-related portfolio .

The process of computing Equation 1, which is the base model or building block, is similar to the approach of Sharpe (1964) and only obtains the market factor. We construct estimating Equation 2 by re-defining the "risk-free" rate and choosing the rate of return on the safe-risk portfolio as the "risk-free" rate, because the influence of the rate of return on the market portfolio is low or is, in other words, a zero-beta portfolio. The model is a two-factor version of the market model, which is consistent with the work of Blume and Friend (1973) and was also adopted by Schlabraum et al. (1978a). Estimating Equation 3 considers the systematical risk of the market and the risk resulting from loans with different credit grades. The previous analysis shows that the rate-of-return series on portfolios consisting of loans with different risk grades varies significantly. Estimation of Equation 3 was used to handle these differences.

Performance of individual-related portfolios

Can larger investors make an excess return?

The investigation is conducted by examining the performance of investors according to the total investment size. The parameters of the three equations are estimated from time series regressions utilizing the 211 weekly return observations available from the four-year interval. The results of these regressions are reported in Table 3.

The estimate a_j changes from negative to positive and is statistically significant (29/30) in most of the regression results, which indicates that investors with a large total investment size will likely obtain an excess return because a_j is the measure of the portfolio's risk-adjusted performance. However, estimate b_j decreases gradually, indicating that the returns of investors with a large investment size are less affected by the market when compared with investors with a small total investment size, or, in other words, the volatility of the rate-of-return series of investors with a large investment size is lower. These results are consistent with the summary statistics of the rate-of-return series in Table 2. R^2 ranges from 0.367 to 0.956. In some cases, our models attribute the relatively large common variations to other possible factors, which cannot be captured in our model. Nevertheless, the average R^2 statistic is equal to 0.7068, which ensures the reliability of our conclusions. The R^2 values in the estimated results of Equation 6 are larger than those of Equations 4 and 5, whereas the differences are almost negligible. The robustness of the empirical results may also be ensured, suggesting that the risk preferences influence investment performance, although the effect is quite limited.

The results show that estimate a_j is consistently negative and different from zero statistically significant when the rate-of-return series belong to the portfolios of investors below the 90th percentile. The smallest figures in the regression results from the three equations are -0.069, -0.039, and -0.092, respectively. Estimate a_j of the portfolios of investors in the 99 to 100th percentile is consistently positive and statistically significant. The largest estimate a_j in the estimation results of the three equations is 0.040, 0.015 and 0.032, respectively. The difference of the "excess return" between the different groups is quite large and far from negligible. The rates of return are annually calculated.

Can more experienced investors make an excess return?

Table 4 reports the estimation results of the rate-of-return series on the portfolios of investors with different investment experiences, which is similar with the previous analysis. Estimate a_j becomes positive as investment experience increases, and estimate b_j becomes lower than 1, suggesting that experienced investors will likely obtain an "excess return" and less volatile rates of return.

In most estimation results, the R^2 values in the estimation results of Equation 6 are larger than those in Equations 4 and 5, which are consistent with the results in Table 3. The average R^2 value of all the estimate results is 0.663. The smallest figures of estimate a_j in the regression results from the three equations are -0.058, -0.039 and -0.102. The largest values of estimate a_j in the results of the three equations are 0.048, 0.019 and 0.040, respectively, and the differences between these figures and those in Table 3 are almost negligible. However, Table 4 indicates that estimate a_j is positive and statistically significant in the estimation results of the portfolios of investors over the 95th percentile. The figures in the estimation results of Equations 4 and 5 from the portfolios of the investors in the 90th to 95th percentile are equal to 0.007 and 0.005, respectively, which are not far from 0, whereas it increases to 0.013 in

Table 3. Individual investor returns analysis by total investment size.

