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Automatic versus manual investing: Role of past performance[☆]

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A B S T R A C T

Using unique data from a leading peer-to-peer (P2P) lending platform, we investigate the link between past investment performance and choice of auto-investing tool. Our results suggest that investors who experience fewer defaults in the manual mode are more inclined to switch to automatic investment. Several factors account for this relationship, including investor inattention, decision speed, investment delegation, and experience. Regarding the latter, our results suggest that experienced investors are more likely to continue self-directed bidding, even if they have faced defaults in manual investments in the past. These investors may attribute their previous mistakes to their own actions rather than the limitations of the self-directed bids. Our results are robust to alternative specifications.

1. Introduction

The first robo-advisory service was launched in 2008, which used algorithms to assist investors with their investment strategies. Since then, the number of financial service providers offering robo-advisory services to clients has dramatically increased, making passive rule-based investments more popular (Germann and Merkle, 2023).[1] The literature identifies several factors that could explain the demand for automated tools, including under-diversification (Loos et al., 2020), spending and saving behavior (D'Acunto and Rossi, 2023), self-improvement and financial well-being (Rossi and Utkus, 2021), and financial literacy (D'Acunto and Rossi, 2021). However, a more important factor could be the passive strategy performance, which could encourage the decision to leave the active investment strategy. This study aims to advance the current knowledge by investigating how past portfolio performance affects the decision to switch to automated investment.

Portfolio allocation is crucial for investors because a lack of diversification can lead to suboptimal financial decisions. Robo-advisors aim to optimize portfolios, offering the greatest benefit to under-diversified investors (D'Acunto et al., 2019; Reher and Sun, 2019). Additionally, individuals with limited self-directed investment knowledge, high cash holdings, and frequent trading activities also gain significantly from adopting robot advice (Rossi and Utkus, 2020).

We use detailed bidding data from Renrendai.com, hereafter Renrendai, a leading P2P lending platform in China. Our data span from 2012–2018 and have several unique aspects. First, it allows investors to access hybrid investment strategies. This helps to identify investors who switch from one bidding mode to another. Second, human investors using automated tools cannot observe borrower characteristics, thus allowing us to identify whether any type of discrimination has been applied. The entire sample comprised more than 890,000 users, with 89 % of their investments made using the auto-bidding tool. Additionally, hybrid users, who accounted for approximately 68,000 investors,

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[1] See "The end of active investing?" (Financial Times, January 19, 2017) (Available at: https://www.ft.com/content/6b2d5490-d9bb-11e6-944b-e7eb37a6aa8e), accessed on August 30, 2022.

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attempted 82 % of automatic bids. Users of this platform are highly dependent on automatic lending, which confirms the popularity of the service.

Peer-to-peer (P2P) lending markets are an ideal environment for this study. These lending platforms propose different frameworks for automated financial tools to help individuals make better financial decisions. Automated tools have gained rapid interest from lenders for several reasons: (i) time-saving, (ii) good at decision-making, (iii) elimination of human biases, and (iv) ease of use. This set of additional features rendered this market an appropriate environment for our investigation. First, P2P lending markets have lower transaction costs and margins charged by platforms than traditional banks do. Second, investors with access to a wide range of lending opportunities have low information costs, with each providing detailed information about the borrowers. Finally, the entry and exit costs are low, which can attract borrowers and lenders. These features make P2P lending markets suitable for comparing self-directed and automatically managed investment decisions.

Our results suggest that past individual underperformance, measured by the weighted average number of defaults, correlates with using an auto-bidding toolbox. This tool shows less discriminatory behavior toward borrowers based on gender, marital status, or employment characteristics. Furthermore, our results indicate that lenders that previously performed well in both manual and automated modes were more likely to switch to automated mode by 0.3 and 1.3 percentage points, respectively. Moreover, we find that lender behavior may be influenced by additional factors. Specifically, we find that those with a higher percentage of auto bids in their portfolios are less likely to embrace automated strategies when they experience an increase in defaults using auto investments. Regarding inattention, we find that inexperienced investors are less responsive to defaults that emerge from automatic bidding. When we tested for time pressure using a fast decision-making indicator, we found no relationship between time pressure and switching to automation. Finally, experienced investors are more likely to continue with or revert to manual investing despite having faced manual defaults in the past, possibly attributing their past errors to their own actions rather than the limitations of self-directed bids.

This study contributes to several strands of literature. First, it contributes to the research on adopting automated financial tools. Previous studies addressed the importance of algorithmic choices in terms of investment (D'Acunto et al., 2019; Rossi and Utkus, 2020; Reher and Sun, 2019; Ge et al., 2021), consumption savings and debt management (D'Acunto and Rossi, 2023), durable investing (Gargano and Rossi, 2024), and cultural biases (D'Acunto et al., 2022). Our research closely aligns with Ge et al. (2021), who focus solely on the relationship between defaults and robo-advisor adoption, attributing their findings to the "recency effect." We extend this by uncovering new factors such as investment delegation and investor inattention. Specifically, our data indicate that increased defaults deter investors with higher auto bids from embracing automation and that decision timelines and investor experience also affect the shift from manual to automated investing.

Additionally, our setting differs from those of existing studies, which are important factors in understanding investor behavior. In our study, investors using the auto-bidding toolbox can change their bidding modes (manual or automatic) without restrictions. By contrast, Rossi and Utkus (2020) analyzed a modern robo-advising tool for indexed mutual funds, where once individuals sign up for the service, they cannot return to a human financial advisor unless they cancel the contract. D'Acunto et al. (2019) investigated a portfolio optimizer tool that only provides stock recommendations to investors, whereas the tool used in the experiment can invest on behalf of lenders. Furthermore, Reher and Sun (2019), Ge et al. (2021), and D'Acunto et al. (2022) employed cross-sectional data, whereas our study uses a large sample size at the investor bid level.

Second, our study contributes to the literature on delegation decisions to investment algorithms. Despite the prevailing preference for human judgment over algorithmic advice, signifying a widespread algorithm aversion (Dietvorst et al., 2015; Longoni et al., 2019), and the social psychology insights into the conflict levels between human and automated decisions (Castelo et al., 2019), the evidence on algorithm aversion remains mixed.[2] We extend the literature by providing evidence that suboptimal auto-bidding performance discourages investors from adopting automated strategies, especially after multiple attempts.

Finally, we supplement the existing literature that investigates the active versus passive investment strategy and performance (Stoughton et al., 2011; Stambaugh, 2014; Easley et al., 2021; Coles et al., 2022; Gârleanu and Pedersen, 2022). We contribute to the literature by showing that investors' underperformance explains their interest in passive rule-based investing, such as automated solutions or robo-advising.

