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Mismatch between investor preferences and financial services/products

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ABSTRACT
In a major peer-to-peer (P.2.P.) lending market in China, we observe that some investors choose not to use auto-investment service and stick to time-consuming manual investment. By analysing over 200 million pieces of data, we find that the do-it-yourself (D.I.Y.) investors pursue 1.20% higher annual return and five to seven months shorter maturity than the auto-investment service can offer. Indeed, D.I.Y. investors obtained 1.25% higher return than auto-investors, but they also took excessive risk. These results are confirmed by dual investors sample, who switch between D.I.Y. and auto-investment services. We also show that the results are not due to algorithm priority. We suggest that financial institutions provide more personalized services and products to accommodate investors with various target returns and risk attitudes.

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1. Introduction

Financial advising services are extensively provided by financial institutions such as banks, asset management companies, insurance companies, and Fintech companies. In the new era of Fintech, financial advice further extends to digital forms, including automated investment plans and robo-advisors (Thakor, 2020). Without direct interaction with clients, the service providers need to put extra effort in analysing investor behaviour to maintain and enlarge their clientele, especially when it is meant for a retail audience. In this article, we analyse the different investment patterns of human clients and trading algorithm in the peer-to-peer (P.2.P.) lending market to stress the mismatch between customer needs and financial service/product design.

Renrendai is one of the major P.2.P. lending markets in China that offers automated investment plan services driven by algorithms with various target net-of-fee returns and investment durations, designed to diversify borrower default risk. It is observed that some investors choose to enroll in investment plans, while the others choose to invest by themselves even though loan listings are not available at all times.

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The release of loans is mostly random, except for three scheduled time points (11:00 am, 1:00 pm and 5:00 pm) on workdays. Therefore, manually screening loans requires much time and effort, including arranging time schedule for planned releases, or checking Renrendai's mobile A.P.P. from time to time for random releases and reading loan descriptions and borrower information, etc.

In this article, we try to disentangle why these do-it-yourself (D.I.Y.) investors persist in manually picking loans rather than simply joining investment plans, given that the screening process is inconvenient and thus subject to a higher searching cost. We investigate whether D.I.Y. investors are not satisfied by the return and liquidity that investment plans offer. We make use of four data sets – loan and user data, bidding data from the primary market, transaction data from the secondary market, and loan repayment performance data – to assemble investor portfolio and to calculate portfolio-level and portfolio-note-level return. With transaction data set, we are able to identify whether an investor is a pure D.I.Y. investor who did not enroll in any plans at all, or auto-investor whose transactions are all made by algorithm, or dual investor who enrolled in at least one issue of plan and also made manual investments. In the following analysis, we first examine different behavioiral patterns of auto-investors and D.I.Y. investors at loan-level, transaction-level, and portfolio-level, and supportive evidence is found. Then, we use dual investor information to test above patterns as a robustness check.

By analysing a total of over 200 million entries of data, we find that D.I.Y. investors indeed prefer engaging in trading loans with higher interest rate and shorter maturity. And as a result, D.I.Y. investors acquire a return of 12.24%, while auto-investors receive a return of 10.99%. The resulting difference of 1.25% is statistically and economically significant. On average, D.I.Y. investors trade loans that are five to seven months closer to maturity than algorithm does. Ordinary least square (O.L.S.) results show that, after controlling for loan and borrower characteristics, for every additional level of borrower risk undertaken by investors, D.I.Y. investors receive a marginal return that is 1.4% lower than auto-investors do.

This article contributes in the following aspects. First, our work complements research on financial services. Extant research on financial service seeking behaviour mainly focuses on characteristics of investors (Amaral & Kolsarici, 2020; Bhattacharya et al., 2012; Gerrans & Hershey, 2017; Hackethal et al., 2012; Hermansson & Song, 2016; Milner & Rosenstreich, 2013), and little is known about whether the characteristics of financial services affect investor choice. Moreover, most studies on financial advice focus on human advisors (e.g., Kramer, 2012), who may commit to biased decision-making (Kaustia et al., 2008) or exacerbate client biases (Mullainathan et al., 2009). Research on online financial products/services is scarce (Wang & Yang, 2019; 2020). Our work studies the interaction between digital financial service variables and investor behaviour variables, and provides strong evidence to the mismatch between service attributes and investor preferences.

Second, it complements P.2.P. lending research. Existing empirical studies on P.2.P. focus on what influences loan successful application (Gavurova et al., 2018), and whether successful application and loan default can be predicted or explained by the information disclosed (Iyer et al., 2009; Mild et al., 2015; Zhao & Qi, 2019), for example gender (Chen et al., 2020), credit score (Klafft, 2008), friend network and social media (Ge et al., 2016; Lin et al., 2013), and alternative information (Wang et al., 2019; Xia et al., 2020). Other than that, some studies look into the role of P.2.P. lending platform (Havrylchyk & Verdier, 2018; Liu et al., 2019; Shi et al., 2019). Moreover, some researchers examine the relationship between traditional banking and P.2.P. lending, such as whether P.2.P. lending is a complement or a substitute of bank credit from a borrower perspective (Tang, 2019), and whether bank misconducts influence P.2.P. market (Bertsch et al., 2020). Only very few papers explore the preference and behaviour of investors in P.2.P. lending market (Paravisini et al., 2017; Tian et al., 2021; Zhang & Liu, 2012).

Last, this article contributes to the studies on retail investor behaviour and household finance (Campbell, 2006). While most of the work on retail investor behaviour focuses on traditional financial market (Kelley & Tetlock, 2013; Kumar & Lee, 2006; Meng & Pantzalis, 2018), this article spends time constructing investor portfolios, computes portfolio returns, and provides insights into P.2.P. lending market.

The rest of this article is organised as follows. Section 2 introduces data source and methodology. Section 3 introduces the data sets used in this study. Section 4 exhibits the empirical results. Section 5 tests the results with dual investor sample. Section 6 inspects whether D.I.Y. investors only have access to the loans sieved out by algorithm. Section 7 discusses the implications of this study and concludes.

2. Data source and methodology

2.1. Data source

The data sets used in this study are obtained from Renrendai. Established in 2010, Renrendai is one of the most popular P.2.P. platforms in China. By the end of 2019, loans of over 99 billion yuan has been originated on Renrendai. Moreover, it is one of the most law-compliant P.2.P. platforms in China. Renrendai was awarded A.A.A. rating by the Internet Society of China and the China Academy of Social Science.

On Renrendai's mobile A.P.P., the borrowers can post loan listings with loan title, description of loan purpose, loan amount, interest rate, and repayment terms. Renrendai automatically assigns a credit level to each borrower according to his or her credit history and other information provided. Successful loans are split into 50 yuan notes.

