Algorithmic Trading in Primary Markets

Abstract

Algorithmic trading (AT) is playing an increasingly important role in the primary market. Order-level data from loan issuance in Online Marketplace Lending (OML) shows that AT precludes human investors from assessing good issues. Consistent with Rock's (1987) theory on underpricing, the biased allocation of good issues towards AT lowers the performance of human investors, who then request higher interest rates as compensation. AT also deploys its user-clients' money to finance low-quality loans, thereby inflating loan origination fees for the underwriting platform. The findings reveal how AT widens the information gaps among investors and automates the conflict of interest in the primary market.

Keywords: Algorithmic trading, Underpricing, Moral hazard, IPO, Algorithmic bias, Online marketplace lending

JEL code: G10, G14, G21, G23, K2

1. Introduction

Algorithmic trading (AT) is a pervasive force in financial markets, comprising 60-73% of U.S. equity trading[1] and executing nearly 75% of global spot foreign exchange orders (SEC, 2020; Chaboud et al., 2023). Extensive research has studied AT's impacts on the liquidity, efficiency, and volatility of secondary markets (Kirilenko and Lo, 2013). [2]

Algorithms are assuming more roles in primary markets as well. The FinTech startup *Overbond* uses algorithms to predict issuance time and pricing with high precision, a service well adopted by Canadian corporations that frequently issue debt and by investors to select investment targets.[3] In IPOs, Bank of America has developed its own Predictive Intelligence Analytics Machine (PRIAM) to match new issues with investors.[4] A columnist from Bloomberg predicts that algorithms will soon pitch IPOs (Levine, 2019). The expansion of AT necessitates a deeper understanding of its investment behavior and its implications for market participants. In this paper, we focus on the primary market.

The primary market is characterized by two features. First, while the secondary market clears through price adjustment, the primary market relies on share allocation and order rationing. Numerous papers investigate IPO share allocation and its implications for investors and issuance pricing (Rock, 1986; Koh and Walter, 1989; Lee et al., 1999, Ritter and Welch, 2002, among others). Second, the multisided business nature requires balancing the interests of issuing firms,

[1] Retrieved from https://finance.yahoo.com/news/algorithmic-trading-market-growth-trends-112400870.html (2022, March 18).
[2] AT monitors trading opportunities in secondary markets and capitalizes on them with fast trading speed. In theory, AT's cherry-picking leads to lowered information asymmetry but reduced information production (Baldauf and Mollner, 2020), improved liquidity (Foucault et al., 2016), as well as adverse selection on slow traders (Biais et al., 2015). Empirical evidence agrees on AT's role in improving pricing efficiency and liquidity (Hendershott et al., 2011; Brogaard et al., 2014; Brogaard et al., 2015; Boehmer et al., 2021; Jain et al., 2021). However, the results are mixed on bid-ask spread. By adversely selecting slow traders (Chaboud et al., 2014), AT enlarges the cost of immediacy (Hendershott and Moulton, 2011). However, the quantity competitor role of AT reduces spread (Brogaard and Garriott, 2019).
[3] Retrieved from https://www.economist.com/finance-and-economics/2018/05/10/a-canadian-startup-applies-machine-learning-to-corporate-bond-issuance (2018, May 10).
[4] Retrieved from https://www.ft.com/content/ee2a5f9c-5f1e-11e9-b285-3acd5d43599e (2019, April 24).

underwriters, and different groups of investors. IPO research also focuses on incentive issues and examines how conflicts of interest distort share allocation and pricing (Loughran and Ritter, 2002; Ljungqvist and Wilhelm, 2003; Loughran and Ritter, 2004; Reuter, 2006, among others). [5]

This paper revisits the above share allocation and incentive issues with the rising AT in the primary market. It investigates how shares are allocated between AT and human investors who do not use AT. How does AT affect human investors and issuance pricing? Will AT alleviate or perpetuate the conflict of interest among market participants in the primary market?

Despite the increasing presence of AT in primary markets, systemic records of AT investment in equity and bond issuance are difficult to obtain. Our research centers on a more transparent market of personal loan issuance in online marketplace lending (OML). In OML, borrowers issue loan applications, and investors submit orders through bidding and crowdfunding.

OML platforms operate under a posted-price mechanism, with the platform setting predetermined interest rates for loan applications prior to listing (Wei and Lin, 2017; Franks et al., 2021). This setting mimics equity and bond issuance, where investors participate in offerings with fixed prices. When investors' demand exceeds the issuing amount, the market clears through order rationing and share allotment. However, different from the allocation rule in IPOs, orders in OML are first-come-first-served. We provide more details in the institutional background section.

Investors in OML either manually evaluate and bid on loan applications or utilize AT services to invest automatically. As described by Balyuk and Davydenko (2023), reintermediation in FinTech has led OML platforms to heavily depend on AT. On the platform from which we collect data, AT's market share surged from 0 to over 90% within five years. The increasing presence of

[5] This paper does not aim to provide an exhaustive summary of IPO research. However, we recommend readers refer to two outstanding survey papers by Ritter and Welch (2002) and Ljungqvist (2007)

AT and its rich interaction with human investors provide an ideal setting to study AT in the primary market.

The seminal work of Rock (1986) models the information heterogeneity among investors. Uninformed investors equally partition their wealth into all offerings, but informed investors only demand the shares of good issues. The uneven participation of informed investors creates biased rationing and allocation, where informed investors obtain more good issues and the uninformed ones receive more bad deals. Given the information advantage of AT, Rock's (1986) model should predict a biased allocation of good deals towards AT.

Using order-level data on AT vis-à-vis human investment, we find supporting evidence that AT bids go to better-performing loans with 12 basis points higher annual return and 0.16 percentage points lower default. The first-come-first-served share allocation rule leads to an extreme case of biased allocation. AT precludes human investors from assessing good deals by cherry-picking them before human investors can react. We find AT on average bids faster than humans by 87.36%, especially when investing in good deals. Loan-level analysis confirms the extreme case of biased allocation. With AT's increasing presence in the market, it purely funds more good loans without human participation.

The biased allocation in Rock (1986) further predicts a winner's curse on the uninformed investors' side. We test this conjecture with an event study that compares the performance of human bids around the introduction of AT. Within the 9-month period surrounding both sides of the introduction of AT, human investors face a 4.22 percentage points decrease in investment return and a 3.79 percentage points higher default probability.

The uninformed investors in Rock (1986) take the winner's curse into consideration and demand underpricing as compensation. Human investors in OML also request higher interest rates

in response to the rise of AT. Controlling for all loan and borrower characteristics, they demand 0.24 percentage points higher interest rates to agree to participate in a loan issuance after the introduction of AT.

The AT under scrutiny is designed and owned by the OML platform. The platform affiliation mimics the business connection between investors and underwriters investigated in IPO literature. Connected IPO investors get more favorable share allotment, and they repay the issuers through side payments, such as future investment banking business (Siconolfi, 1997; Ljungqvist and Wilhelm, 2003), and excessive trading commissions (Loughran and Ritter, 2004; Reuter, 2006).

In OML, the platform that designs and owns AT not only collects service fees on AT users but also profits from loan origination fees. For every underwritten loan, the platform collects a proportion of the loan amount from the borrowers. The loan origination fee is similar to the side payment in IPOs that creates moral hazard in AT's investment (Baker and Dellaert, 2017). Although an independent AT maximizes its service fee by optimizing user investments, a platform-affiliated AT maximizes the sum of service fees and loan origination fees for its designing platform. When the origination fee outweighs the expected losses in service fees due to poor investment decisions, AT can increase the platform's revenue by filling the unfunded amount of bad loans that human investors refuse to originate. This is similar to bank-affiliated investors supporting the underwriter through intensively subscribing to the shares of some ill-performing issuers (Hao and Yan, 2012).