The remainder of this paper is organized as follows: Section 2 introduces the Renrendai platform and auto-bidding tool, Section 3 introduces our data and sample collection process, Section 4 reviews the methodology and econometric model used, Section 5 presents our main results, Section 6 includes a robustness check, and Section 7 concludes the paper.

2. Renrendai platform and automation

Renrendai is a leading P2P lending platform (Caglayan et al., 2020a) founded in 2010 (Liao et al., 2021). It holds an AAA rating, and the Chinese Academy of Social Sciences can provide P2P lending platforms. By 2015, the platform had over two million registered users and was among China's top 100 Internet companies. In 2018, Renrendai reported more than one million approved loans and more than 10 billion RMB in total investments. However, the platform ceased operations in 2021 due to regulations issued by the Chinese government that impacted the P2P lending industry.

Renrendai presents a unique institutional landscape in the Chinese P2P lending market. In particular, the platform operates with a blended online-offline model, unlike pure online platforms, such as Paipaidai. This offline model helps in reducing further asymmetric information that originates from online authentication models.[3] Renrendai offers additional risk mitigation for investors through a bad loan reserve fund managed by a third-party bank. This reserve fund aims to cover the losses on an investor's principal (Cheng et al., 2022), which could make automatic bidding services more attractive to risk-averse lenders. [4]By the end of 2018, Renrendai had accumulated 966,446 personal lenders and 10.07 million borrowers, indicating a sizable market presence. The platform provides loans similar in range to Paipaidai for online borrowers without a third-party referral but offers higher minimum loan amounts (around 50,000 CNY) for offline borrowers, with interest rates ranging from 7 % to 24 %. These diverse loan offerings combined with reserve funds may influence lenders' decisions to use or abstain from automatic bidding services.

For borrowers to apply for credit loans ranging from 3000 RMB (ca. 450 US$) to 500,000 RMB (ca. 72,250 US$), they needed to provide information such as marital status, monthly income, educational level, gender, and other personal details. After receiving these documents, the

[2] See for example Logg et al. (2019) or Germann and Merkle (2019).

[3] The platform offers individuals the opportunity to submit their documents in person by visiting one of the Ucredit branches. After these documents are reviewed and verified by Ucredit, the application is then transferred to the Renrendai platform. Additionally, once Ucredit approves the application, the borrower is assigned an A-class credit rating for their online applications listing.

[4] Renrendai assures lenders of repayment by maintaining a reserve fund to handle potential defaults and delays. This fund is regularly refilled using service fees. Should the platform not manage to recover a loan, a collection agency will take over, and any funds recovered are added back to the reserve.

Table 1
Descriptive statistics for whole sample.

	(1)	(2)	(3)	(4)	(5)
Variable	Mean	Std	P25	P50	P75
Panel A: Investor-Bid Level (Obs = 23,579,588)					
Auto Bidding	0.89	0.31	1.00	1.00	1.00
Share Auto Bidding	0.82	0.26	0.78	0.95	0.99
General Switch	0.04	0.20	0.00	0.00	0.00
Switch to Auto	0.02	0.15	0.00	0.00	0.00
Switch to Manual	0.02	0.14	0.00	0.00	0.00
Default	0.47	0.80	0.00	0.00	0.68
Auto Default	0.48	0.84	0.00	0.00	0.69
Manual Default	0.41	0.76	0.00	0.00	0.60
Profile Age	4.67	1.41	3.91	4.99	5.72
Bid Volume	5.68	1.48	4.78	5.83	6.73
Decision Time	0.07	0.36	0.00	0.00	0.00
Relative Decision Time	0.49	0.29	0.24	0.49	0.74
Panel B: Investor Level (Obs = 67,902)					
Auto Bidding	0.82	0.24	0.77	0.94	0.98
Share Auto Bidding	0.73	0.29	0.58	0.85	0.96
General Switch	0.06	0.08	0.01	0.03	0.08
Switch to Auto	0.04	0.05	0.01	0.02	0.05
Switch to Manual	0.02	0.04	0.00	0.01	0.03
Default	0.19	0.44	0.00	0.00	0.68
Auto Default	0.19	0.44	0.00	0.00	0.69
Manual Default	0.17	0.41	0.00	0.00	0.60
Profile Age	3.25	1.26	2.25	3.31	4.24
Bid Volume	4.02	1.34	3.05	4.03	4.99
Decision Time	0.12	0.21	0.02	0.04	0.12
Relative Decision Time	0.50	0.06	0.47	0.50	0.53
Panel C: Loan Level, Obs = 830,300					
Maturity	3.42	0.39	3.22	3.61	3.61
Interest Rate	0.10	0.02	0.10	0.10	0.11
Loan Amount	11.02	0.77	10.51	11.19	11.58
Panel D: Borrower Level (Obs = 797,199)					
Married	0.58	0.49	0.00	1.00	1.00
High Education	0.01	0.12	0.00	0.00	0.00
Male	0.66	0.47	0.00	1.00	1.00
Self Employed	0.18	0.38	0.00	0.00	0.00
Borrower Risk	4.23	0.14	4.20	4.20	4.20

This table shows the mean (1), standard deviation (2), and quartiles (3)–(5) of the variables. Auto Bidding is a dummy variable that equals 1 if the investor uses automatic bidding and 0 otherwise. Share Auto Bidding is the cumulative percentage of investors who use automated bidding. General Switch is a dummy variable that takes a value of 1 when the investor switches to either automatic or manual and 0 otherwise. Switch to Auto is a binary variable that takes the value of 1 if an automatic switch occurs and 0 otherwise. Switch to Manual is a binary variable equal to 1 if manual switch and 0 otherwise. Default is the logarithm of one plus the number of defaults weighted by the bid amount. Auto Default is the logarithm of one plus the number of automatic defaults weighted by the bid amount. Manual Default is the logarithm of one plus the number of manual defaults weighted by the bid amount. Profile Age is the logarithm of one plus the number of active days investors spend in the market. Bid Volume is the logarithm of one plus the number of bids attempted by investors. Decision Time is the logarithm of one plus the time (in hours) for an investor to bid on a loan. The Relative Decision Time is the average of investor relative decision times for all bids. Maturity is the logarithm of one plus the duration (in months) of a loan. Interest Rate (%) is the interest earned on the loan. The Loan Amount is the logarithm of one plus the loan amount. The Risk-Adjusted Interest Rate is the loan's risk-adjusted interest rate. Marital Status is a dummy variable for borrowers, equal to 1 if married and 0 otherwise. High Education is a dummy for borrowers, where 1 is master's degree or above, and 0 otherwise. Male is a dummy for borrowers, equal to 1 if male and 0 otherwise. Self-Employed is a dummy variable for borrowers, equal to 1 if self-employed and 0 otherwise. Borrower Risk is the logarithm of one plus the borrower risk score, which varies between one and 245

platform evaluated the borrower's application and assigned customers a credit rating from AA to HR (high risk). These ratings allow investors to determine borrowers' level of riskiness.