On the lending side, Renrendai offers its lenders the choice to invest by themselves or to enroll in automatic investment plans: U Plan ('Uxiang'), Premium Plan ('Youxuan'), and Salary Plan ('Xinxiang'). The underlying algorithm helps clients choose a variety of loan contracts in the portfolio such that default risk is diversified and certain level of return is realized. The Premium Plan and U Plan require lump-sum investment at the beginning of the plan, while the Salary Plan requires a fixed amount of investment from 500 to 20,000 yuan every month. The U Plan offers fixed investment time ranging from 1 month to 36 months, and their corresponding target annual return varies from 5% to 11%. The Premium Plan has a closed-end investment term of 12 months, followed by six months of optional open-end term. The Premium Plan sets its target return around 9%, which changes over time. The Salary

Plan lasts 12 months with a target annual return of 8%. Despite the aforementioned differences, all of the three plans are driven by auto-investment algorithm whose investment parameters are out of investor's control. It is worth noting that, although these plans are very similar to products in nature, they are essentially services as clarified in the contracts.

If a lender chooses to pick loans by him/herself, he/she has to pay attention to available loans. The loans are released on 11:00 am, 1:00 pm, and 5:00 pm on workdays, and are randomly released at other time of workdays or on non-workdays. Since April 2020, the scheduled releases are cancelled, and thus all releases become random in time.

On the secondary market, the loan contract can be transferred as long as it has been originated for 90 days and is not in default. Both algorithm and D.I.Y. lenders buy and sell loan contracts at the price set by Renrendai, which is the present value of expected future cash flows. On the loan contract transfer interface, all public information about the loan is shown to potential investors, together with next repayment day and repayment history. Renrendai charges D.I.Y. investors 0.5% of loan transfer on the secondary market as a service fee.

2.2. Hypothesis development

To elucidate why some investors do not enroll in investment plans, we develop the following hypotheses:

> H_1: Some investors stick to manual investing because they look for returns higher than offered by the plans.

The target returns of investment plans range from 5% to 11%. However, in the loan bidding market, many borrowers offer an interest rate much higher than 11%. Therefore, some investors may not be satisfied by the net-of-fee return offered by automatic investment plans and thus they decide to manually choose loans to pursue a higher return.

> H_2: Some investors stick to manual investing because they desire liquidity and do not want to be constrained by investment plans.

Since all the investment plans are subject to a fixed period of investment time. Some investors may desire more flexible use of their spare cash and thus choose to make investments by themselves, so that they can liquidate their loan notes on hand in the secondary market when in need of money. Therefore, we suspect that some investors are uncertain about their cash needs and do not enroll in auto-investment plans due to the lock-up period.

3. Data and summary statistics

3.1. Original data sets

The data used in this study come from the information posted by Renrendai on its website. To be specific, the data sets used in this study are as follows:

1. Loan data set. It contains loan listings from 13 October 2010 to 31 July 2017, and provides information on loan characteristics (e.g., loan amount, A.P.R., repayment terms, etc.) and borrower characteristics (e.g., gender, age, education, income, credit rating, etc.). Loan listings that do not receive full requested amount within seven days are considered unsuccessful and the biddings on unsuccessful loans are invalid. Among 1,046,313 loan listings, 579,055 are unsuccessful and thus are removed in the upcoming analysis.
2. Bidding data set. This data set reports investor I.D. and his/her investment amount in each loan in the primary bidding market.
3. Transaction data set. This is a universe of 73,149,796 entries of transactions in the secondary market, executed by investment plan algorithm or by investor him/herself. The vast majority (over 72 million) of transfer data can be matched with the loan and bidding data set such that we can examine the characteristics of the contracts traded. In this data set, user plan I.D. is provided for each transaction, and thus we are able to identify whether a transaction is executed by investor or by algorithm. Note that user plan I.D. is not unique for each investor and it varies when investors enroll in different issues of plans.
4. Repayment performance data set. This data set provides monthly repayment records of loans.

3.2. Constructing portfolios and computing returns

Using loan, bidding, and transaction data sets, we are able to construct a portfolio data set, which contains buy and sell date of loans by each investor. Next, we exclude the observations that would result in false internal rate of return (I.R.R.). To be specific, if the first record or the only record on a loan note is a 'sell' record, or the loan is still in repayment, the observation is removed before the next step. Because in these situations, I.R.R. is erroneous or undervalued. After removal, over 186 million entries remain in the portfolio data set.

The portfolio data is then combined with repayment performance data to obtain the cash flows of the investor in order to compute portfolio-level I.R.R. and portfolio-note-level I.R.R. We compute the monthly return r that satisfies the following equation for each investor's portfolio as an aggregate return (Ross et al., 2011).

$$\sum\nolimits_i Outflow_i * (1+r)^{n_i} = \sum\nolimits_j Inflow_j * (1+r)^{m_j} \tag{1}$$

$$\mathrm{APR} = \mathrm{r} * 12 \tag{2}$$

$Outflow_i$ denotes outflows (or investments) of a user; $Inflow_j$ denotes inflows (or return) of a user; n_i represents the number of months (in fraction) between occurrence of $Outflow_i$ and the end date of the corresponding loan; m_j represents the number of months (in fraction) between occurrence of $Inflow_j$ and the end date of the loan. Annual percentage rate (A.P.R.) is computed as effective monthly rate times 12. It is a technically demanding task to match cash flows of over 14 million loan repayment records with 186 million entries of portfolio data. Eventually, we obtain

374,103 portfolio-level IRR. Among them, 15.3% are D.I.Y. investors. Note that the returns obtained from previous procedures are gross-of-fee returns.

3.3. Summary statistics

Loans that do not receive requested amount are considered unsuccessful and the biddings on them are invalid and rescinded. Thus unsuccessful loans are irrelevant to investor return. Therefore, we restrict our sample to successfully-funded loans only. Table 1 shows the definition of variables, and Table 2 exhibits the summary statistics of the consummated loans. As an average loan contract in our sample, the borrower requests 71,645 yuan with an A.P.R. of 11.00% scheduled to be repaid in 30.39 months. A successful loan listing on average includes a title of four to five Chinese characters and a body of around 105 Chinese characters. Only 3.8% of the loans are with interest-then-principal repayment structure, while most of the borrowers repay with equal installments. Female borrowers account for 30.3% of all loanees. Compared with earlier data where only about 13% of borrowers are female (Chen et al., 2020), it seems that the proportion of female borrowers has grown. Successful borrowers are well educated, with limited working experience. About 80% of them have a monthly income of over 5000 yuan. 48.6% of them own real estate properties and 23% of them own cars. Fewer have mortgages or car loans.