Different from precluding human investors and cherry-picking good loans, AT waits for human investors to submit as many orders to bad loans as possible, reducing its own exposure. Descriptive evidence shows that AT bids on good loans with superior performance and ratings during the early stage, but it only invests in bad loans at the end of their funding period. This

pattern aligns with the hypothesis that AT cherry-picks good loans but also facilitates bad loans in the late stages. Regression analysis presents a positive relationship between bid performance and early-stage AT participation, but AT's position accumulated at the last stages predicts worse performance.

The inferior performance associated with late-stage AT investment is more pronounced when AT has a smaller stake in the target loan. The cross-sectional difference indicates that AT preferentially facilitates bad loans with minimal exposure by filling their unfunded amounts in the late stages. The moral hazard directly hurts AT users, as their money goes to bad loans. It also locks human investors' positions into bad loans which would otherwise be unfunded, exposing them to greater risk.

The key contribution of this paper is to reveal the possible ramifications of AT's proliferation into the primary market. As described by Kirilenko and Lo (2013), "While technology has advanced tremendously over the last century, human cognitive abilities have been largely unchanged over the last several millennia" (Kirilenko and Lo, 2013, p. 60). The increasing presence of AT in the primary market widens the information gap among investors in primary markets to an unprecedented level. The paper uses order-level data from OML, a highly transparent domain characterized by high AT participation, to study AT in the primary market. We provide evidence in line with the prediction of Rock's (1986) information heterogeneity model, warning human investors, issuers, and regulators about the rise of AT in primary markets.

These findings also echo AT research in the secondary market that models AT's adverse selection (Biais et al., 2015) and cream skimming (Bolton et al., 2016) [6]. Empirically, Hendershott and Moulton (2011) and Chaboud et al. (2014) present evidence of AT cherry-picking the best

[6] Although Bolton et al. (2016) do not directly model AT, the model studies informed traders with a speed advantage, which mimics AT.

trading opportunities in the market. However, as AT's trading incorporates information into stock prices, results from the secondary market are often mixed with improved information efficiency and liquidity (Hendershott et al., 2011; Brogaard et al., 2014; Brogaard et al., 2015; Boehmer et al., 2021).

The second contribution is providing direct evidence of moral hazard in AT investment. Moral hazard is common among human money managers and investors. Examples include cross-subsidizing across funds under the same manager (Guercio et al., 2018) or family (Wang, 2024), self-purchase of issuer-clients' equity (Hao and Yan, 2012) and debt (Ding et al., 2022), universal banking selling poor-performing stocks in their proprietary portfolio to retail clients (Fecht et al., 2018), and crowdfunding group leaders originating bad loans for the leader's incentive (Hildebrand et al., 2017).

We extend their findings from human money managers to AT. A large strand of literature demonstrates that (well-designed) algorithms are more impartial than human experts (D'Acunto et al., 2019; Coleman et al., 2022; Liu, 2022; Aubry et al., 2023; Bao and Huang, 2023; Howell et al., 2024). Our new evidence shows algorithms can also perpetuate moral hazard by automating the misaligned interests between their designers and clients (Mullainathan and Obermeyer, 2017). Detecting AT's moral hazard is challenging due to its complexity and proprietary nature (Ji, 2017). However, this paper serves as forensic finance research advocated by Ritter (2008) and provides the "statistical smoking gun." To the best of our knowledge, we provide the first order-level evidence of AT's moral hazard in financial research.

Results on AT's moral hazard also join the ongoing discussion on algorithmic bias. Cowgill and Tucker (2019) classify the five sources of algorithmic bias, namely unrepresentative training

samples,[7] mislabeling or omitted payoffs,[8] feedback loops,[9] biased programmers, and spillover effects.[10] Our results fall into the category of biased programmers. Existing evidence emphasizes the unintended biases associated with the programmer's life experiences (Blodgett and O'Connor, 2017) or fairness requirements (Fu et al., 2022), such as a translation algorithm developed by white men performing better when translating text by white men than by African-American women. In contrast, the moral hazard in AT we uncover is the intentional and overt bias.

Additionally, this paper extends the niche literature on AT in OML. AT outperforms humans in OML investment (Fu et al., 2021), and investors increasingly rely on automated investment tools (Vallée and Zeng, 2019; Balyuk and Davydenko, 2023). Our research uncovers AT's investment strategy in OML and reveals its implications for human investors.

2. Institutional Background

2.1. From Information Intermediaries to Underwriters

OML platforms appeared as disintermediated FinTech lending marketplaces, functioning as information intermediaries. Borrowers post uncollateralized loan applications, and investors bid and crowdfund them. Each loan application has a financing period within which investors can evaluate it based on borrower information and submit bids indicating the investment amount and

[7] Ludwig and Mullainathan (2021) illustrate the issue of an unrepresentative training sample through examples of the selective label problem in the criminal justice system.

[8] Mullainathan and Obermeyer (2021) provide an example of how using medical expenses as an inaccurate measure for the severity of an illness can lead to algorithmic bias caused by mislabeling or omitted payoff.

[9] "Feedback loops" refer to self-fulfilling prophecies where algorithm predictions influence the outcomes. Cowgill (2018) examine the discontinuities around the cutoff threshold of recidivism scores and finds that defendants who are slightly above the cutoff have a higher recidivism rate within two years.

[10] Lambrecht and Tucker (2019) provide an example demonstrating that even an unbiased algorithm can generate biased results when interacting with other biased algorithms. They illustrate how women are less likely to see STEM job advertisements, despite the algorithm itself being unbiased towards or against them. This phenomenon is primarily caused by consumer-packaged goods advertisements bidding higher prices for women's attention, thereby crowding out STEM advertisements.

minimum interest rate they accept. Loan applications that fail to attract enough bids to meet the requested amount will be canceled, and the bid amount returns to investors. If a loan receives more investment than its requested amount, similar to book building in IPOs, orders accepting lower interest rates receive priority in loan share allotment. The loan originates at the lowest interest rate at which the cumulative bid amount meets the requested amount. Note that the platform does not set the offering interest rate; it is the bids from investors that jointly determine loan pricing. Wei and Lin (2017) refer to this mechanism as auction-based pricing. In the traditional disintermediated business model, investors determine loan origination, loan allotment, and equilibrium interest rates, and they provide funds and bear credit risk. OML platforms only serve as information intermediaries and collect loan origination fees.

Since its inception in 2005, OML has grown rapidly, reaching a market size of over USD $105 billion by 2022 (Cambridge Center for Alternative Finance, 2024). The platforms have transitioned from disintermediation to reintermediation (Balyuk and Davydenko, 2023), evolving into underwriters. To reduce information asymmetry, platforms started to screen borrowers and calculate credit ratings using proprietary algorithms (Buchak et al., 2018; Jagtiani and Lemieux, 2019).