In contrast, the investors verification process on Renrendai was notably streamlined. Upon registration, investors were verified immediately, granting them instant access to search for and bid on loans. This procedure reflects the platform's commitment to facilitating rapid investor engagement.

Investors on the Renrendai platform could select from three distinct investment strategies: self-directed, automated bidding, or a hybrid method that combines both modes. In the manual mode, investors bid on loans that meet their specific criteria. Conversely, the automated mode restricted investors' choices to predefined investment plans that carried out bidding based on predetermined loan parameters. Within the auto-bidding toolbox, the parameters that investors could control were limited to investment amount, loan maturity, and interest rate within the context of the selected plan.

The use of automated tools has gained popularity in the financial industry over the past decade.[5] In equity investments, machine-learning algorithms help identify high-performing stocks.[6] A similar trend is evident in P2P lending where automated solutions are increasingly favored by lenders.

Renrendai offered two unique auto-bidding features. The first allowed lenders to conduct decentralized bidding and recurring lending according to the lender's bidding scope without access to borrower characteristics. The second feature permitted human intervention if the machine-generated results were unsatisfactory.

[5] Popular platforms, such as eToro in the UK and Robinhood in the US, provide automated services for their clients.

[6] See "Will bots replace humans in active equity investment?" (Financial Times, October 02, 2019) (Available at: https://www.ft.com/content/efe4f97a-adb1-3cea-b098-2b616b5ce531), accessed on August 30, 2023.

Table 2
Descriptive statistics: manual users vs automatic users.

	Mean	Std	Mean	Std	Difference
	Only Manual Bids		**Only Automatic Bids**		**Manual vs Auto**
Default	0.77	0.96	0.43	0.78	0.35***
Profile Age	3.81	1.57	4.78	1.35	−0.97***
Bid Volume	4.71	1.65	5.79	1.41	−1.08***
Decision Time	0.41	0.85	0.03	0.21	0.38***
Relative Decision Time	0.51	0.29	0.49	0.29	0.02***
Maturity	3.18	0.56	3.54	0.24	−0.36***
Interest Rate	0.12	0.02	0.10	0.01	0.01***
Loan Amount	11.03	0.79	11.44	0.58	−0.41***
Borrower Risk	4.35	0.36	4.21	0.03	−0.15***
Married	0.70	0.46	0.67	0.47	0.03***
High Education	0.02	0.14	0.02	0.15	−0.00***
Male	0.72	0.45	0.64	0.48	0.08***
Self Employed	0.28	0.45	0.20	0.40	0.09***

This table presents the t-test for the mean difference between the manual and automatic users. Definitions of the variables are presented in Table 1. *** indicate statistical significance at the 1 % level.

Table 3
Determinants of automatic biddings.

	(1) Auto Bidding	(2) Auto Bidding	(3) Auto Bidding	(4) Auto Bidding
Default_{t-1}	0.040***	0.010***	0.021***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Share Auto Bidding}_{t-1}$	0.740***	0.143***	0.143***	0.108***
	(0.001)	(0.001)	(0.001)	(0.001)
Maturity_t	0.029***	0.008**	0.008**	
	(0.001)	(0.004)	(0.004)	
Interest Rate_t	0.052***	−1.737***	−1.693***	
	(0.019)	(0.124)	(0.122)	
Loan Amount_t	−0.000	0.018***	0.018***	
	(0.000)	(0.002)	(0.002)	
Borrower Risk_t	−0.340***			
	(0.004)			
Married_t	−0.003***			
	(0.000)			
High Education_t	0.000			
	(0.001)			
Male_t	0.000			
	(0.000)			
Self Employed_t	0.003***			
	(0.000)			
Investor Fixed Effect	No	No	Yes	Yes
Borrower Fixed Effect	No	Yes	Yes	No
Loan Fixed Effect	No	No	No	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes	Yes
Observations	73,474,248	73,457,934	73,423,164	73,421,443
R^2	0.574	0.912	0.921	0.942

The dependent variable in all columns is a binary variable that equals 1 if the investor bids using the auto-bidding tool and 0 if the investor bids. Independent variables are defined in Table 1. All the regressions include a constant term. Robust standard errors are in parentheses and are clustered at the loan level. *** and ** indicate statistical significance at the 1 % and 5 % level, respectively.

The automated bidding tool was popular among Renrendai investors and comprised three services. The first, a preferred service, granted investors 12 months of continuous automatic bidding for a fee. The second service offered a fixed-term contract that expired three, six, nine, or 12 months after signing the contract. The third service guaranteed a fixed monthly investment during the first year. The choice between these services depended solely on investor preferences, and the differences mainly pertained to service duration and investment amount.

3. Data description

We collected data from Renrendai between March 2012 and October 2018. On this platform, 890,664 lenders placed more than 74 million bids on approximately 0.6 million listings. First, we collected information on loans and borrowers for both funded and unfunded loan applications made on the platform. Second, we gathered investor-level data based on each bid's timestamp, the amount invested in each loan, and the bidding methods used to fund each loan. By combining investor- and listing-level data, we obtained a sample of approximately 74 million observations at the investor bid level. Each loan application included financial information such as maturity, interest rate, and loan riskiness, as well as borrower characteristics such as employment, marital status, educational level, and gender. This study focused on investors who conducted both manual and automated bidding. The final sample included 890,664 investors, with 822,762 choosing to use only one bidding method, either automatic or manual, while 67,902 investors opted to switch between bidding methods.

Panel A of Table 1 provides basic summary statistics for the key variables in this study. The average number of automatic bids is 89 %, with a standard deviation of 31 %, implying that some users rely heavily on the auto toolbox, whereas others attempt to limit their usage of this service. Share Auto Bidding represents the share of automatic bidding

Table 4
Switching mode of bidding.