The transaction data set incorporates 73,149,796 entries of transactions with 453,723 unique investors. Among them, 46,025 (10.1%) are dual investors that have

Table 1. Definition of variables.

Variable	Definition
Annual percentage rate (APR)	Annual percentage rate of a loan
Amount (yuan)	Total amount of a loan
Ln_amount	The natural log of the total loan amount
Transaction amount (yuan)	The transacted amount of a loan
Repayment terms (month)	Loan maturity in month
Payment structure	How loans are repaid. 1 if interests are repaid each month and principal is repaid at maturity; 0 if equal installments are repaid each month
Title length	The number of Chinese characters contained in the loan listing title
Description length	The number of Chinese characters contained in the loan description
Gender	Borrower's gender. 1 = male and 0 = female
Age	Borrower's age by the time of loan origination
Education	Borrower's education level. 0 = middle school or high school; 1 = college graduate; 2 = university graduate; 3 = postgraduate
Income (yuan)	Borrower's monthly income. 1 = less than 1000; 2 = 1001–2000; 3 = 2001–5000; 5000; 4 = 5001–10,000; 5 = 10,001–20,000; 6 = 20,001–50,000; 7 = more than 50,000
Married	Borrower's marital status. 1 = married; 0 = single, widowed, or divorced.
Work experience	Borrower's working experience. 0 = no work experience or less than 1 year; 1 = from 1 to 3 years; 2 = from 3 to 5 years; 3 = more than 5 years
Credit risk	Credit risk is measured according to the credit rating by Renrendai. 1 = credit rating is 'AA'; 2 = credit rating is 'A'; 3 = credit rating is 'B'; 4 = credit rating is 'C'; 5 = credit rating is 'D'; 6 = credit rating is 'E'; 7 = credit rating is 'HR', where 'HR' stands for high risk.
Homeowner	1 if borrower owns real estate property; 0 otherwise
Mortgage	1 if borrower has outstanding mortgage; 0 otherwise
Car owner	1 if borrower owns automobile; 0 otherwise
Car loan	1 if borrower has outstanding car loan; 0 otherwise

Notes: Both *Amount* and *Ln_amount* are measurements of total amount of a loan; *Amount* is shown in summary statistics while *Ln_amount* is used in regressions.
Source: Authors.

Table 2. Summary statistics of loans.

Variable	Obs	Mean	SD	Min	Max
Loan characteristics					
APR (%)	462,716	11.002	1.359	3	24.4
Amount	462,716	71645.09	50755.77	1000	3000000
Repayment terms	462,716	30.393	9.275	1	48
Payment structure	462,716	0.038	0.190	1	2
Title length	462,716	4.495	2.395	0	50
Description length	462,716	104.983	44.004	0	476
Borrower characteristics					
Gender	462,716	0.697	0.459	0	1
Age	462,716	36.344	8.681	0	73
Income	449,362	4.428	1.250	1	7
Income = less than 1,000	467,226	0.014	0.117	0	1
Income = 1,001–2,000	467,226	0.002	0.046	0	1
Income = 2,001–5,000	467,226	0.209	0.407	0	1
Income = 5,001–10,000	467,226	0.338	0.473	0	1
Income = 10,001–20,000	467,226	0.199	0.399	0	1
Income = 20,001–50,000	467,226	0.133	0.339	0	1
Income = more than 50,000	467,226	0.068	0.251	0	1
Education	444,843	1.203	0.726	0	3
Education = middle/high school	467,226	0.160	0.367	0	1
Education = college graduate	467,226	0.466	0.499	0	1
Education = university graduate	467,226	0.318	0.466	0	1
Education = postgraduate	467,226	0.017	0.129	0	1
Work experience	446,999	1.267	1.221	0	3
Work experience = less than 1 year	467,226	0.364	0.481	0	1
Work experience = 1 to 3 years	467,226	0.230	0.421	0	1
Work experience = 3 to 5 years	467,226	0.107	0.309	0	1
Work experience = more than 5 years	467,226	0.256	0.436	0	1
Credit risk	467,226	2.243	1.014	1	7
Credit risk = 1 (credit rating is 'AA')	467,226	0.003	0.056	0	1
Credit risk = 2 (credit rating is 'A')	467,226	0.937	0.243	0	1
Credit risk = 3 (credit rating is 'B')	467,226	0.002	0.041	0	1
Credit risk = 4 (credit rating is 'C')	467,226	0.003	0.055	0	1
Credit risk = 5 (credit rating is 'D')	467,226	0.012	0.110	0	1
Credit risk = 6 (credit rating is 'E')	467,226	0.012	0.109	0	1
Credit risk = 7 (credit rating is 'HR')	467,226	0.031	0.173	0	1
Homeowner	445,044	0.486	0.500	0	1
Mortgage	445,044	0.279	0.448	0	1
Car owner	445,044	0.230	0.421	0	1
Car loan	445,044	0.056	0.230	0	1

Source: Authors.

both D.I.Y. trading records and auto-trading records; 29,325 (6.5%) are D.I.Y. investors; 378,373 (83.4%) are auto-investors.

4. Results

Since both H_1 and H_2 refer to the mismatch between auto-investment plan features and investor preference, we collectively investigate H_1 and H_2 at transaction-level, loan-level, and portfolio-level.

4.1. Transaction-level evidence

The loan and borrower characteristics of transactions in the secondary market are summarized in Table 3 by executor (D.I.Y. investors or algorithm) and position (buyer or seller).

Table 3. Summary statistics of transactions in the secondary market.