More importantly, through the reintermediation process, the platforms take over loan pricing. They adopt a posted-price mechanism that determines an interest rate for each loan application before listing it (Franks et al., 2021). After submitting application documents, borrowers receive a non-negotiable offer that specifies the borrowing rate. They have no bargaining power over loan pricing. Investors assess loan applications and invest at a predetermined interest rate. Loans that are not fully financed during the funding period will be cancelled. Once a loan receives funds meeting the requested amount, it originates immediately. Investors cannot further bid down the

interest rate under this posted-price mechanism. Wei and Lin (2017) rationalize these changes and illustrate that the posted-price mechanism shortens the funding time and eliminates interest rate uncertainty.

Under the posted-price mechanism, the market clears through rationing of orders, mimicking the offering in primary markets. This is different from IPOs and the issuance of debt, where an underwriter accepts all orders but fills them with probability. OML platforms allocate loan shares in a first-come-first-served manner.

The evolution from information intermediaries to underwriters appears across platforms around the world, including the US (Balyuk and Davydenko, 2023), China (He and Li, 2021), and Europe (Hornuf and Schwienbacher, 2018). We collect data from one of the largest OML platforms in China, which assumes the above-mentioned underwriter's roles of evaluating loan applications, loan pricing, and share allotment.

The platform collects borrowers' personal information such as national ID number, gender, age, marital status, education, income level, property ownership, and credit history on the platform. Similar as issuers pre-IPO earning management (Teoh, Welch, and Wong, 1998), borrowers tend to overstate their merits to attract lenders. Thus, the platform performs a cross validation with the credit reference report from the People's Bank of China, which keeps the applicants' education, asset ownership, tax payment and credit records. The platform verifies the authenticity of documents and rejects applications with counterfeit documents. Before listing a loan application, it assigns a seven-notch credit grade (AA, A, B, C, D, E, or High Risk) to each loan and decides an interest rate. All investors observe the loan credit grade, interest rate, and the borrower and loan characteristics of each loan.

Some IPO investors possess private information that underwriters do not have access to (Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Spatt and Srivastava, 1991). However, OML investors cannot privately interact with borrowers. They can only obtain a borrower's information from the platform. The simplified information environment shuts down investors' information advantage over underwriters, allowing us to focus on the information asymmetry among investors.

After a loan originates, the platform in this study underwrites all funded loans and charges the borrower a loan origination fee in proportion to the funded amount.[11] Similar to the positive relationship between expenses and risk in IPO (Beatty and Welch, 1996), the loan origination fee is higher for riskier borrowers. For instance, a loan with an AA rating incurs a fee of 0.3% of the loan amount, whereas a loan with an HR rating incurs a fee of 5.3% of the loan amount. Consequently, originating lower-quality loans is more profitable for the platform.

Funded borrowers make equally amortized monthly payments to the investors. We use the monthly repayment records to calculate the internal rate of return (*IRR*) of each loan and construct a dummy variable indicating loan *Default*.

2.2. Platform Affiliated AT

Through reintermediation, platforms also offer AT services to investors. These services, offered for a fee, provide investment advice or automatically invest users' money into loan applications. Some AT providers operate independently, such as LendingRobot (Vallée and Zeng, 2019), while others are offered directly by the OML platform itself, like Quick Invest and AutoInvest (Balyuk and Davydenko, 2023). The AT studied in our paper is designed and offered by the OML platform.

[11] The US platform Prosper cancels certain suspicious loans even after they are fully funded. However, our studied platform unconditionally underwrites all funded loans.

Investors on the platform can evaluate loan applications independently based on borrower and loan characteristics, as well as the publicly available seven-notch credit grade provided by the platform. They can choose to manually submit orders, and we name them human investors. Panels A and B of Appendix A demonstrate the manual bidding procedure.

Alternatively, investors can purchase the AT service, designed and offered by the platform. In addition to the publicly available credit grade, the AT calculates a credit score ranging from 0 to 245 for each loan. This credit score is not disclosed to human investors but is exclusively used by the AT to evaluate and select loan applications. Unlike the AT services among US platforms, which allow investors to set investment criteria or customize the algorithm using their own screening models, the AT studied here does not support customization or configuration.

The AT studied in our paper resembles an algorithm-based money manager. It automatically invests users' funds into loan applications based on the algorithm's judgment and charges a service fee proportional to the assets under management. AT only invests on an agency basis, and its users bear the credit risk of their invested loans. AT's affiliation with the platform that profits from loan origination creates a misalignment of interest (D'Acunto et al., 2019). We leverage this platform affiliation to investigate the moral hazard in its investment.

The platform maintains bidding records for each loan. Panel C of Appendix A presents the bidder's (encrypted) name, amount, and time of each bid. Human investors cannot distinguish if a bid is placed through AT, thus they cannot leverage AT's judgment and follow AT's investment. Fortunately, our dataset includes an indicator that allows us to identify AT bids from human bids.

Figure 1 illustrates the bidding and underwriting process. The platform has a group of investors $I=\{I_1, I_2, \ldots, I_N\}$ and a set of loans $L=\{L_1, L_2, \ldots, L_M\}$. The arrowhead lines connecting investors and loans represent investors' bids (B_{il}). Solid lines indicate bids placed through AT,

while dashed lines represent manual bids. At the loan level, some of the loans are unfunded (i.e., L_1 and L_3), some are fully funded (i.e., L_2, L_4, and L_M). For funded loans, we observe their repayment records (i.e., R_2, R_4, and R_M) and classify them as either repaid or defaulted.

Unlike on the US platform Prosper, where manual bidders and institutional algorithm-based bidders invest in segmented pools of loans, this platform's AT and human investors are pooled to crowdfund the same set of loan applications. Consequently, we have loans that are purely funded by human investors (L_M), hybrid funded by human and AT (L_2), and purely funded by AT (L_4). This setting allows for rich interaction between human and AT in loan issuance.

[Insert Figure 1 Here]

2.3. Key Features

In summary, the platform has three advantages. First, newly issued loans have predetermined prices, and the market clears through rationing of orders. This setting mimics new offerings in primary markets. Second, AT's platform affiliation may give rise to moral hazard in its investment. Third, a shared loan pool between human and AT allows for rich interactions.

However, the presence of credit risk insurance poses challenges to our empirical analysis of loan performance. Chinese OML platforms often use loan guarantees to improve repayment performance and attract investors. While Chinese regulations prohibit platforms from providing direct guarantees, many platforms, including the one under study, get around this rule by entering separate agreements with third-party insurance companies. These platforms use their own money to purchase credit risk insurance covering a portion of the loans. In case of default, the insurance company will repay the outstanding principal to investors of the protected loans. The provision of third-party insurance falls into a regulatory gray area, thus the platform does not openly advertise this feature nor disclose to investors whether a loan is guaranteed.

The influence of third-party insurance centers around ex-post repayment of originated loans, not the loan underwriting process. Still, it could potentially bias our results in two ways. First, it may reduce investors' incentives in selecting loan applications. However, since investors are unaware of whether a specific loan is insured, this distortion is unlikely to occur. Additionally, the insurance only protects the invested principal, and investors still lose the time value of their investment in case of default. Second, the insurance compensation could introduce measurement errors into the calculation of investment performance. Fortunately, our data include detailed information on payment sources, allowing us to differentiate between payments made by the original borrower and those covered by the insurance company. In calculating repayment performance, we only consider direct repayments, excluding insurance company payouts. This ensures investment performance calculations are unaffected by third-party insurance.

3. Hypotheses Development

3.1. Biased Allocation

AT holds an advantage over human investors in trading due to its superior information processing ability and speed. Theoretical research models ATs as better-informed investors who operate more quickly than human investors (e.g., Biais et al., 2015; Foucault et al., 2016; Baldauf and Mollner, 2020). Under the framework of investor information heterogeneity in IPOs (Rock, 1986), we elaborate on how the introduction of AT into the primary market affects share allocation.