$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + e_{jt} \quad (4)$$
$$R_{jt} - R_{zt} = a_j + b_j(R_{jt} - R_{zt}) + e_{jt} \quad (5)$$
$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + m_j MML_t + h_j HML_t + e_{jt} \quad (6)$$

Quantile		Low	2	3	4	5	6	7	8	9	High
	(1)	-0.052	-0.069	-0.014	-0.032	-0.027	-0.019	-0.005	0.019	0.020	0.040
a	(2)	-0.039	-0.035	-0.020	-0.021	-0.015	-0.009	-0.001	0.008	0.011	0.015
	(3)	-0.092	-0.072	-0.053	-0.040	-0.031	-0.012	0.010	0.023	0.032	0.020
	(1)	1.163	1.399	0.942	1.135	1.141	1.121	1.041	0.874	0.895	0.717
b	(2)	1.182	1.410	0.972	1.153	1.153	1.126	1.033	0.870	0.886	0.718
	(3)	1.576	1.443	1.366	1.241	1.207	1.056	0.899	0.825	0.765	0.902
	(1)	-6.803	-8.515	-3.495	-6.974	-9.047	-7.882	-2.524	8.757	5.867	6.084
$t(a)$	(2)	-10.932	-10.775	-7.772	-10.229	-11.954	-9.116	-1.835	9.454	7.806	6.246
	(3)	-7.365	-5.879	-6.380	-5.818	-7.261	-3.856	3.485	6.878	5.786	2.439
	(1)	13.615	17.318	15.378	22.473	37.317	45.311	60.364	41.659	24.247	11.101
$t(b)$	(2)	12.999	16.827	15.053	21.904	36.560	44.356	59.447	41.413	24.289	11.261
	(3)	11.545	10.795	15.069	15.572	25.528	26.219	34.231	23.371	12.358	7.936
	(1)	0.466	0.586	0.527	0.705	0.868	0.907	0.945	0.892	0.736	0.367
R^2	(2)	0.443	0.572	0.517	0.694	0.864	0.903	0.944	0.890	0.736	0.374
	(3)	0.511	0.589	0.650	0.737	0.890	0.912	0.956	0.896	0.753	0.374

*R_{jt} is the return on an individual-related or re-intermediation-related portfolio in week t. R_{ft} is "risk-free" rate, one-year deposit rate of China is used as the "risk-free" rate in place of the rate of treasury bills observed at the beginning of the week. R_{zt} is the return on the safe-risk portfolio (consisting of loans with risk grade AAA) in week t, and MML_t (middle minus low) is the difference in each week between the return on the middle-risk portfolio (consisting of loans with a middle-risk grade) and the return on the low-risk portfolio (consisting of loans with low-risk grade). HML_t (high minus low) is the difference in each week between the return on the high-risk portfolio (consisting of loans in high-risk grade) and the return on the low-risk portfolio.

the regression results of Equation 6. When compared with the corresponding estimated a_j in Table 3, the differences between estimate a_j are relatively small. The figures are -0.005, -0.001, and 0.010, respectively, as shown in Table 3. The empirical results in Table 4 are consistent with that in Table 5 in most situations.

Performance of the re-intermediation-related portfolios

As described above, PPDai.com developed the portfolio tools to help the investors to bid on loan listings automatically. Another type of re-intermediation is the financial products provided by the platform, the financial products are managed by the platform, and the platform make investment choices independently of individual investors. Both approaches, which are employed by the majority of P2P lending platforms all over the world, are considered as different types of re-intermediation in this paper and the performance of them are analyzed. Firstly, the rate-of-return series was calculated on the two different portfolios of the portfolio tools and the financial products, respectively, and then the same time-series-regressions method is employed to measure the performance of these portfolios. The results of such regressions are presented in Table 5.

The performance return of the portfolio tools was first examined. Table 5 indicates that the values of estimate a_j in the three models are 0.032, 0.001 and 0.023, respectively. The figures are positive, but estimate a is only statistically significant in the estimation results of Equation 4. Concluding that portfolio tools help individuals obtain a better return than the market is unreliable. However, estimate b_j in the three models is smaller than 1, which indicates that the return of portfolio tools may not outperform the market but obtains an average and more stable return than the market.