		DIY investor				Algorithm				Difference
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean
As seller	Loan characteristics									
	APR (%)	12.07	1.05	8	24	10.86	1.02	8	14.1	1.21
	Repayment terms	29.63	8.89	3	48	33.81	6.75	3	48	−4.18
	Amount	77090.13	53014.34	50	3,000,000	101302.00	54964.21	1000	500000	−24211.87
	Transaction amount	261.24	937.83	1.44	83,480	325.94	636.61	1.44	95700	−64.70
	Title length	4.88	3.02	0	50	4.15	1.89	0	50	0.73
	Description length	110.04	62.55	0	499	102.97	30.48	0	384	7.06
	Days to maturity	521.69	289.22	0	1920	745.93	288.03	0	1440	−224.24
	Payment structure	0.00	0.03	0	1	0.02	0.13	0	1	−0.02
	Borrower characteristics									
	Gender	0.71	0.45	0	1	0.67	0.47	0	1	0.04
	Credit risk	2.71	1.69	1	7	2.00	0.02	1	4	0.71
	Age	38.77	8.48	0	67	38.05	8.67	0	64	0.72
	Education	1.06	0.75	0	3	1.29	0.73	0	3	−0.23
	Income	4.55	1.23	1	7	4.54	1.18	1	7	0.01
	Homeowner	0.565	0.50	0	1	0.567	0.50	0	1	−0.002
	Mortgage	0.382	0.49	0	1	0.354	0.48	0	1	0.028
	Car owner	0.267	0.44	0	1	0.230	0.42	0	1	0.037
	Car loan	0.071	0.26	0	1	0.056	0.23	0	1	0.015
	Number of observations	6,338,717				66,149,799				
As buyer	Loan characteristics									
	APR (%)	12.01	1.07	8	24	10.81	0.99	8	14.1	1.20
	Repayment terms	30.37	8.56	3	48	33.91	6.69	3	48	−3.54
	Amount	79181.97	50459.24	50	3,000,000	102175.90	55314.00	1000	500000	−22993.93
	Transaction amount	280.97	917.91	1.44	95,700	325.94	636.61	1.44	95700	−44.97
	Title length	4.75	2.93	0	50	4.14	1.84	0	50	0.61
	Description length	109.84	56.99	0	499	102.65	29.74	0	384	7.18
	Days to maturity	556.86	295.02	0	1920	726.37	295.01	0	1920	−169.51
	Payment structure	0.00	0.04	0	1	0.02	0.14	0	1	−0.02
	Borrower characteristics									
	Gender	0.67	0.47	0	1	0.70	0.46	0	1	−0.04
	Credit risk	2.49	1.44	1	7	2.00	0.02	1	4	0.49
	Age	38.86	8.49	0	67	38.00	8.67	0	66	0.86
	Education	1.07	0.75	0	3	1.30	0.73	0	3	−0.23
	Income	4.55	1.22	1	7	4.54	1.18	1	7	0.01
	Homeowner	0.581	0.49	0	1	0.564	0.50	0	1	0.017
	Mortgage	0.398	0.49	0	1	0.350	0.48	0	1	0.048
	Car owner	0.266	0.44	0	1	0.229	0.42	0	1	0.037
	Car loan	0.071	0.26	0	1	0.055	0.23	0	1	0.016
	Number of observations	62,998,978				9,489,538				

Notes: This table shows summary statistics of loan and borrower characteristics by executor (D.I.Y. investor or algorithm) and position (buyer or seller), and the last column report the differences between D.I.Y. investors and algorithm, whose p-values are all 0.00 and thus are omitted in the table.
Source: Authors.

Among the 72,488,516 transactions that can be matched with loan data, algorithm sells most (66,149,799) of the contracts, and D.I.Y. investors buy most (62,998,978) of the loan contracts. The differences of these statistics mainly reside between D.I.Y. investors and algorithm, not between buy side and sell side.

Generally, compared to investment plans, D.I.Y. investors prefer dealing with – both buying and selling – loan notes with higher interest rates, shorter repayment terms, smaller amount, and fewer days to maturity, and those with equal installments. The average A.P.R. of loans traded by D.I.Y. investors is slightly higher than 12%, and that of algorithm is slightly lower than 11%, resulting in a significant difference of 1.2%. D.I.Y. investors trade loans with A.P.R. from 8% to 24%. In great contrast, algorithm never touches upon loans with A.P.R. higher than 14.1%. D.I.Y. investors trade loan contracts that are three to four months shorter in repayment terms and 5 to 7 months closer to maturity than algorithm. D.I.Y. investors almost never trade loan contracts with interest-then-principal repayment structure, indicating that faster cash inflows are strongly preferred. Moreover, D.I.Y. investors trade loans with all levels of credit risks while algorithm strictly restricts credit risk to no more than four. Moreover, the standard deviations of other borrower traits are generally lower for algorithms than D.I.Y. investors.

4.2. Loan-level evidence

We then ask the question if certain types of loans are more likely to be actively traded by D.I.Y. investors. We investigate transaction data at loan-level with O.L.S. regressions. We include loan variables, borrower characteristics, and origination year fixed effect in the following model:

$$\begin{aligned} &The\ number\ of\ trades\ made\ on\ a\ loan = \alpha + \beta\ Loan\ characteristics \\ &\quad + \gamma\ Borrower\ characteristics + \theta\ Year\ dummy + \varepsilon \end{aligned} \tag{3}$$

To disentangle if certain types of loans are favoured by D.I.Y. investors, the trading pattern of algorithm is considered as a benchmark in comparison. Therefore, the dependent variable is decomposed by trading position (buy side or sell side) and who the trading party is (D.I.Y. investor or algorithm).

Table 4 shows how many times a loan contract is traded by different parties. In Column (1), the dependent variable is the total trade times of a loan contract. From Column (2) to Column (9), the dependent variables are the trade times of a loan contract by specified seller (S) and buyer (B) by algorithm (A) or D.I.Y. investor (D). For example, 'SA, BA' means both seller and buyer are algorithm; 'SD, BA' means seller is D.I.Y. investor and buyer is algorithm. 'With A' means buyer or seller – at least one trading party – is algorithm, and 'With D' means buyer or seller is D.I.Y. investor. The t-statistics are shown in parentheses and are adjusted for heteroskedasticity. Column (1)–(7) incorporate loans in repayment and paid-off loans, and Column (8)–(9) only consider paid-off loans.

To study the preference of D.I.Y. investors, we mainly focus on Column (5), (7), and (9); other columns are references. Compared with Column (1)–(4), Column (5)

Table 4. The number of trades on loan contracts by D.I.Y. investors and algorithm.