	(1) General Switching	(2) Switch to Automatic	(3) Switch to Manual
Auto Default$_{t-1}$	0.097***	−0.003***	0.100***
	(0.002)	(0.001)	(0.002)
Manual Default$_{t-1}$	−0.066***	−0.013***	−0.053***
	(0.003)	(0.001)	(0.002)
Share Auto Bidding$_{t-1}$	−0.033***	−0.237***	0.203***
	(0.003)	(0.002)	(0.002)
Auto Default$_{t-1}$* Share Auto Bidding$_{t-1}$	−0.157***	−0.049***	−0.108***
	(0.004)	(0.003)	(0.003)
Manual Default$_{t-1}$* Share Auto Bidding$_{t-1}$	0.126***	0.060***	0.066***
	(0.004)	(0.003)	(0.003)
Investor Fixed Effect	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Observations	23,430,232	23,430,232	23,430,232
R^2	0.190	0.150	0.326

The dependent variables are General Switching, Switch to Automatic, Switch to Manual in columns (1), (2) and (3), respectively. These variables are defined as switching indicators for investors. General Switch is a binary variable that equals one if the investor attempted a general switch (manual or automatic), and 0 otherwise. Switch to Automatic is a binary variable that equals 1 if the investor switch to an automated mode, and 0 otherwise. Switch to Manual is a binary variable that equals 1 if the investor switch to a manual mode, and 0 otherwise. Independent variables are defined in Table 1. All the regressions include a constant term. Robust standard errors are in parentheses and are clustered at the loan level. *** and ** indicate statistical significance at the 1 % and 5 % level, respectively.

Table 5
Inattention and time pressure before changing mode of investing.

	(1) Switch to Automatic	(2) Switch to Manual	(3) Switch to Automatic	(4) Switch to Manual
Auto Default$_{t-1}$	−0.014***	0.106***	−0.013***	0.107***
	(0.000)	(0.000)	(0.000)	(0.000)
Manual Default$_{t-1}$	−0.003***	−0.057***	−0.004***	−0.058***
	(0.000)	(0.000)	(0.000)	(0.000)
Share Auto Bidding$_{t-1}$	−0.221***	0.195***	−0.221***	0.195***
	(0.001)	(0.000)	(0.001)	(0.000)
Auto Default$_{t-1}$* Share Auto Bidding$_{t-1}$	−0.041***	−0.114***	−0.041***	−0.114***
	(0.001)	(0.001)	(0.001)	(0.001)
Manual Default$_{t-1}$* Share Auto Bidding$_{t-1}$	0.050***	0.070***	0.050***	0.070***
	(0.001)	(0.001)	(0.001)	(0.001)
Decision Time$_t$	0.083***	−0.046***	0.083***	−0.047***
	(0.000)	(0.000)	(0.000)	(0.000)
Auto Default$_{t-1}$* Decision Time$_t$	0.040***	−0.026***	0.040***	−0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
Manual Default$_{t-1}$* Decision Time$_t$	−0.035***	0.014***	−0.035***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)
Relative Decision Time$_t$			0.001	0.005***
			(0.000)	(0.000)
Auto Default$_{t-1}$* Relative Decision Time$_t$			−0.002***	−0.001
			(0.000)	(0.000)
Manual Default$_{t-1}$* Relative Decision Time$_t$			0.003***	0.002***
			(0.001)	(0.001)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes	Yes
Observations	23,430,232	23,430,232	23,430,232	23,430,232
R^2	0.180	0.339	0.180	0.339

The dependent variables were Switch to Automatic and Switch to Manual. These variables are defined as investors' switching indicators. Switch to Automatic is a binary variable that equals 1 if the investor switches to the automated mode and 0 otherwise. Switch to Manual is a binary variable that equals one if the investor switches to manual mode and zero otherwise. Independent variables are defined in Table 1. All the regressions include a constant term. Robust standard errors are in parentheses and are clustered at the loan level. *** and * indicate statistical significance at the 1 % and 10 % level, respectively.

held by investors on the platform, and we find that, on average, 82 % of automatic bids are recorded in lenders' portfolios. The high share of auto-bidding confirms the increasing popularity of robotic investing in P2P lending platforms.

Popular P2P platforms in China that introduced robo-investing tools, such as PPdai.com, have shown that investors are heavily dependent on automation. Ge et al. (2021) documented that the number of bids attempted by machines outnumbered those attempted by lenders on PPDAI. Moreover, Ge et al. (2021) found that within the first 18 months of launching a robo-advising service on Renröm, 63 % of lenders utilized this service to invest in at least one loan. The average duration of active investor profiles (Profile Age) was up to 106 days (in logs, 4.67), and the mean volume of bids attempted by users was approximately 292 bids (in logs, 5.68).

Panel B of Table 1 shows investor-level statistics. There are no major differences from those reported in Panel A. However, it is worth

Table 6
Experience before changing mode of investing.

	(1) Switch to Automatic	(2) Switch to Manual	(3) Switch to Automatic	(4) Switch to Manual
Auto $Default_{t-1}$	−0.066***	0.164***	−0.079***	0.194***
	(0.003)	(0.004)	(0.004)	(0.004)
Manual $Default_{t-1}$	0.049***	−0.078***	0.053***	−0.108***
	(0.004)	(0.004)	(0.005)	(0.005)
Share Auto $Bidding_{t-1}$	−0.219***	0.190***	−0.223***	0.190***
	(0.002)	(0.002)	(0.002)	(0.002)
Auto $Default_{t-1}$ * Share Auto $Bidding_{t-1}$	−0.057***	−0.094***	−0.062***	−0.083***
	(0.003)	(0.003)	(0.003)	(0.003)
Manual $Default_{t-1}$ * Share Auto $Bidding_{t-1}$	0.062***	0.074***	0.063***	0.066***
	(0.003)	(0.003)	(0.003)	(0.003)
Decision $Time_t$	0.083***	−0.046***	0.083***	−0.046***
	(0.001)	(0.001)	(0.001)	(0.001)
Auto $Default_{t-1}$ * Decision $Time_t$	0.040***	−0.027***	0.041***	−0.027***
	(0.001)	(0.001)	(0.001)	(0.001)
Manual $Default_{t-1}$ * Decision $Time_t$	−0.035***	0.014***	−0.036***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Profile Age_{t-1}	−0.000	0.001***		
	(0.000)	(0.000)		
Auto $Default_{t-1}$ * Profile Age_{t-1}	0.012***	−0.013***		
	(0.001)	(0.001)		
Manual $Default_{t-1}$ * Profile Age_{t-1}	−0.012***	0.005***		
	(0.001)	(0.001)		
Bid $Volume_{t-1}$			−0.003***	0.000
			(0.000)	(0.000)
Auto $Default_{t-1}$ * Bid $Volume_{t-1}$			0.013***	−0.017***
			(0.001)	(0.001)
Manual $Default_{t-1}$ * Bid $Volume_{t-1}$			−0.011***	0.010***
			(0.001)	(0.001)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes	Yes
Observations	23,430,232	23,430,232	23,430,232	23,430,232
R^2	0.181	0.340	0.181	0.340

The dependent variables were Switch to Automatic and Switch to Manual. These variables are defined as investors' switching indicators. Switch to Automatic is a binary variable that equals 1 if the investor switches to the automated mode and 0 otherwise. Switch to Manual is a binary variable that equals 1 if the investor switches to manual mode and 0 otherwise. Independent variables are defined in Table 1. All the regressions include a constant term. Robust standard errors are in parentheses and are clustered at the loan level. *** and * indicate statistical significance at the 1 % and 10 % level, respectively.

mentioning that 4 % of lenders switch to automatic, and 2 % switch to manual.