Table 4. Individual investor returns analysis by experience.

$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + e_{jt} \quad (1)$$
$$R_{jt} - R_{zt} = a_j + b_j(R_{jt} - R_{zt}) + e_{jt} \quad (2)$$
$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + m_j MML_t + h_j HML_t + e_{jt} \quad (3)$$

Quantile		Low	2	3	4	5	6	7	8	9	High
	(4)	-0.058	-0.011	-0.043	-0.026	-0.020	-0.017	0.007	0.014	0.018	0.048
a	(5)	-0.039	-0.015	-0.026	-0.016	-0.012	-0.008	0.005	0.008	0.009	0.019
	(6)	-0.102	-0.021	-0.058	-0.043	-0.021	-0.017	0.013	0.012	0.026	0.040
	(4)	1.313	0.927	1.293	1.162	1.150	1.170	0.958	0.907	0.843	0.493
b	(5)	1.276	0.890	1.266	1.145	1.139	1.164	0.965	0.916	0.844	0.497
	(6)	1.977	1.112	1.529	1.402	1.176	1.164	0.874	0.915	0.725	0.610
	(4)	-4.019	-1.281	-6.858	-6.244	-7.359	-9.784	4.821	7.533	7.612	11.335
$t(a)$	(5)	-5.965	-3.679	-8.936	-8.577	-9.144	-9.225	6.757	9.751	8.120	9.721
	(6)	-4.662	-1.534	-6.061	-6.772	-4.933	-5.984	5.716	4.374	7.280	6.012
	(4)	7.843	9.031	17.695	23.994	35.450	56.462	55.075	42.828	31.299	10.006
$t(b)$	(5)	7.580	8.660	17.149	23.426	34.734	55.317	55.044	42.729	31.176	9.994
	(6)	7.147	6.558	12.642	17.614	21.841	32.703	30.717	25.573	16.209	7.278
	(4)	0.223	0.276	0.597	0.731	0.856	0.938	0.935	0.897	0.823	0.320
R^2	(5)	0.211	0.260	0.581	0.722	0.851	0.935	0.935	0.896	0.821	0.319
	(6)	0.274	0.325	0.622	0.752	0.864	0.937	0.940	0.899	0.833	0.327

*R_{jt} is the return on an individual-related or re-intermediation-related portfolio in week t. R_{ft} is the "risk-free" rate, one-year deposit rate of China is used as the "risk-free" rate in place of the rate of Treasury bills observed at the beginning of the week. R_{zt} is the return on the safe-risk portfolio (consisting of loans with risk grade AAA) in week t, and MML_t (middle minus low) is the difference each week between the return on the middle-risk portfolio (consisting of loans with a middle-risk grade) and the return on the low-risk portfolio (consisting of loans with low-risk grade). HML_t (high minus low) is the difference each week between the return on the high-risk portfolio (consisting of loans in high-risk grade) and the return on the low-risk portfolio.

The performance record of the financial products managed by the platform is statistically indistinguishable from that of the indicated market benchmarks. This result is not surprising because of the close similarities of the various rate-of-return series involved. Table 5 shows that estimate a_j has not been statistically significant for the period. Neither superior nor inferior over-all performance can be detected in these returns. Nevertheless, estimate b_j in the three models is not larger than 1, suggesting that the returns on the financial products are less risky.

DISCUSSION

According to the results displayed in Table 3, the performance of approximately 90% of the investors is inferior to the performance of the market. Table 1 shows that 50% of the investors have a total investment size not more than RMB1400, and that 80% of the investors have not more than 14249.8 even when small investors are excluded. These relatively large investors with a total investment size around RMB10000 can still hardly earn a positive excess return from the P2P market. Only investors in the 99th percentile consistently gain a positive excess return. Investors with large investment size tend to obtain high returns. Moreover, compared with Tables 5 and 4 shows that the regressions using individual-related portfolio returns yield virtually identical findings regardless of whether the results is examined on the total investment size or the investment experience of the individual investors. Superior overall performances were observed in the returns of the portfolios of experienced investors and investors with a large investment size, implying that a few investors perform better than others during the period systematically.