	Paid-off loans and repayment in progress loans							Paid-off loans only	
	(1) Total	(2) SA, BA	(3) SD, BA	(4) SA, BD	(5) SD, BD	(6) With A	(7) With D	(8) With A	(9) With D
APR	−4.758***	−17.26***	0.0199***	0.875***	4.378***	−16.36***	5.273***	−20.90***	4.109***
	(−22.60)	(−78.90)	(9.97)	(69.85)	(102.75)	(−75.80)	(116.60)	(−82.05)	(71.01)
Repayment terms	−0.350***	0.0306	−0.00406***	−0.00734***	−0.361***	0.0192	−0.373***	0.548***	−0.426***
	(−9.71)	(0.83)	(−8.29)	(−3.96)	(−50.71)	(0.52)	(−51.62)	(13.82)	(−33.09)
Ln_amount	114.2***	96.72***	0.0626***	0.549***	4.879***	97.33***	5.490***	44.21***	8.873***
	(165.57)	(146.75)	(11.42)	(23.99)	(51.95)	(147.94)	(57.66)	(69.86)	(45.33)
Title length	−0.0476	0.0113	−0.000647*	−0.00120	0.00631	0.00943	0.00446	0.0807***	0.0631***
	(−1.21)	(0.30)	(−1.78)	(−0.50)	(0.85)	(0.25)	(0.59)	(3.20)	(6.49)
Description length	−0.0291***	−0.0665***	0.000137***	0.00157***	0.0169***	−0.0648***	0.0186***	−0.0591***	0.0194***
	(−16.33)	(−39.73)	(4.29)	(13.38)	(34.29)	(−38.90)	(37.57)	(−40.49)	(31.69)
Gender	3.055***	2.757***	0.0132**	0.0267	0.223**	2.797***	0.262***	−3.265***	0.568***
	(3.97)	(3.72)	(2.32)	(1.01)	(2.33)	(3.78)	(2.72)	(−4.06)	(2.84)
Age	1.637***	1.107***	0.00101**	0.0215***	0.0773***	1.129***	0.0998***	0.486***	0.0927***
	(36.73)	(25.77)	(2.35)	(12.78)	(13.31)	(26.37)	(16.92)	(11.29)	(8.42)
Income	−8.519***	−8.254***	0.00352	0.0741***	0.0591	−8.176***	0.137***	1.588***	0.676***
	(−29.41)	(−29.52)	(1.55)	(7.12)	(1.64)	(−29.32)	(3.74)	(5.31)	(8.99)
Education	−0.118	−0.231	0.00478*	0.0193*	−0.0651*	−0.207	−0.0411	−0.467***	−0.286***
	(−0.59)	(−1.22)	(1.88)	(1.94)	(−1.88)	(−1.09)	(−1.17)	(−2.62)	(−5.47)
Married	−1.265*	−1.665**	0.00384	0.0367	0.0317	−1.624**	0.0722	−1.795**	−0.360*
	(−1.68)	(−2.29)	(0.69)	(1.45)	(0.34)	(−2.24)	(0.76)	(−2.40)	(−1.96)
Work experience	−8.116***	1.240***	−0.0215***	−0.256***	−1.681***	0.963***	−1.958***	−2.400***	−1.589***
	(−25.53)	(4.03)	(−9.53)	(−24.31)	(−43.87)	(3.14)	(−49.58)	(−7.06)	(−22.45)
Homeowner	9.330***	6.036***	0.0234***	0.00270	0.766***	6.062***	0.792***	1.361	0.884***
	(9.90)	(6.61)	(2.88)	(0.09)	(7.25)	(6.65)	(7.36)	(1.50)	(4.06)
Mortgage	31.57***	24.03***	−0.0110	−0.184***	1.643***	23.84***	1.448***	−0.126	1.550***
	(28.96)	(22.93)	(−1.04)	(−4.68)	(12.12)	(22.81)	(10.49)	(−0.12)	(5.90)
Car owner	−10.29***	−8.593***	0.00204	−0.295***	−0.0100	−8.885***	−0.303**	−3.114***	−0.942***
	(−10.41)	(−9.06)	(0.22)	(−8.56)	(−0.08)	(−9.39)	(−2.31)	(−3.39)	(−4.00)
Car loan	5.223***	2.595	0.00280	0.0288	0.477**	2.627*	0.509**	7.390***	0.592
	(3.13)	(1.64)	(0.19)	(0.45)	(1.96)	(1.67)	(2.07)	(4.83)	(1.48)
City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	442468	442468	442468	442468	442468	442468	442468	172012	172012

Notes: This table reports O.L.S. regression results where the dependent variable is the number of trades of each loan made by D.I.Y. investor and/or algorithm. Columns (1)–(7) include loans that are paid-off and still in repayment; Columns (8) and (9) include paid-off loans only. In Column (1), the dependent variable is the total number of times a loan contract is traded. From Column (2) to Column (9), the dependent variables are the times a loan contract is traded by specified seller (S) and buyer (B) by algorithm (A) or D.I.Y. investor (D); For example, 'SA, BA' means seller is algorithm and buyer is algorithm; 'SD, BA' means seller is D.I.Y. investor and buyer is algorithm. 'With A' means buyer or seller is algorithm and 'With D' means buyer or seller is D.I.Y. investor. The t-statistics are shown in parentheses and are adjusted for heteroskedasticity and autocorrelation. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Authors.

indicates that loans with higher A.P.R. have a higher liquidity among D.I.Y. investors. This pattern is also supported by comparing Column (6) with Column (7) and comparing Column (8) with Column (9). The result that D.I.Y. investors love trading high A.P.R. loans is in accordance with the results observed in Table 3. Across specifications, the coefficients of *Repayment terms* are negative and significant except when the dependent variable is 'SA, BA' or 'With A'. In fact, the coefficients of *Repayment terms* are most negative in Column (5), (7), and (9). It implies that loans with longer repayment periods are more illiquid from D.I.Y. investors' perspective. The coefficients of *Ln_amount* are all positive across columns because larger loans are split into more notes by Renrendai, and thus are traded more often.

In summary, loans with higher A.P.R. and shorter repayment periods are more actively traded among D.I.Y. investors. In addition, in view of the comparison between Column (6) and Column (7) or the comparison between Column (8) and Column (9), the coefficients of borrower characteristics are closer to zero in (7) and (9) than in (6) and (8) in most cases, indicating that D.I.Y. investors are less sensitive to borrower characteristics than algorithm is. This may result from varied preferences across D.I.Y. investors, or bounded rationality in face of excessive information, or both.

4.3. Portfolio-level evidence

The histogram of user portfolio return is shown in Figure 1. The average return received of D.I.Y. investors is 12.24% and that of auto-investors is 10.99%. Both distributions have a long right tail but the return of D.I.Y. investors is much more dispersed than auto-investors.

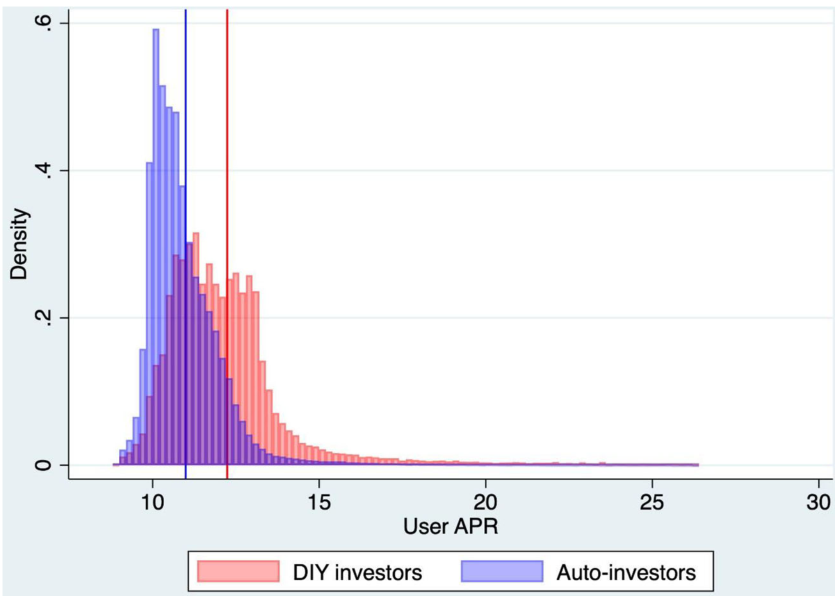

Figure 1. Distribution of portfolio return by investor type.
The red and blue bars show the distribution of D.I.Y. investor A.P.R. and auto-investor A.P.R., respectively. The red and blue vertical lines are the means of D.I.Y. investor A.P.R. (12.24%) and auto-investor A.P.R. (10.99%), respectively.
Source: Authors.