Panel C of Table 1 reports summary information for approximately 843,300 loan observations. The average maturity is just over 30 months, implying that these loans have a long-term maturity. The average interest rate earned on loans was 10 %, and the average amount requested was 59,000 RMB (approximately 8535 US$).

Panel D of Table 1 reports summary statistics for the sample at the borrower level. The data shows that, on average, 58 % of the borrowers were married, 1 % were highly educated, 66 % were male, and 18 % were self-employed. Additionally, the borrowers had a risk score of 68 (in logs, 4.23), meaning that, on average, they were not high-risk borrowers.

4. Methodology

4.1. Portfolio performance calculation

We construct a measure of portfolio performance using the number of investors' defaulted loans (see Ge et al., 2021). This measure changed at the time of each bid based on historical performance. Additionally, we weighted defaults against the number of investor bids to obtain a plausible measure of portfolio performance. We compute the average number of defaults across successful bids within each lender's portfolio, weighted by the bid amount. We then categorize defaults into two distinct variables, one representing defaults in auto-bidding and the other representing defaults in manual bidding, each weighted by their respective bid amounts.

4.2. Econometric specification

Our aim is to investigate the relationship between past portfolio performance and the decision to switch to an automatic bidding tool. We begin our analysis by establishing the characteristics of the loans and borrowers who choose an auto-bidding tool. To do so, we estimate the following regression: [7]

$$\begin{aligned}\mathrm{AutoBidding}_{i,t} &= \beta_0 + \beta_1 \mathrm{Auto\ Default}_{i,t-1} + \beta_2 \mathrm{Manual\ Default}_{i,t-1} \\ &\quad + \beta_3 \mathrm{ShareAutoBidding}_{i,t-1} + \beta_4 \mathrm{Loan}_{i,\gamma} + \beta_5 \mathrm{Borrower}_{i,\gamma} \\ &\quad + \delta_i + D_t + \mu_t + \varepsilon_{i,t}\end{aligned} \tag{1}$$

where *AutoBidding* is a dummy variable that takes the value of 1 if bid *t* of investor *i* is automated and 0 if manually executed. $Auto\ Default_{i,t-1}$ and $Manual\ Default_{i,t-1}$ are the lagged automatic and manual portfolio performance measures for investor *i*. $ShareAutoBidding_{i,t-1}$ is the share of automatic bidding by investor *i* at the one-bid attempt lag. $Loan_i$ is a vector of loan characteristics that includes the logarithm of one plus maturity, interest rate, and the logarithm of one plus loan amount. $Borrower_{i,\gamma}$ is a vector of borrower characteristics that includes dummy variables for self-employment, marriage, higher education, gender, and borrower risk score. By including borrower characteristics, we argue that automation is likely to reduce discriminatory practices against

[7] We choose a linear probability model instead of a logit model because of the sample size and because we do not seek to predict probabilities.

Table 7
Cox-proportional hazard – Duration analysis.

	(1) Switch to Automatic	(2) Switch to Automatic	(3) Switch to Manual	(4) Switch to Manual
Auto Default	0.918	0.929	1.108***	1.116***
	(0.134)	(0.138)	(0.035)	(0.035)
Manual Default	0.917***	0.913***	0.596***	0.595***
	(0.016)	(0.016)	(0.047)	(0.047)
Share Auto Bidding	3.692***	3.667***	0.005***	0.005***
	(0.009)	(0.009)	(0.020)	(0.020)
Month Dummies	No	Yes	No	Yes
Observations	1,232,329	1,232,329	55,369,170	55,369,170

Columns (1) – (2) sample consist of manual biddings, while columns (3) - (4) sample contains only automatic biddings. The dependent variables are Switch to Automatic and Switch to Manual, which are defined as investors' switching indicators. Switch to Automatic is a binary variable that equals 1 if the investor switches to the automated mode and 0 otherwise. Switch to Manual is a binary variable that equals 1 if the investor switches to manual mode and 0 otherwise. Independent variables are defined in Table 1. All regressions include a constant term. Hazard ratios are reported. Robust standard errors are in parentheses and clustered at the lender level. *** and * indicate statistical significance at the 1 % and 10 % level, respectively.

specific groups of individuals. We include fixed effects δ_i, D_t, andμ_t to control for investor-level, monthly, and hourly heterogeneity. The standard errors are robust and clustered at the investor level to account for investor-specific characteristics.

In the next step, we aim to establish the factors that determine the change in the bidding mode, switching from manual to automatic, or vice versa. We estimate the following regression:

$$\begin{aligned}\mathrm{Switch}\{\mathrm{G,A,M}\}_{\mathrm{i,t}} &= \beta_0 + \beta_1 \mathrm{Auto\ Default}_{\mathrm{i,t-1}} + \beta_2 \mathrm{Manual\ Default}_{\mathrm{i,t-1}} \\ &+ \beta_3 \mathrm{ShareAutoBidding}_{\mathrm{i,t-1}} \\ &+ \beta_4 \mathrm{Auto\ Default}_{\mathrm{i,t-1}} * \mathrm{ShareAutoBidding}_{\mathrm{i,t-1}} \\ &+ \beta_5 \mathrm{Manual\ Default}_{\mathrm{i,t-1}} * \mathrm{ShareAutoBidding}_{\mathrm{i,t-1}} \\ &+ \delta_i + \varphi_i + D_t + \mu_t + \varepsilon_{\mathrm{i,t}}\end{aligned} \quad (2)$$

where $Switch\{G,A,M\}_{i,t}$ is a dummy variable that takes the value of one if investor *i* switches modes during the bid attempt. We distinguish these three investor choices by employing three dummy variables. The first binary variable indicates $General\ Switch_{i,t}$ equals 1 if a lender switches to either manual or automatic mode, and 0 otherwise. The second variable, $Switching\ to\ Automatic_{i,t}$, equals one if investors switch to automatic mode and zero otherwise. The third variable, $Switching\ to\ Manual_{i,t}$, is a dummy variable that equals one if investors switch to manual mode and zero otherwise. δ_i, φ_i , $D_t and \mu_t$ are the fixed effects for investor, loan, month, and hour of bid, respectively. These are employed in the model to control for various forms of heterogeneity, replacing the need for loan and borrower characteristics; as above, the standard errors are robust and clustered at the loan level.