The performance of different types of re-intermediation, such as portfolio tools or financial products, is displayed in Table 5. The return series of portfolio tools and financial products during the interval of period studied can hardly be distinguished statistically from the

Table 5. Investments return analysis of the re-intermediation.

$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + e_{jt} \quad (4)$$
$$R_{jt} - R_{zt} = a_j + b_j(R_{jt} - R_{zt}) + e_{jt} \quad (5)$$
$$R_{jt} - R_{ft} = a_j + b_j(R_{mt} - R_{ft}) + m_j MML_t + h_j HML_t + e_{jt} \quad (6)$$

	Portfolio tools			Financial products		
	(4)	**(5)**	**(6)**	**(4)**	**(5)**	**(6)**
a	0.032	0.001	0.023	0.011	0.006	0.028
$t(a)$	2.281	0.201	1.272	0.569	0.983	0.939
b	0.645	0.927	0.746	0.899	0.861	0.676
$t(b)$	4.358	7.967	3.643	4.529	5.030	2.043
R^2	0.367	0.668	0.360	0.265	0.310	0.308

*R_{jt} is the return on an individual-related or re-intermediation-related portfolio in week t. R_{ft} is the "risk-free" rate and, the one-year deposit rate of China is used as the "risk-free" rate in place of the rate of Treasury bills observed at the beginning of the week. R_{zt} is the return on the safe-risk portfolio (consisting of loans with risk grade AAA) in week t, and MML_t (middle minus low) is the difference each week between the return on the middle-risk portfolio (consisting of loans with a middle-risk grade) and the return on the low-risk portfolio (consisting of loans with a low-risk grade). HML_t (high minus low) is the difference each week between the return on the high-risk portfolio (consisting of loans in high-risk grade) and the return on the low-risk portfolio.

performance of the market. Individuals can benefit from the empirical results. Firstly, given the poor performance of the individual investor which has been verified in Tables 3 and 4, it is wiser to employ the portfolio tools and financial products to obtain a market level return. Then, availing of the financial products offered and managed by the platform entails fees and the portfolio tools can be used without any charge, while their performance varies a little. Thus, employing such portfolio tools is a viable option for individuals.

Conclusion

In this paper, the performance of individual investors in the online P2P lending market as well as the performance of the re-intermediation was estimated for the first time. These findings indicate that most of the investors do not obtain returns commensurate to the amount of systematic risk they assume and not more than 5% of the investors can outperform the market in the aggregate. The investors with a small investment size or with less experience tend to get a much low return of high volatility. Moreover, the empirical analysis shows that the performance of the re-intermediation, which is neither superior nor inferior overall performance, can be detected in these returns on different types of the re-intermediation. This conclusion holds both for portfolio tools and financial products.

The results have significant implications for practitioners in the P2P lending market, particularly individual investors, since individual investors tend to be less skillful and less informed, especially in China. Not more than 5% of individual investors can earn an "excess return"; thus, employing the re-intermediation provided by the platform, such as portfolio tools and financial products, is reasonable to obtain an average return. Platforms may be (and are) increasing intermediation to improve product offerings and enhance lending efficiency, because they incorporate content fields into risk scoring and investment decisions to redress possible biases when individual investors assess the creditworthiness of their peers, as verified by Herzenstein et al. (2011), Michels (2012), Duarte et al. (2012) and Hildebrand et al. (2016), as well as this study. The algorithmic extraction of valuable signals of borrowers seems possible, and investment decisions according to these signals should obtain an "excess return." However, the findings do not support this. This result indicates that other measures must be adopted to improve the performance of the re-intermediation and help less-skilled individual investors to earn high returns.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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