The seminal work of Rock (1986) consists of two types of investors. The informed investors, through paying an information collection cost, learn about the realized value of new issues. They only submit orders for new shares with realized value exceeding the offering price (i.e., good issues), and they will not subscribe to the issuance of overpriced shares (i.e., bad issues). The

uninformed investors cannot predict the realized share value and thus equally partition their wealth to all offerings. In case of oversubscription, the orders will be rationed. Because the informed investors only participate in good issues, the uninformed orders are less likely to be filled in cases of good issues than the bad ones. This bias in rationing is the key working force of Rock's (1986) model.

In the context of OML, AT mimics the informed investors as it has access to the finer measure of each loan's quality, the credit score. Human investors are less informed. As explained in the institutional background, the difference between our setting of OML and IPO is the share allocation rules. IPO underwriters take all orders, build an order book, and then ration the orders. However, loan shares in OML are first-come-first-served. A loan immediately closes right after the submitted orders reach the offering amount. All orders before a loan is funded will be fully filled, and later orders will not be accepted. This dissimilarity in microstructure predicts two testable hypotheses on share allocation.

First, the first-come-first-served rule leads to a corner solution, i.e., an extreme case of biased allocation. IPO underwriters accept all orders and then fill them with probability. The rationing mechanism determines share allocation, and informed investors in IPOs cannot fully crowd out the uninformed ones from good issues. Under the first-come-first-served rule in OML, order arrival sequence governs share allocation. AT in OML can preclude human investors from investing in good loans with its speed advantage. In particular, it can submit orders to fully fund good loan applications before human investors can react. AT's cherry-picking crowds human investors out from good deals while leaving the bad ones to them. As AT's market share increases, the good issues become insufficient relative to AT's investment amount. The scarcity of good issues

intensifies AT's incentive to preclude human investors, leading to more corner solutions. Second, similar to Rock's (1986) model prediction, the allocation of good issues is biased towards AT.

We propose the first set of hypotheses on share allocation as follows:

H1a (Corner solution): As AT's market share increases, it purely funds more loan applications without interacting with human investors.

H1b (Biased allocation): AT invests more in good loan applications than human investors do.

To preclude human investors from investing in good loan applications, AT needs both information and speed advantages. The proprietary credit score gives AT an information advantage to identify good investment opportunities (Bolton et al., 2016). The fast investment speed that humans cannot match allows AT to cherry-pick good deals before human investors (Biais et al., 2015; Baldauf and Mollner, 2020). The second set of hypotheses summarizes AT's preclusion of human investors using its speed and information advantages.

H2a (Information advantage): AT invests in loans with higher credit scores, which explains its superior performance.

H2b (Speed advantage): AT bids faster than human investors, especially when investing in loans of higher quality.

3.2. Winner's Curse

An important implication of biased rationing in Rock's (1986) model is the winner's curse facing uninformed investors. An uninformed order is more likely to be filled when the new issue is bad rather than good. At the aggregate level, the uninformed investors win more bad deals than good ones, leading to a winner's curse and losses. Evidence from IPOs shows that the winner's curse

heightens with stronger informational heterogeneity among investors (Carter and Manaster, 1990; Michaely and Shaw, 1994).

Despite a different microstructure in share allotment from IPOs, the same logic applies to OML. AT identifies good loans and precludes human investors from assessing them with a speed advantage. Loans that are available for human investors to bid on are worse deals that AT chooses not to cherry-pick. As AT cherry-picks more good deals, human investors face a more severe winner's curse. Bolton et al. (2016) refer to informed investors' selection of good deals as *cream skimming*.

H3 (Winner's curse): The increasing presence of AT reduces human investors' performance.

3.3. Loan Pricing

The winner's curse model of Rock (1986) further predicts underpricing. Uninformed investors take the biased allocation and winner's curse into consideration, and they demand a lower price as compensation, leading to underpricing.

In our setting, the increasing presence of AT precludes human investors from assessing good loans. Being aware of AT's cream skimming, human investors update their posterior belief and request higher interest rates for their investments.

H4 (Underpricing): Controlling for loan quality, human investors respond to the increasing presence of AT by requesting higher interest rates (i.e., underpricing).

We are fully aware that our setting differs from Rock's (1986) model as investors can choose to get informed through purchasing the platform's service. However, this difference should not affect the above key hypotheses. In Vallée and Zeng's (2019) model, they allow sophisticated investors to get informed through "purchasing an information technology at cost" (pp. 1950, Vallée

and Zeng, 2019), which mimics the AT adoption in our setting. Although their model focuses on the platform's optimal screening and information provision to maximize loan volume, it also predicts biased allocation and underpricing in an endogenous adverse selection framework. In particular, informed investors in OML fund good loan applications, which decreases the average quality of loans available to uninformed ones. In response, the uninformed investors downward update their beliefs about investment performance. With the lowered posterior belief, uninformed investors request for higher interest rates to agree to finance a loan application.

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3.4. Side Payment and Moral Hazard

So far, we have been focusing on the information heterogeneities among investors. Apart from information asymmetry, side payment in the underwriting process is another important factor that affects the allocation of shares and pricing in IPOs (Ritter and Welch, 2002; Loughran and Ritter, 2004). In the US, underwriters allocate underpriced shares to connected investors. These connected

investors repay the underwriters through side payments, such as future investment banking business (Siconolfi, 1997; Ljungqvist and Wilhelm, 2003) and excessive trading commissions (Loughran and Ritter, 2004; Reuter, 2006). As explained in the institutional background, the AT studied in this paper is closely connected to the underwriter, as it is designed and owned by the platform. We examine whether the algorithm is more impartial and whether AT can alleviate the above conflict of interest in the primary market.

Well-designed algorithms are less biased (Coleman et al., 2022; Liu, 2022; Aubry et al., 2023; Bao and Huang, 2023). However, perfect impartiality is difficult to achieve due to algorithmic bias (Cowgill and Tucker, 2019). For example, algorithms can automate and perpetuate the misaligned interests between designers and clients (Mullainathan and Obermeyer, 2017). Legal research warns that AT may abuse its clients' money for its own benefit (Ji, 2017), and "honesty, competence, and suitability [of AT] cannot simply be assumed" (Baker and Dellaert, 2017, pp. 713). In OML, D'Acunto et al. (2019) show AT effectively reduces investors' behavior bias, but they also warn AT might be subject to its designer's biases, conflicts, and limitations.

The conflicts of the AT in our setting arise from its platform affiliation. An independent AT maximizes its service fees by optimizing the investment performance of its users. However, in the case of a platform-affiliated AT, its objectives are aligned with the profit maximization of the platform, which includes both the service fees and the loan origination fees.

While service fees require AT to selectively invest in good loan applications to improve performance and attract more users, loan origination fees are proportional to the quantity of loans originated. This quality-quantity tradeoff resembles the conflicts in Vallée and Zeng (2019). In their model, sophisticated investors improve loan quality with rigorous screening; however, their endogenous adverse selection increases financing costs and reduces loan origination amounts. The

profit-maximizing platform in their model partially sacrifices investors' screening, through reduced information provision, to boost loan origination volume.