5. Results

5.1. Descriptive statistics

We start our analysis by splitting the sample into two categories that control only for manual and automatic bids, and show the t-test mean difference between the two bidding modes. Table 2 reports the means and standard deviations for the two subsamples. We find that more loan defaults occurred in self-directed bids (3.13) than in automatic bids (1.58). Users employing machine-made bids are more likely to be active and bid more on the market than those relying on manual bids. When inspecting the inattention indicator *Decision Time*, the auto-funding tool seems to be more aware of the information flow in the market, because once a loan is issued, it instantly attempts a bid to fund the loan. Moreover, on average, manual users preferred to see the loan halfway before starting to bid (0.52 %). Users who rely on automation start funding loans (on average, 0.49 %) before being half-way funded. Automation is also associated with long-term investments, as indicated by *Maturity*. Machines prefer investing in long-term projects. Additionally, the auto-investing tool on Renrendai places bids on lower-risk borrowers with a mean of 4.21. Consequently, automatic users can invest in loans that are less profitable than those of manual users. Moreover, automatic users were more likely to fund unmarried female borrowers.

5.2. Usage of automated biddings

Table 3 presents the results for determining the use of automation options. We find that the coefficient of default is positive and statistically significant, at least at the 1 % level, across all specifications. These findings suggest that investors are more likely to engage in machine-made bids than self-directed bids if their past performances are poor. These results are notable. Column 4 reveals that a 100 % increase in the weighted average default increases the utilization of automated biddings by 2.1 percentage points. This outcome aligns with Rossi and Utkus (2020) and Hao et al. (2022), who demonstrate that robo-advising investments outperform self-directed accounts. They evaluated investment performance using portfolio returns, volatility, and the Sharpe ratio, and reported that robo-advising improves investment performance mainly by lowering portfolio volatility. Furthermore, D'Acunto et al. (2019), report that investors diversify their stock portfolios better after adopting robot advice. Overall, the results show a positive effect of robo-advising on investment performance compared with self-directed accounts, which explains why investors choose robo-advising.

Our results show that loan characteristics play a role in investors' choices of automated bidding. In all the specifications, the coefficients of loan maturity are positive and statistically significant at the 1 % level. This finding implies that individuals who rely on automation invest in higher-maturity loans. This can be explained by the fact that automated services prefer long-term, passive projects (Menkveld, 2013).[8] Furthermore, the results suggest that the automated bidding is associated with more profitable loans, as the coefficient for the interest rate is positive and statistically significant in Column 1. However, in Columns 2 and 3, the coefficients for interest rate change sign when we introduce borrower and investor fixed effects into the regression. In other words, automated bids are considered less profitable investments when controlling for investors' and borrowers' heterogeneity. In our opinion, this effect occurs because investors and borrowers can control the interest rates. Borrowers are the ones who set interest rates, and investors, before using the automated bidding, can set an interest rate target on the system. Thus, the automated financial tool on this platform bids for less risky and more profitable loans. However, when investors interact with this automated tool, they appear to set lower interest rates.

[8] In their paper, they report that the majority of HFT trades are considered passive trades (by 78.1 %)

Column 1 shows that women, unmarried individuals, and self-employed individuals are likely to receive funding from the auto toolbox. The coefficients for married and male workers are negative, whereas those for self-employed workers are positive. All three coefficients were statistically significant at the 1 % level. By contrast, we find that the coefficient for higher education is statistically insignificant.

Existing literature shows that human investors prefer to fund financially literate (Caglayan et al., 2020a), married, and male individuals (Chen et al., 2020). Additionally, human investors would usually show high uncertainty when evaluating an application created by a female applicant (Duan et al., 2020). Overall, this is related to the fact that human investors are more prone to bias (see, e.g., Foerster et al., 2017). Our findings partly confirm the existing results but also show that automatic bidding is likely to fund borrowers with whom human investors discriminate.

These results were consistent with those reported by D'Acunto et al. (2022), who provide evidence of how investors in microlending markets face significant losses when discriminating against a particular group of borrowers. Their results show that investors who self-direct their investments tend to make investment mistakes, such as lending to borrowers who share the same religion and those with a higher social class. When investors adopted the automated bidding tool, these behavioral biases started to be corrected, resulting in lower default rates (by 32 %) and higher returns (by 11 %). Finally, machine-made bids prefer borrowers with lower risk scores, as evidenced by the negative significance of the borrower risk coefficient. This might not be preferable for some individuals because human investors are not risk averse and would like to be involved in riskier investments to maximize their profits.

5.3. Decision to switch

Next, we investigated the relationship between past performance and investors' switching decisions. Investors can alternate between automatic and manual bidding modes when lending. Because we are interested in investors' switching behavior, we exclude users who rely on one bidding mode, either manual or automatic. To control for the influence of past performance on the decision to switch modes, we utilized two categories, automatic and manual defaults, following Ge et al. (2021).

Column 1 in Table 4 presents the results of the decision to switch from one bidding mode to another. We find that the coefficients of auto and manual defaults are positive and negative, respectively, and both are statistically significant at the 1 % level. This finding indicates a correlation between investors making general switches and experiencing more defaults from automatic bids and fewer defaults from self-directed investments. To further investigate the switching behavior, we split switching into two indicators: switching to automatic and switching to manual. This allowed us to investigate how past defaults affected users' decisions to switch to automated investment tools.

Column 2 presents the results of the decision to switch from manual to automatic switching. In contrast to previous results, we observe that the coefficients for both auto and manual defaults are negative and statistically significant at the 1 % level. In other words, investors who experienced fewer defaults in either bidding mode were more inclined to switch automatically. The results indicate that a 100 % decrease in either the Auto or Manual Default increases the likelihood of switching to an automated toolbox by 0.3 and 1.3 %, respectively. This implies that lenders may prefer changing their behavior to adopt automation when they experience fewer defaults from both the manual and auto-bidding modes. However, a closer look at the negative coefficient of the interaction term between auto default and auto share bidding reveals that investors with a higher percentage of auto bids are less likely to embrace automated strategies when they experience an increase in default auto investments. In other words, poor auto-bidding performance discourages investors from further adopting automated strategies, especially when a significant proportion of their bids are already automated.