We then ask the question if D.I.Y. investors in pursuit of high return simply received higher risk-adjusted return or they actually undertook excessive risk. In other words, can D.I.Y. investors' returns compensate the risk they took? To answer this question, an O.L.S. model is developed as follows:

$$\begin{aligned} User\ return = \ & \alpha + \beta\ No\ plan + \gamma\ Average\ borrower\ risk \\ & + \theta\ No\ plan{*}Average\ borrower\ risk + \delta\ Average\ loan\ characteristics \\ & + \eta\ Average\ borrower\ characteristics + \varepsilon \end{aligned} \tag{4}$$

No plan is a dummy variable differentiating between D.I.Y. investors ($No\ plan = 1$) and auto-investors ($No\ plan = 0$). *Average borrower risk* is the simple average of borrower risk of loans in investor portfolio. The same applies for *Average loan characteristics* and *Average borrower characteristics*. *No plan* * *Average borrower risk* is the interaction term of our interest.

Theoretically, investor characteristics should also be considered in the calculation of portfolio return. However, Renrendai only requires investor's national identity card number, which is confidential and unavailable. Other personal information is not mandatory. Therefore, investor variables are not included in the model.

The O.L.S. results adjusted for heteroskedasticity are shown in Table 5. Column (1) only includes variables of our interest. Column (2) also includes simple average value of loan characteristics in the portfolio. Column (3) includes simple average value of borrower characteristics. Column (4) includes simple average value of both loan and borrower characteristics. Across all the specifications, the coefficients of *No plan* and *Average borrower risk* are all positive and significant, indicating that being '*No plan*' and lending to borrowers of higher risk indeed result in a higher return. After considering all the control variables, *auto-investors* yield a return approximately 3.5% higher than their peers, and taking additional unit of credit risk brings about 2.4% higher return. This is in consistent with our previous findings. However, the coefficients of the interaction term *No plan* * *Average borrower risk* are all negative and significant at 1% level, indicating that for every one unit of credit risk undertook by investors, D.I.Y. investors receive a marginal return 1.45% lower than auto-investors do. Therefore, taking auto-investors as benchmark, D.I.Y. investors bear high credit risk in exchange for return that cannot compensate such risk.

4.4. Risk-taking of D.I.Y. investors and auto-investors

We combine portfolio data with loan characteristics and calculate the average of these variables. Portfolio-level borrower credit risk and assets-related variable statistics by investor type is shown in Table 6. The average credit risk of auto-investor portfolio is about two, while that of D.I.Y. investors is around five. A higher proportion of borrowers in auto-investors' portfolio are homeowners, mortgage payers, car owners, and car loan payers. The standard deviations of these variables are lower for auto-investors, suggesting that the auto-investment algorithm is programmed to consider collaterals.

Table 5. Investment plan, risk and return.

	(1) Portfolio return	(2) Portfolio return	(3) Portfolio return	(4) Portfolio return
No plan	5.623***	4.357***	2.883***	3.496***
	(17.40)	(20.31)	(11.15)	(17.01)
Average borrower risk	3.191***	2.509***	2.154***	2.405***
	(20.37)	(25.19)	(17.60)	(25.36)
No plan * Average borrower risk	−2.233***	−1.759***	−1.155***	−1.448***
	(−13.88)	(−16.55)	(−9.03)	(−14.26)
Average holding days		0.00310***		0.00164***
		(94.02)		(30.15)
Average repayment terms		0.0336***		0.0515***
		(32.95)		(26.63)
Average title length		0.0914***		0.173***
		(19.09)		(22.15)
Average description length		0.00391***		0.00604***
		(18.60)		(20.46)
Average repayment structure		−2.776***		−2.092***
		(−79.73)		(−13.41)
Average Ln_amount		−1.050***		−0.586***
		(−63.09)		(−19.51)
Average age			0.0213***	0.0191***
			(11.02)	(9.65)
Average income			−0.242***	−0.147***
			(−20.47)	(−10.94)
Average gender			0.133***	0.107***
			(16.12)	(13.24)
Average education			−0.638***	−0.506***
			(−30.37)	(−21.60)
Average married			−0.0176	0.0368
			(−0.46)	(0.96)
Average homeowner			−0.762***	−0.554***
			(−17.52)	(−11.94)
Average mortgage			1.179***	0.877***
			(27.25)	(19.06)
Average car owner			0.281***	0.508***
			(7.14)	(12.50)
Average car loan			0.189***	0.223***
			(2.75)	(3.28)
City	No	Yes	Yes	Yes
N	366179	366154	146545	146520

Notes: This table reports O.L.S. regression results where dependent variable is portfolio A.P.R., or investor return (%). Column (1) only includes variables of our interest. Column (2) also includes simple average value of loan characteristics in the portfolio. Column (3) includes simple average value of borrower characteristics. Column (4) includes simple average value of both loan and borrower characteristics. *Average holding days* refers to the average number of days a loan stays in the portfolio. The t-statistics are shown in parentheses and are adjusted for heteroskedasticity and autocorrelation. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Authors.

Table 6. Investor type and borrower characteristics in their portfolio.

	Auto-investors					DIY investors				
Variables	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Credit risk	371,364	2.041	0.403	1	7	291,555	5.084	2.408	1	7
Homeowner	365,296	0.560	0.255	0	1	286,764	0.302	0.418	0	1
Mortgage	365,296	0.347	0.227	0	1	286,764	0.133	0.290	0	1
Car owner	365,296	0.223	0.199	0	1	286,764	0.173	0.335	0	1
Car loan	365,296	0.052	0.100	0	1	286,764	0.042	0.171	0	1

Notes: This table reports simple average of borrower credit risk and assets-related variables of loans held or once held in each portfolio, by investor type.
Source: Authors.

Table 7. Probit regression results.