The platform-affiliated AT can increase the loan origination amount by facilitating some bad loans that would otherwise be unfunded. The additional origination fee generated mimics investors' side payments to the underwriters in IPO literature. If facilitating a bad loan brings more loan origination fees than the expected losses in service fees due to bad investment, then the benefit from side payments will distort AT's investment. For instance, consider a bad loan that is 99% funded by human investors one minute before the funding deadline. The AT could secure the loan origination fee with a very small stake in the risky deal by filling the remaining 1% unfunded amount. Hao and Yan (2012) document similar behavior among bank-affiliated funds, which hold larger shares of the bank clients' ill-performing new issues.

Unlike the good loans that AT precludes humans from assessing, the bad loans carry low expected returns that AT tends to avoid. This predicts an opposite strategy of cherry-picking: *wait-and-facilitate*. When a bad loan is listed, AT waits for human investors to fund as much of the loan as possible, if not fully fund it. It minimizes its exposure to a bad loan by only filling the remaining amount after human investors refuse to invest more money.

H5 (Moral hazard): AT facilitates bad loans at the end of their funding period.

4. Data Description and AT's Investment Strategy

4.1. Data Description

We use a proprietary dataset from Changsha Aijie Information Technology Co., Ltd. (Aijie). The platform introduced its AT service in March 2012, and our analysis primarily focuses on data from that point until December 2016. Sections 5.2 and 5.3 include event studies centered around the

introduction of AT, with the sample period extending to March 2011. The dataset comprises both bid-level and loan-level records.

Loan-level data consist of 218,877 loans, with 56,479 purely funded by human investors and 162,398 receiving bids from AT. We utilize the loan-level data to investigate loan share allocation between AT and humans.

Bid-level data include 1,945,610 human bids and 11,217,985 AT bids. The market share of AT is comparable to that reported by Braggion et al. (2019). We use bid-level data to contrast the investment performance of AT and human bids. In our sample, many investors submit multiple bids. Thus, bid-level data enable us to control for investor-specific characteristics through investor fixed effects.

The first performance measure is the annualized IRR (*IRR*) calculated using the repayment records of each funded loan. The second is a dummy variable, *Default*, indicating if a loan defaults. To ensure the performance measures are not contaminated by third-party insurance, we solely consider direct repayments from borrowers when calculating the *IRR* and define a loan as *default* if the borrower fails to fully repay it, irrespective of any payouts received from the insurance company. The IRR of a fully repaid loan is its annualized interest rate. For default loans, we calculate the IRR using their actual monthly repayments. Following Duarte et al. (2012), we find IRR using the equation $BidAmount = \sum_{t=1}^{T} \frac{Monthly\ payment_t}{(1+IRR/12)^t}$, where T is the loan maturity that the bid goes to, and t denotes the month.

Table 1 Panel A presents the loan-level summary statistics. On average, loans that receive AT bids have higher quality than the purely human-funded loans, as reflected by a 1.78-notch higher credit grade and a 41.49-point higher credit score. These loans are also funded within a shorter time. To account for the positive skewness of funding time, we compare the medians between the

two loan types. The median funding time for purely human-funded loans is 145 seconds, whereas loans with AT participation have a median funding time of 9 seconds.[12] The results are consistent with our second set of hypotheses that AT cherry-picks good deals.

We also find evidence in line with the prediction that AT facilitates bad deals at the end of their funding period. Despite a shorter median funding time of loans with AT participation, the maximum funding time appears in the AT participation group. The loan takes 6.98 days to be funded, which is 46.99% longer than the maximum funding time of the purely human-funded loans. The pattern suggests that AT also invests in loans that remain unfunded after being listed for a very long time.

Loans with AT participation have higher IRR and lower default rates compared to purely human-funded ones. We leave the detailed performance comparison to bid-level analysis where we directly contrast AT and human bids. Furthermore, purely human-funded loans have higher interest rates, aligning with our fourth hypothesis that human investors adjust their beliefs about loan performance with the rise of AT, demanding higher interest rates.[13]

Table 1 Panel B summarizes the key variables of human and AT bids separately and presents the mean differences with t-test significance.[14] 4.61% of human bids go to default loans, and the average realized annual return rate of human bids is 8.06%. In contrast, AT significantly outperforms human bids, with a default rate of 0.03% and an annual return rate of 11.23%. AT tends to invest in loans of superior quality, with the average credit grade being around 1.1 notches

[12] Manually submitting an order within 9 seconds is nearly impossible for human investors. Even if human investors see a loan immediately after it is posted online, they still need to complete the following steps before bidding: click the link (and wait for the website to respond), skim through the loan's and borrower's information, input the bid amount, click the confirmation button, and wait for the website to respond again.

[13] The results are highly descriptive. An alternative explanation is that human investors in OML tend to focus on interest but ignore the risk features in choosing investment targets, as suggested by Liao et al. (2021). We provide formal evidence in section 5.

[14] Investment performance, borrower characteristics, and loan characteristics are loan-level features. For bid-level analysis, we penetrate each bid to the loan that it goes to. For example, we use the IRR and default status of loan m to measure the performance of investor n's bid to loan m (B_{nm}).

higher and the credit score being 25.59 points higher compared to human-invested loans. Additionally, AT exhibits a speed advantage in investment. At the bid level, a median human bid arrives 293 seconds after the loan listing time, while AT only takes 14 seconds.

[Insert Table 1 Here]

4.2. AT's Investment Strategy

Figure 2 shows the rise of AT on the platform and its interaction with human investors. The solid line represents the percentage of bids placed by AT each day, while the dashed line represents the daily percentage of the amount funded by AT. In 2012, when AT was initially introduced, it accounted for approximately 9.88% of the investments. Despite a decrease in 2014, AT's market share exhibited an upward trend during our sample period, reaching a peak of 92.07% in 2016.

Each gray dot in Figure 2 also represents a funded loan. The x-axis represents the date when the loans were listed, and the y-axis represents the percentage amount funded by AT for that loan. Loans that were purely funded by human investors are on the x-axis, while the line y=1 are loans fully funded by AT. The dots in the inner region indicate hybrid-funded loans that received funding from both AT and human investors.

Upon the introduction of AT in March 2012, most of the dots are in the bottom half of the graph, indicating that AT actively interacted with human investors by funding a small proportion of the requested loan amount.

AT's market share increased sharply from December 2012, and it began to fully fund loan applications starting from the same time point. As AT increased its presence in the market, dots in the inner region became sparser, indicating AT interacted less with humans by either fully funding loan applications or leaving them to human investors entirely. The reduced interaction between AT and humans coincides with the first set of hypotheses.

[Insert Figure 2 Here]

Hypotheses 2 and 5 conjecture that AT cherry-picks good loans before human investors and also facilitates bad loans at the end of their funding stage. Summary statistics cannot distinguish them as they pool all AT bids together and mask the arrival stage differences. Below, we rely on the timing of AT bids to separately illustrate AT's two investment strategies.

The first decile of human bid time is 7.02 seconds after loan listing. AT bids that arrive before it preclude more than 90% of human bids, and we consider them as *immediate* AT bids. The 9th decile of loan funding time is 840 seconds. AT bids placed beyond this time point belong to the *close-to-end* AT bids. The *intermediate* group includes AT bids between these two cutoffs. Figure 3 demonstrates the average credit grade and default rate of AT bids in these three groups.

AT invests in high-rated (average credit grade of 6, i.e., A rating) and well-performing loans immediately after listing, with a near 0 default rate. In the intermediate period, AT maintains this standard in terms of credit grade, and the default rate remains low, albeit approximately 7 times higher than AT bids immediately after loan listing. During the last funding stage, the average credit grade of AT bids decreases to 5.8, and the default rate surges to 0.86%, indicating AT invests in poorer quality and performance of loans at a late stage.