Our findings are consistent with those of Ge et al. (2021) who find that investors encountering higher defaults in their manual investments are less likely to adopt automation services. Rossi and Utkus (2020) found that users with lower returns and higher risks sign up for robot advice. Capponi et al. (2022), D'Hondt et al. (2020), and Reher and Sun (2019) demonstrated that automated financial tools can improve portfolio performance. Loos et al. (2020) show that investors who use robot advice are likely to mitigate diversification by 11.7 percentage points when controlling for both time and investor-fixed effects. Additionally, D'Acunto et al. (2019) found that adopting robotics advice benefits investors because it increases portfolio diversification and reduces portfolio volatility. At the same time, robot advisors do not improve the performance or volatility of the portfolios of already diversified investors. On average, they found that investors have a better-diversified portfolio of 0.16 units, which is approximately 1.3 % of the median number of stock investors held before using the portfolio optimizer. Therefore, underperformers believe that switching to an automated mode is better for them because it might result in better financial outcomes.

By contrast, investors who perform well with manual bidding tend to continue relying on manual strategies. Those experiencing a higher default rate in auto-bidding are also more likely to revert to manual mode for better control. In Column 3, we find a positive coefficient for Auto Default that is statistically significant at the 1 % level. The coefficients suggest that a 100 % increase in the weighted average Auto Default corresponds to a ten percentage point increase in switching to manual mode. This implies that users who underperform in the automated mode will likely discontinue this service and rely on the manual mode. Concurrently, the negative coefficient of Manual Default reinforces this notion, indicating that users who make fewer mistakes during manual bidding are more inclined to continue relying on it. One could argue that individuals want to get involved in riskier loans and hence achieve higher returns when funding loans. As reported in Tables 1 and 2, the automated toolbox bids for less risky investments.

We investigate the sensitivity of our results using an alternative performance measure: the weighted average Sharpe Ratio. Table A3 shows results that are consistent with those presented in Table 4. These findings confirm that strong performance of automated bids encourages investors to persist with automated strategies. Conversely, those that performed well through manual bids were more inclined to switch to manual investments.[9]

To further support this evidence, we run a cross-sectional regression at the loan level to explore the relationship between the loan shares of automatic bidding and the loan status indicators.[10] The results in Table A5 confirm that loans funded by a higher percentage of automated bidding were less likely to default. However, these loans are less likely to be fully funded and have a higher share of failed loans.[11]

5.4. Investor inattention, time pressure, and experience

Thus, our results show that investors are likely to switch bidding modes depending on their historical risk-adjusted portfolio performance. However, other factors may also play important roles in lenders' automation decisions. Thus, we verify the robustness of our results and investigate other factors that may determine investors' decisions.

First, we analyzed investor inattention during bidding. Caglayan et al. (2020b) show that lenders in P2P markets are simultaneously

[9] These results are robust to several tests as we restrict the bid attempts to not less than 10 or 20 bids and still obtain consistent results, as presented in the Online Appendix: Tables A1 and A2. Further, we run the regression at the loan level (Table A4) and find consistent results to those reported in Table 3.

[10] These indicators are dummy variables that indicate whether a loan has defaulted, been funded, or failed.

[11] These results are reported in the Online Appendix: Table A5.

exposed to thousands of publicly available listings, which can lead to distractions. This can result in a reliance on automated financial tools that are smooth in processing vast amounts of information On Renrendai, the average loan completion time is less than five hours (Caglayan et al., 2021). This implies that users who invest in loans in the first few hours are likely to pay close attention to the loans listed on the market. Thus, we use the number of hours spent investing since listing a loan as a proxy for investors' inattention[12] and the flow of information during that hour using the hour-of-bid fixed effects.

Second, we explore whether time pressure affects changing modes of investment. Due to physiological stress, time pressure can affect individual portfolio strategies. However, Kocher et al. (2013) present a contradictory result, showing no relationship between time pressure and preferences (e.g., risk attitudes toward gains). In our opinion, time pressure does not affect investors' switching between investment modes. We follow Zhang et al. (2021) and proxy for time pressure using the relative decision time.

The results in Table 5 show that the indicator of inattention, *Decision Time*$_{t-1}$, is positively associated with automatic switching. Across all the specifications, the coefficient proxying for inattention is statistically significant, at least at the 1 % level. Moreover, the results are economically important, as we find that a 100 % increase in the time spent attempting a bid corresponds to an 8.3 percentage point increase in switching to automation, ceteris paribus. The interaction terms between auto or manual default and the inattention proxy are positive and negative, respectively, and are statistically significant at the 1 % level. This finding suggests that lenders with more auto defaults are surprisingly inclined toward auto-bidding, possibly because they trust the system's ability to mitigate default risks. However, those with a history of manual defaults are hesitant to switch to auto-bidding, likely attributing their past defaults to their own lack of attention rather than a weakness in manual strategies.

In Column (2), we find that a 100 % decrease in the time individuals spend making a decision leads to a seven percentage point increase in switching to the manual mode. Examining the interaction terms reveals that users with higher auto defaults are less inclined to switch to manual bidding, likely because they lack confidence in their manual risk management skills. Conversely, inattentive investors who have experienced more manual defaults are more likely to persist with manual strategies, suggesting that they attribute their defaults to their own inattention rather than to the shortcomings of manual bidding.

D'Acunto et al. (2019) find that investors pay close attention to their portfolios regardless of the number of stocks held, even before adopting an automated financial tool. On a fast-moving platform such as Renrendai, where investors are exposed to many loans with detailed information, it is easy to get distracted by the flow of information on the market and end up with poor-performing portfolios. This is where automation can play a role, given that the auto-investing tool can simultaneously robotize millions of portfolios. Investors who are more likely to become distracted may switch to automation as a possible solution. However, some individuals are less prone to being distracted and making good decisions, which is why they prefer to rely on themselves in the manual mode.

In investigating the effects of time pressure in Column 3, we observe that the coefficient of the relative decision time is statistically insignificant. This suggests that factors such as time and peer pressure exert less influence on individuals when deciding to switch to the automated mode. However, in Column 4, our results show that the coefficient of relative decision time is positive and statistically significant at least at the 1 % level. This implies that users with longer relative decision times are likelier to switch to manual mode. The interaction term between Auto Default and Relative Decision Time is statistically insignificant.

Furthermore, the positive coefficient for the interaction term between Manual Default and Relative Decision Time suggests that individuals with higher relative decision times and more manual defaults are somewhat inclined to switch to manual bidding. This could be attributed to their delayed decision-making, which is consistent with what was previously observed through the inattention proxy. These results indicate a weak but existent relationship between a loan approaching its completion rate (being fully funded) and an investor's changing bidding behavior.