	(1) No plan	(2) No plan
Gender	0.168***	0.155***
	(21.95)	(18.82)
Age	0.00269***	0.000901
	(3.84)	(1.40)
Registration date	−0.000846***	−0.000845***
	(−36.19)	(−40.66)
Average borrower risk	0.056***	0.043***
	(5.47)	(3.59)
Portfolio characteristics	No	Yes
City	No	Yes
N	147,755	147,755

Notes: This table reports Probit regression result where dependent variable is *No plan*. The t-statistics are shown in parentheses and are adjusted for heteroskedasticity and autocorrelation. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Authors.

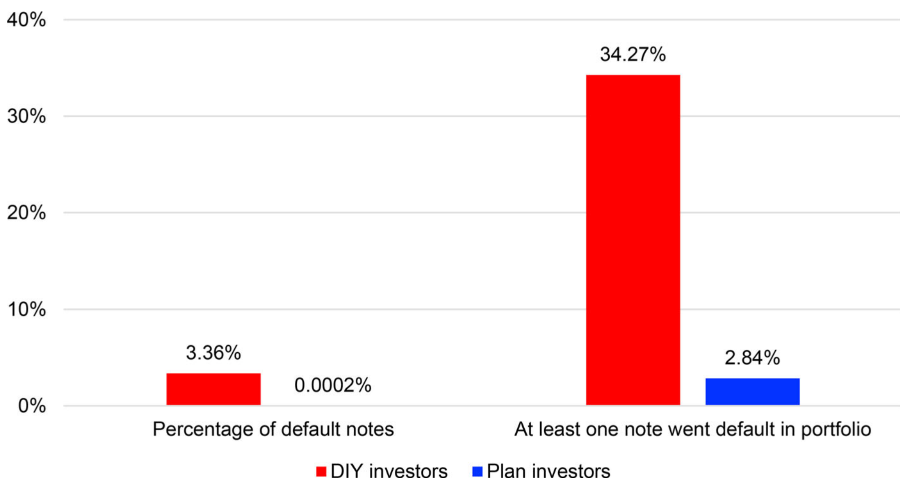

Figure 2. Investor type and default experience.
The two bars on the left show the percentage of default note, calculated as the number of default note divided by total number of notes purchased by the specified investor type. The two bars on the right represent the percentage of investors who experienced at least one default in their portfolio.
Source: Authors.

Table 7 shows results of Probit regressions in which the dependent variable is *No plan*. After controlling for portfolio characteristics and residence city, average borrower risk within portfolio (risk taking of investor) has a significant and positive explanation power on *No plan*, in accordance with findings in Table 6. Moreover, it is revealed that males and more experienced investors (measured by registration date) are more likely to be D.I.Y. investors. It is in line with previous literature (Clark et al., 2019) that males are less likely to seek financial advice.

Next, we examine if algorithm does a better job than D.I.Y. investors in avoiding default loans. As shown in Figure 2, at portfolio-note level, less than 0.01% of auto-investors' loan notes went default and 3.4% of D.I.Y. investors' notes went default. Of all the 478,397 investors, only 2.84% of auto-investors encountered at least one loan default, while that number for D.I.Y. investors is 34.27%.

Table 8. The number of transactions by trading parties (human and algorithm) and default time.

Trading parties	Loan went default before transaction	Loan went default after transaction
SD, BD	207,283	112,659
SA, BA	66	76
SD, BA	0	0
SA, BD	0	2
Total	207,349	112,737

Notes: This table gives the number of transactions on default loans made by human and algorithm and by the time of default (before or after the transaction is made). Trading parties are specified by seller (S) and buyer (B), and by algorithm (A) and D.I.Y. investor (D). For example, 'SD, BA' means seller is D.I.Y. investor and buyer is algorithm.
Source: Authors.

Moreover, we further inspect if default happened before or after transactions are made. After combining transaction data with loan performance, transactions with default records are classified into two groups: the loan went default before the transaction, or the loan went default after the transaction. This procedure is to identify if the algorithm evaluates the loans by loan and borrower characteristics only or together with loan performance. Table 8 reports the results by trading parties. Trading parties are specified by seller (S) and buyer (B), and by algorithm (A) and D.I.Y. investors (D).

Of all the transactions made on default loans, most happened within investor type. The vast majority took place between D.I.Y. investors, and about a third of them went default after the transaction. On the contrary, the algorithm strongly restricts trading loan contracts with a default record. There are only two cross-investor-type transactions in which the seller is algorithm and the buyer is D.I.Y. investor, and both went default afterwards.

In summary, D.I.Y. investors take higher level of credit risk than auto-investors do. The algorithm is programmed to invest in loans with average borrower credit rating 'A' and without default record. On the contrary, D.I.Y. investors on average invest in loans with credit rating 'D' and do not attach as much caution to default record as algorithm does. As a result, D.I.Y. investors experience much more defaults at note-level and at portfolio-level.

5. Robustness check: dual investors

We make use of dual investors' information to verify the results elaborated in Section 4. Since dual investors not only enrolled in auto-investment plans but also made manual investments, we conceive that their portfolio return and risk taking should be a compromise of D.I.Y. investors and auto-investors. The results support our projection and are omitted due to the length limit of this manuscript.

Of all the 46,025 dual investors, by comparing the dates of the earliest transactions made by themselves and by algorithm, they are further classified by whether they switched from D.I.Y. to plans, or from plans to D.I.Y. 26,714 of the dual investors are D.I.Y.-auto switchers, and 18,390 are auto-D.I.Y. switchers. The remaining 921 dual investors initiated D.I.Y. and auto-trading on the same day. Note that D.I.Y.-auto switchers do not necessarily abandoned manual investments after the switch, and vice versa. In this section, we investigate the differences between D.I.Y.-auto switchers and auto-D.I.Y. switchers.

Table 9. Note A.P.R. and months to maturity bought by switchers.

		Auto-DIY switchers	DIY-auto switchers
Before the switch	Algorithm-executed transactions	10.71%, 33.2 months	–
	Self-executed transactions	–	11.57%, 31.7 months
After the switch	Algorithm-executed transactions	10.70%, 33.9 months	10.69%, 33.8 months
	Self-executed transactions	12.03%, 28.3 months	12.06%, 30.1 months

Notes: Based on 4790 transactions, this table describes the A.P.R. and months to maturity of the notes bought by Auto-D.I.Y. switchers and D.I.Y.-auto switchers, by transaction time (before or after the switch), and by actual executor of the transaction.
Source: Authors.