[Insert Figure 3 Here]

One can interpret the inferior quality and performance of AT's last-stage investment in two very different ways. First, as hypothesis 5 predicts, AT deliberately fills up the unfunded amount of some bad loans, causing the deteriorated performance. Second, all of the remaining applications in the last stage are bad, and AT has no choice but to invest in them.

The second explanation is highly unlikely for two reasons. In the absence of good investment opportunities, AT does not have to invest all the money it manages. Instead, it can wait for newly

listed good loan applications. Most importantly, AT does not have to wait until the last stage to invest, unless it intends to do so. In our sample period, AT invests a total amount of RMB 44.6 billion in the last stage, which is much smaller than human investors' contribution in the immediate and intermediate stages (RMB 76.3 billion). With its information and speed advantage, AT could have invested all of its money under management before the last stage.

Panel A of Figure 4 provides more compelling evidence by illustrating the distribution of AT's investment amount over time, by credit grade. For loans with HR rating, only 0.83% of AT's investment amount arrives immediately after listing, with 4.18% accumulated in the intermediate stage. The remaining 94.99% of AT's investment arrives in the last stage. A similar distribution appears among E, D, C, and B-rated loans. However, for A- and AA-rated loans, AT quickly establishes its position early on. Particularly for AA-rated loans, 47.07% of AT's investment flows in within the first 7.02 seconds, before 90% of human investors have sufficient time to react. Only 3.42% of the AT investment amount arrives close to the end of the funding period.

In addition to credit grade, AT has access to a more refined measure, the credit score. Within the same credit grade band, we divide loans into high- and low-score groups by the median credit score. Panel B illustrates the distribution of AT's investment amount across funding stages for high- and low-score loans separately. When investing in loans with higher credit scores within the same credit grade, AT is more likely to select them early on and establish a position. The pattern is reversed for low-score loans, with over half of AT's position established through late-stage investments. These findings become even more pronounced when we partition loans by repayment status. For repaid loans, the majority of AT's investment amount occurs in the immediate and intermediate stages. However, 98.72% of AT's position in default loans is built in the late stage. When AT invests in default loans, it almost always does so in the late stage.

[Insert Figure 4 Here]

Despite limited information on the proprietary design and investment strategy of the platform's AT, a thorough analysis of AT's investment patterns in terms of time, quality, and performance reveals descriptive evidence that supports our main hypotheses. AT precludes human investors, selectively choosing good loans immediately after they are listed. Besides, AT also facilitates the funding of bad loans at late stages. In the following section, we formally investigate and analyze these hypotheses.

5. Empirical Results

5.1. Biased Allocation and Precluding Human Investors

AT's market share may expand through the extensive margin by independently funding more loans, or through the intensive margin by financing a larger proportion of each loan. The extensive margin growth predicts less intensive interaction with human investors and more corner solutions, whereas the intensive margin growth indicates the opposite. Table 2 tests hypothesis 1a on corner solutions by investigating AT's expansion path.

Specifications (1) to (3) of Table 2 focus on the extensive margin where the dependent variable is *Pure AT*, which equals 1 if a loan is purely funded by AT. The focal variable is AT's daily market share, measured as the percentage amount funded by AT on a given day. Specification (1) controls only for time trend using month fixed effects. Specifications (2) and (3) progressively include loan contract terms, credit grade fixed effects, and borrower characteristics. We convert all categorical variables, including credit grade, education level, income range, and age, into fixed effects. We always cluster standard errors by their listing date for loan-level analysis. Given these

high-dimensional fixed effects, we use OLS regression for consistent estimation. The unreported Logit regression produces similar results.

AT's market share has significantly positive coefficients across the first three specifications. For every percentage point increase in AT's market share, a loan has a 0.44 percentage point higher chance of being purely funded by AT. Over our sample period from 2012 to 2016, AT's market share increases by 82.19 percentage points. Controlling for everything else, a loan is more likely to be purely AT-funded by 36.16 percentage points.

Specifications (4) to (6) explore the intensive margin using a subsample of loans that are not purely funded by AT. AT's market share exhibits an insignificant correlation with the percentage amount funded by AT of each loan. For loans that AT does not fully fund, AT maintains a relatively stable share.

Results in Table 2 demonstrate that AT expands through the extensive rather than the intensive margin. When AT manages more money, it purely funds more loan applications without interacting with human investors. The findings align with our first hypothesis that AT tends to preclude human investors and interacts less with them as its market share increases.

[Insert Table 2 Here]

To contrast human and AT investment performance and test hypothesis 1b on biased share allocation, Table 3 uses bid-level data that clearly label the investor's identity for each bid. The focal variable is the *AT* dummy, indicating if a bid is placed by AT. Apart from the full set of control variables used in Table 2, the bid-level analysis further includes investor fixed effects, which absorb time-invariant individual features that may be correlated with AT adoption (Ge et al., 2021). We cluster standard errors at the investor level for bid-level analysis.

Specifications (1) to (3) use bid *IRR* as the dependent variable, and (4) to (6) use the default indicator. We report OLS regression results for both settings, despite *Default* being a dummy variable. Results are consistent using panel Logit regression. Similar to the settings of Table 2, we start by controlling for month and investor fixed effects, and then gradually include a full set of borrower and loan-level controls that may affect loan performance (Iyer et al., 2016). Within the same investor, the usage of AT predicts a 12 basis point higher annual return and a 0.16 percentage point lower default. The superior performance of AT supports our hypothesis that the allocation of good deals is biased towards AT. The findings are also consistent with OML literature (Vallée and Zeng, 2019; Fu et al., 2021; Balyuk and Davydenko, 2023).[15]

[Insert Table 3 Here]

We move on to test the second set of hypotheses regarding AT's information and speed advantage. Specifications (1) and (2) of Table 4 present Poisson regressions of credit score on the AT dummy. Without controlling for credit grade fixed effects, AT invests in loans with an 8% higher credit score compared to humans. Notably, the coefficient remains significant in specification (2) after including credit grade fixed effects. Within the same credit grade, AT invests in loans with higher ex-ante quality, leveraging its information advantage. As explained in the institutional background, AT calculates credit scores based on the borrower characteristics that are also available to human investors. Thus, AT derives its information advantage from its superior information processing ability.

Specifications (3) and (4) re-examine AT's superior performance over humans but include the credit score of the target loan as an additional control variable. Different from the results in Table

[15] Apart from bid-level evidence, loan-level evidence also supports biased allocation. Appendix B shows higher credit score loans receive more AT investments, and they are more likely to be purely funded by AT.

3, AT's significance disappears. The loss of significance indicates AT's higher return and lower default are largely explained by its information advantage, proxied by *Credit Score*.

The last two specifications present Poisson regressions on bid time. On average, AT invests significantly faster than humans by 87.36%, highlighting its speed advantage. Specification (7) introduces an interaction term between the *AT* dummy and *Credit Score*. Its negative coefficient suggests that AT extensively uses its speed advantage when investing in better deals, supporting our second hypothesis that AT cherry-picks good loans before human investors can react. The AT dummy turns positive and loses its significance, meaning that AT does not exhibit a speed advantage over human investors when investing in the lowest quality loans.

[Insert Table 4 Here]

5.2. Human Performance

As summarized by hypothesis 3 on the winner's curse, the rise of AT predicts deteriorated performance on the human investor side. Table 5 uses a sample of human bids and regresses bid IRR and Default indicator against AT's daily market share.