Investors can decide their mode of investment at any stage of loan funding. This may be because investors in this market are less concerned about time pressure, as not all individuals are informed or experienced. Some investors may be unprofessional lenders or have low bidding requirements. Therefore, time pressure has less impact on individual portfolio strategies, and psychological stress has less influence.

Next, we believe that lenders' experience can directly impact the decision to rely on (or not rely on) machines. Investors who are active and spend more time in the market (i.e., are more experienced) are more likely to be overconfident about how they place their investments. This creates an environment where overconfident investors are less interested in relying on algorithms. Chen et al. (2007) show that Chinese individuals seem to be overconfident investors, which explains their poor stock-trading decisions. Following the literature, we use two proxies to measure investor overconfidence. In the first two columns, we use the age of the investor, and in the last two columns, we use the bidding volume.

Table 6 reveals that when we control for experience, the persistent negative coefficients for both manual and auto faults, as seen in Table 4, undergo a significant shift. Specifically, the coefficient on manual default is positive. This indicates that investors with a higher frequency of manual defaults are more inclined to transition to automated bidding when experience is factored in. This shift highlights the nuanced role experience plays in shaping investors' decision-making behaviors.

Our results indicated a positive relationship between the two proxies for overconfidence and manual switching. Specifically, in Column 2, the coefficient of overconfidence is positive and statistically significant at the 1 % level. Although the coefficient remains positive in Column 4, it becomes statistically insignificant. The results in Column 2 suggest that the more active individuals are, the more likely they switch to relying on themselves in a self-directed mode. These results align with Odean's (1998) theoretical model, which shows that the more investors trade, the more likely they are to be overconfident. In a later model, Gervais and Odean (2001) showed that investors take too much credit for success. Therefore, investors overestimate success when they learn about their own abilities. This can cause investors to believe more in their decisions because they are overconfident, resulting in them relying more on themselves. Our results confirm their findings. In economic terms, the results in Column 2 show that a 100 % change in the number of bids attempted by lenders increases switching to manual by 0.1 percentage points ceteris paribus.

6. Robustness check

Next, we broaden our study by incorporating a proportional hazard model to evaluate the probability of transitioning to or discontinuing a specific bidding strategy. The proportional hazard model specification is:

$$\lambda(tX) = \lambda_0(t)\exp(X'\beta) \tag{3}$$

where $\lambda(t)$ is the hazard function, representing the instantaneous failure rate, or the likelihood of transitioning from one bidding strategy to another, t denotes the time spent in a bidding mode, X represents the set of explanatory variables, and β is a vector of unknown parameters.

The dependent variable used in our estimation is a dummy variable,

[12] In our case, more hours spent to attempt a financial decision means that investors are more likely to be distracted and not pay attention to what is being listed on the market.

consistent with the specification in Eq. 2. We estimate the baseline hazard function using a semi-parametric approach, specifically the Cox proportional hazards model, adapted to handle a scenario involving multiple failures. This model accounts for the fact that investors can switch between bidding strategies multiple times. To address the recurrent nature of these events, we cluster standard errors at the lender level. This clustering ensures that multiple transitions of the same investor are accounted for in the analysis.

The findings from this analysis are presented in Table 7. Columns (1) and (2) include manual bidding data, with "Switch to Automatic" as the dependent variable, while columns (3) and (4) contain automatic bidding data, using "Switch to Manual" as the dependent variable.

The results reported in Table 7 are consistent with our earlier findings in Table 4. Column 1, reveals that although the association between Auto Default and Switch to Automatic bidding is statistically insignificant, it indicates a negative relationship. Concerning Manual Default, we observe that each 1 % increase in the natural log of manual defaults reduces the hazard of switching to automatic bidding by 8.3 % (1 – 0.917 = 8.3 %). This pattern remains consistent in Column 2 with the inclusion of month dummies.

Furthermore, Column 3, shows that a 1 % increase in the natural log of automatic defaults increases the hazard of discontinuing automatic mode by 10.8 %. Conversely, a similar increase in the natural log of manual defaults reduces the hazard of switching to manual bidding by about 40.4 %. This suggests that investors may be deterred by high manual failure rates, potentially perceiving manual control as less reliable. Consistent results are also achieved in Column 4 after adjusting for month dummies.

7. Conclusion

Recent technological developments have changed lending and borrowing from a process that involves banks to one that can be easily accessed online. P2P lending platforms connect investors and borrowers, by acting as financial intermediaries. These platforms are evolving by offering customers new services to ease their lending processes. As investors change their investing methods by adopting new technological developments that can save time and ease their investment processes, they are less interested in relying on traditional strategies. Recently, automated solutions have emerged as suitable alternatives to human financial advisors. Our study confirms investors' growing interest in automated solutions based on our analysis of the relationship between past loan portfolio performance and switching to automated bidding.

To conduct this investigation, we use data from Renrendai, a leading online P2P lending platform in China. The initial analysis reveals several key patterns. First, past underperformance correlates with increased usage of auto-bidding tools, which, notably, do not discriminate based on borrowers' social or demographic characteristics. When focusing on hybrid users, we find that lenders with a history of strong performance in both manual and automated settings tend to favor automated systems. Various factors, such as investment delegation and investor inattention, underlie this behavior. In particular, investors with more auto bids but rising defaults shy away from automation. Additionally, automated defaults seem to influence inattentive investors less, possibly because of their inexperience. Finally, irrespective of past manual defaults, experienced investors prefer manual to automated strategies, often attributing errors to personal oversight rather than systemic limitations.

Our research broadly aligns with the theory of algorithmic aversion (e.g., Germann and Merkle, 2023) to shed light on investor behavior. This theory suggests that people may be reluctant to use automated systems, even when statistical evidence supports their reliability. Dietvorst et al. (2018) and Gogoll and Uhl (2018) discuss the human aversion to delegating tasks to algorithms. This reluctance appears to wane when the algorithms demonstrate efficacy, as observed by Castelo et al. (2019) and Kleinberg et al. (2018). We explore the impact of defaults in either manual or automated investments on future investment choices.

Our results provide new insights into the P2P lending market and explain why an increasing number of clients use automated tools to make investments. Therefore, the results are also important from a policy perspective, as the better performance of automated tools could provide greater stability to the financial system. However, the related advantage(s) could disappear over time with automated tools on a greater scale. Whether this may be the case remains to be explored in future studies.

CRediT authorship contribution statement

Oskar Kowalewski: Writing – review & editing. **Said Kaawach:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Oleksandr Talavera:** Writing – review & editing, Methodology, Formal analysis, Conceptualization.

Data availability

The authors do not have permission to share data.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jfs.2024.101319.

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