Table 9 exhibits A.P.R. and months to maturity of the notes bought by switchers. The auto-D.I.Y. switchers purchase notes with A.P.R. of 10.71% and 33.2 months to maturity with the assistance of algorithm before the switch, and purchase notes with A.P.R. of 12.03% and 28.3 months to maturity by themselves. This result indicates a strong preference for notes with high returns and shorter lock-up period. On the other hand, D.I.Y.-auto switchers purchase notes with A.P.R. of 11.57% and 31.7 months to maturity by themselves before the switch, and purchase notes with even higher A.P.R. and shorter maturity after the switch. With the inclusion of notes executed by algorithm in their portfolio, D.I.Y.-auto switchers purchase high return notes to level up portfolio return to its before-switch value. Table 9 provides supportive evidence on the conjecture that some investors are not satisfied by the return of auto-investment plans.

6. Are loans in D.I.Y. portfolios the leftovers of algorithm?

In Section 4, evidence is found that D.I.Y. investors seek for a higher interest rate and better liquidity than investment plans can offer. In this section, we ask the question if the loans available to D.I.Y. investors are actually the remainders of algorithm screening. Since once a loan application is submitted to Renrendai server, the algorithm can have the priority to choose the loans that match the criteria programmed into it. Therefore, if D.I.Y. investors are only able to access to loans listings that do not survive the algorithm screening, the findings in Section 4 would not be a pure reflection of D.I.Y. investor preference. Hence, it is necessary to unravel if D.I.Y. investors and trading algorithm have equal opportunities to access loan notes.

In Figure 3, we align all loans by their earliest bidding time in the primary market as release time, and separately plot algorithm and D.I.Y. investors bidding time on x-axes of left and right panels. Loan biddings are stratified by their release time to show layers. It is shown that across the span of years from 2010 to 2017, both D.I.Y. investors and algorithm bid loans at the moment of release and they keep bidding in the following days. In more recent years, the biddings reach maximum within four days. D.I.Y. investors and algorithm biddings almost follow the same pattern at all times. It is suggested that D.I.Y. investors and algorithm are under the same competing status, and the results from previous sections are not a result of algorithm priority.

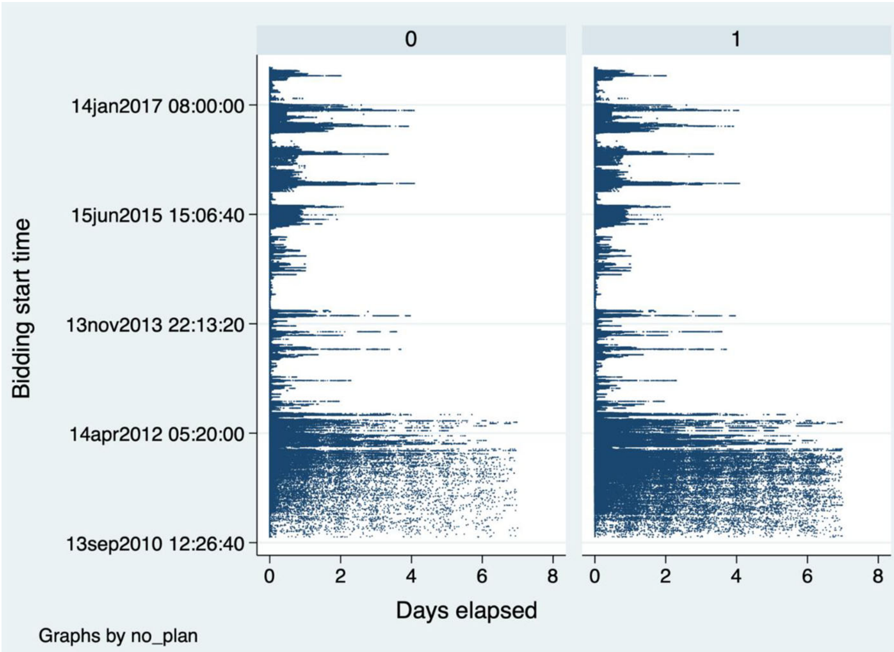

Figure 3. Bidding time by D.I.Y. investor and algorithm.
This figure plots all the biddings in the primary market by investor type. The x-axis measures the days elapsed since the earliest bidding of the loan. The y-axis is the earliest bidding time of each loan. Both time measures are of precision to seconds. The left panel plots algorithm biddings (*no plan* = 0) and the right panel plots D.I.Y. investor biddings (*no plan* = 1).
Source: Authors.

7. Discussion and conclusion

Online financial services have been widely provided by Fintech companies. However, without direct interaction with clients, the service providers need to devote extra effort in analysing customer behaviour to enlarge the clientele and to improve customer satisfaction, especially when it is meant for a retail audience.

We observe that in P.2.P. lending market facing algorithm-driven investment plans, some investors persist in screening and lending by themselves, even though the loans are only released at certain time points. It is shown that D.I.Y. investors trade loans with higher return, shorter repayment terms, and fewer days to maturity than auto-investment plans offer. These patterns are supported by dual investor sample as well and are shown not a result of algorithm priority in choosing loans. An implication for auto-investment service providers is to offer personalised investment plans, allowing investors to set their own target returns and investment time horizons.

In view of the results, just as one size of financial advice provided by advisors does not fit all (Foerster et al., 2017), one size of automated investment plan does not attract all neither. Our work suggests that personalised financial services need to be provided to satisfy a variety of investors' preferences.

It remains an open question why Renrendai has not yet provided investment plans with higher return and shorter maturity. We conjecture that Renrendai remains conservative with credit risk in order to build reputation. The results in previous sections show that the algorithm does not invest in loans with high risk, and only low-risk and low-return notes are purchased on client's behalf. As for investment time horizon, since a typical loan has an average repayment length of around 30 months, providing short-term (e.g., one to two months) investment plans exposes Renrendai to a higher level of platform risk than providing those with longer terms, because locking investor capital longer means the platform can be more robust to unexpected negative shocks. In conclusion, for the best interests of both financial institutions and investors, regulatory authorities should encourage financial service/product innovation while closely monitor unethical conducts.

This article is not without flaws. Due to availability of data, we have only limited demographic information about investors. Therefore, we are unable to investigate how investor behaviour is affected by income, occupation, wealth and other factors. Despite this limitation, our work complements behavioural finance literature by documenting two distinct types of investors in a financial market with the option to use financial service. Also, our work provides a possible answer to why Chinese households do not invest sufficiently in the financial market.

Future research may examine other possible reasons why investors refuse to adopt financial services/products, for example: (1) some investors may simply enjoy investing by themselves (Dorn & Sengmueller, 2009); and (2) some investors may perceive these services/products as unreliable. Moreover, we suggest that the investor behaviours related to other financial services/products should also be analysed in order to examine whether such mismatch is a common phenomenon. Furthermore, future research may further explore the interaction of investors with other digital financial services such as robo-advisors.

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Conflict of interest

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