Our focal variable exhibits significant negative coefficients when the dependent variable is *IRR* and significant positive coefficients when the dependent variable is *Default*. These results suggest that the performance of human investors declines as AT's market share increases. However, the relationship should not be interpreted as causal.

[Insert Table 5 Here]

Similar to Brogaard and Garriott (2019), our sample period covers the introduction of AT, allowing for an event study. We normalize AT's initiation month to 0 and use a sample of human bids placed in the 9 months around both sides of the launch of AT, excluding the event month. To ensure robustness, we also examine alternative time windows of 6 months and 1 year.

Panel A of Table 6 reports an unconditional deterioration in the performance of human bids across all time windows. After the introduction of AT, human bids experience a 4.22 percentage point decrease in IRR and a 3.79 percentage point increase in default probability in a [-9m, 9m] time window.

Panel B presents regression-based evidence, where the focal variable is *Post*, indicating whether a bid is placed after the introduction of AT. The *Month* of each bid controls for time trends. The coefficient of *Post* reflects the changes in IRR or default rate of human bids around the introduction of AT. In the [-9m, 9m] window, human investors face a 3.88 percentage point higher default rate and a 3.70 percentage point lower return.

One concern is that the event study may pick up investors' self-selection in AT adoption. In particular, if more sophisticated investors choose to use AT, then human investors' performance may also decrease. However, this cannot be the driving force as the model controls for investor fixed effects. Even within the manual bids from the same investor, we observe performance deterioration after the introduction of AT. Additionally, we address this issue in Panel C by examining a subsample of bids from human investors who did not use AT in the [-1y, 1y] window. These results, which come from a consistent group of human investors, remain highly significant and are comparable to those in Panel B.

Another potential confounding factor is the change in loan application quality. If the platform lists more bad loans after the introduction of AT, the observed decline in human performance could just reflect overall market condition changes. In the loan underwriting process, the platform first checks an application's authenticity before posting it. Technically speaking, the platform can time the market and postpone an application's listing time by extending the checking period. However, this is very unlikely to happen as the platform relies on its loan underwriting speed to compete

with traditional financial institutions (Fuster et al., 2019). Instead of delaying certain loan applications from investors' assessment, the platform is more likely to list them as quickly as possible.

Even if the platform did time the market, it would postpone good loans so that AT can invest. This predicts an increase, rather than a decrease, in loan quality, biasing the results against us. Panel D compares the average credit grade and credit score of all funded loans before and after the introduction of AT. The quality improves for both applications and funded loans. Therefore, the deteriorated human performance captures the winner's curse, not the selection effect or changes in market conditions.

[Insert Table 6 Here]

5.3. Loan Pricing

Next, we examine how human investors respond to the rise of AT that precludes them from assessing good loans in the market. Table 7 tests Hypothesis 4 on underpricing.

The first specification uses all human bids and relates AT's daily market share to the interest rate of their invested loans. Controlling for a full set of factors, a human investor tends to invest in loans with higher interest rates as the presence of AT increases. Given the investor fixed effects, the result is free from the influence of the investor's characteristics, such as risk preference.

Specifications (2) to (4) present the event study results under the same setting as Table 6 Panel B. The regressions use human bids around the introduction of AT with different time windows. Within the 9-month period surrounding both sides of the introduction of AT, humans invest in loans with 0.24 percentage points higher interest rates, representing a 2% increase compared to the mean. This increase in interest rates reflects a change in human investors' belief about investment performance. They require higher interest rates to agree to finance loan applications as AT cream

skims the market. The results are in line with Rock's (1986) prediction on IPO underpricing and Vallée and Zeng's (2019) prediction of endogenous adverse selection in OML.

To address the concern of human investors' self-selection in adopting AT, we restrict the sample to bids from investors who have no AT usage in the time window of [-1y, 1y] and find consistent results in specifications (5) to (7). In unreported analysis, we also compare the average interest rate of the funded loans around the introduction of AT. The average interest rate decreases in the post-event windows, alleviating the confounding factor of a market-level increase in interest rates.

[Insert Table 7 Here]

5.4. Moral Hazard

AT provides side payments to the underwriting platform through financing bad loan applications that would otherwise be unfunded. Hypothesis 5 summarizes the moral hazard in AT as wait-and-facilitate bad loans. AT first waits for human investors to fund as much of the requested amount of a bad loan as possible, and then fills the unfunded amount. This moral hazard arises only among hybrid-funded loans through the interaction between AT and human investors. Therefore, this section uses the sample of bids that go to hybrid-funded loans.

For each hybrid loan, we divide its funding process into four equal stages based on the percentage amount funded. For example, the four stages of a loan requesting RMB4,000 are RMB1 to RMB1,000, RMB1,001 to RMB2,000, RMB2,001 to RMB3,000, and RMB3,001 to RMB4,000. Within each stage, we calculate the percentage funded by AT as *%AT_Q1* to *%AT_Q4*.

The dependent variable in Panel A of Table 8 is the *IRR* of each bid. Specifications (1) to (4) separately include *%AT_Q1* to *%AT_Q4* of the loan that the bid goes to. Bid-level analysis allows for the inclusion of investor fixed effects, absorbing investor characteristics. The models also

control for a full set of loan characteristics, borrower characteristics, and month fixed effects. *%AT_Q1* is significantly positive, indicating that a bid performs better when it goes to a loan that receives more AT funds in the first quarter. This pattern aligns with our previous findings that AT cherry-picks good deals at early stages. However, *%AT_Q2* to *%AT_Q4* turn significantly negative, and the coefficients become quantitatively smaller at later stages. The results demonstrate an inverse relationship between bid performance and AT's late-stage investment in the targeted loan.

[Insert Table 8 Here]

Why does AT invest in bad loans at late funding stages? An intuitive explanation is that only bad loans are available at the late stage. This argument is invalid because we define the funding stage at the loan level, by the funded amount of each loan. Both good and bad loans take bids from Q1 to Q4. Other arguments such as more aggressive risk-taking, miscalculation of loan performance, and diversification motives may explain why AT invests in bad loans. However, they cannot justify why these bad investments are concentrated at the late stage. We interpret the findings as AT waiting and filling the unfunded amount of bad loans that humans refuse to originate.

If AT indeed knowingly invests in bad loans for loan origination fees, a testable implication is that AT is more likely to facilitate bad loans in which it has a smaller stake. Specification (5) examines the cross-sectional difference by interacting *%AT_Q4* with AT's total position in the funded loan (*%AT*). The coefficient of *%AT_Q4* remains negative, confirming our previous finding that last-stage AT investment predicts worse performance. More importantly, the interaction term exhibits a significantly positive coefficient, showing that AT's own stake weakens its incentive to facilitate bad loans at late stages.

We are fully aware of the endogeneities in the interaction term, as AT's total stake is related to its investment decisions in the last quarter. Therefore, we only focus on the sign of the interaction term, without making any quantitative interpretations. In an unreported regression, we interact *%AT_Q4* with AT's position accumulated in the first three quarters (*%AT_Q1-Q3*), which is determined before the last stage. The results are highly consistent.

Figure 5 visualizes how AT adopts different strategies in investing in good and bad loans. It displays the estimated coefficients of *%AT_Q1* to *%AT_Q4*, with the error bars representing the confidence intervals at the 10% significance level. The solid line connecting the coefficients of *%AT_Q1* to *%AT_Q4* exhibits a consistently declining trend over the bidding stages, indicating that AT transitions from cherry-picking good loans immediately after they are listed to facilitating bad loans in the later stages.

[Insert Figure 5 Here]

Panel B replaces the dependent variable with the *Default* indicator. AT investment in the first quarter of the funded amount goes to loans with low default rates, while last-stage AT investment predicts a higher default rate. The interaction term in specification (5) also suggests that the higher default associated with last-stage AT investment is weaker when AT holds a greater position in the facilitated loans. Logit regression produces similar results but is not reported. Figure 5 plots these coefficients and connects them with a dashed line; the upward slope indicates an increase in the default rate as AT bids at a later stage.

Before moving forward, we discuss the ramifications of AT's facilitation of bad loans. Most directly, AT's clients suffer from this moral hazard, as AT invests their funds in loans with poor performance. This is similar to Hao and Yan (2012) that investors of bank-affiliated funds receive

inferior returns, as the funds use their money to support the underperforming new issues that their banks underwrite.

Additionally, the moral hazard leads to the origination of more bad loans. The less rigorous screening indirectly worsens human investors' performance as well. Specifically, human investors who have a stake in the facilitated bad loans are the victims. Without AT filling the unfunded amount in the final stage, some of the bad deals may be screened out by humans and remain unfunded. In this case, their invested amount will be returned in full. By facilitating bad loans, AT "locks in" the position of human investors, exposing them to the credit risk associated with these deals. We illustrate the influence of AT's facilitation through a back-of-the-envelope calculation. The sample includes 104 hybrid-funded loans that default, and we focus on half of them with above-median *%AT_Q4*. Through coarsened exact matching, we pair each of them with a loan application listed before March 2012, the time period before AT's first appearance.

Matching on loan contract terms and credit grade only, the funding success rate for the matched loans is 9.47%. This is much smaller than the average funding success rate of 12.23% before March 2012. Without AT's facilitation, human investors could have partially identified some bad loans and screened them out. With more precise matching based on all loan characteristics, borrower characteristics, and credit grade, none of the matched loans were funded, suggesting human investors could have detected and avoided these problematic loans.

5.5. Robustness Tests

A loan's interest rate is a comprehensive measure of its credit risk. Table 9 replaces the interest rate control with its bin fixed effects to control for the non-linear influence of interest rates. The interest rates in our sample range from 7% to 24.4%, and we divide them into 35 bins of 0.5%. This setting facilitates the comparison of loans and bids with the same ex-ante interest rate.

Panel A replicates Table 2 and presents consistent results that AT expands through extensive margin rather than intensive margin. It confirms that as AT's market share increases, it has less interaction with human investors in funding loan applications.

Panel B replicates the results in Tables 3 and 4. Specifications (1) and (3) confirm that AT achieves better performance. Results in specification (2) are similar to our previous findings that the high credit score of AT's investment target fully explains AT's superior investment IRR. Specification (4) presents slightly different results where AT remains significantly negatively correlated with bid default, even after controlling for credit score. However, the relationship is quantitatively weakened by 81.67% (=1-0.044/0.24). The last three specifications provide consistent evidence that AT leverages its information and speed advantage to cherry-pick good deals.

Panel C presents an event study of AT's introduction on human performance, controlling for interest rate bin fixed effects. The findings align with those in Table 6, showing that human investors experience reduced realized returns and higher default rates after AT's introduction.

Panel D confirms the results in Table 8 and Figure 5, showing AT invests in loans with poorer performance in later stages.

[Insert Table 9 Here]

Table 10 employs an alternative setting to illustrate AT's different investment strategies for good and bad deals. Besides *%AT_Q1* to *%AT_Q4*, the new model further includes the AT-funded ratio of the targeted loan (*%AT*). In Table 8, the coefficients of *%AT_Q1* to *%AT_Q4* reflect the relationship between investment performance and AT's absolute position in each stage. Table 10 estimates the distributional effects of AT's stake over different stages, conditional on AT's total position in the targeted loan. Different from the results in Table 8 where the coefficients change

direction between Q1 and Q2, the switches in sign appear between Q2 and Q3 in Table 10. These dissimilarities do not conflict with the baseline model results as the financial implications are different. Most importantly, we find a consistent pattern that later-stage AT positions predict worse investment performance, which shows how AT transitions from cherry-picking good loans to facilitating bad loans.

[Insert Table 10 Here]

6. Discussion

6.1. Fully Automating the Primary Markets?

Why should we care about AT's impacts on human investors in the primary market? If AT outperforms humans in choosing new issues, why not fully automate the issuance process and let AT replace humans? The increasing market share of AT to more than 90% also seems to suggest that full automation may be the new paradigm of the primary market.

The answer to the above questions hinges upon the relationship between AT and the underwriter. For independent AT that faithfully serves the best interest of its investor-clients, it may enhance their efficiency in selecting issuance targets and improve their performance (Fu et al., 2021).

On the contrary, automation through underwriter-affiliated AT transfers the underwriter's business model into "originate-and-distribute," which exaggerates the moral hazard in the issuance process (Balyuk and Davydenko, 2023). With AT dominating the OML market, the platform underwrites loans for origination fees and then distributes them to investors with little skin in the game. Consequently, it has an incentive to underwrite more bad loans for greater funding volume and ultimately higher loan origination fees.

Balyuk and Davydenko (2023) provide compelling evidence that human investors play a crucial role in mitigating this moral hazard, as they select issuance independently from the platform's control. Table 6 Panel A shows the raw IRR for human investors is between 6.36% and 7.86% in the year following AT's introduction. Despite being lower than AT's IRR, the return for human investors is still almost double the benchmark rate, which ranged from 3% to 3.5% in 2012.

6.2. Algorithmic Pricing?

AT's performance demonstrates the algorithm's superior ability in processing information and predicting loan performance. Instead of using this algorithm to more accurately price loan applications, the platform under study uses it to select underpriced loan applications for its users. US-based platforms adopt a similar business model and deploy algorithms on the investor side (e.g., see Balyuk and Davydenko (2023) for the example of Quick Invest and AutoInvest). So why do OML platforms use algorithms in selecting loan applications rather than pricing them?

A thorough investigation of this question is beyond the scope of this paper. Still, literature on discrimination in FinTech lending provides insights (Bartlett et al., 2022). Platforms may not have the incentive to accurately price all loan applications, especially those from borrowers with lower bargaining power. Charging a higher interest to applications in financial deserts or with low shopping tendency, and then cherry-picking these juicy deals with its own AT, is more profitable for the platform.

6.3. Implications to Secondary Markets

Although the results of biased allocation, winner's curse, and underpricing rely on the unique fixed price setting of the primary market, our findings may also inform markets beyond primary issuance. One of the key differences between the secondary market and primary market is that the former clears through price adjustment. However, even in the secondary market with flexible prices,

traders' price competition is constrained by tick sizes due to discrete pricing. And within the tick size, the time priority rule allocates trading opportunities to faster trading. The microstructure of the secondary market within a tick size mimics our setting of fixed price with a first-come-first-served share allotment rule. Our findings on AT's cherry-picking echo the key idea of Yao and Ye (2018) that discrete pricing in the secondary market creates adverse selection rents, giving rise to speed competition and high-frequency trading.

7. Conclusion

Using order-level data on AT *vis-à-vis* human investment in OML loan issuance, we find that AT uses its information and speed advantage to preclude human investors from assessing good issues. The biased allocation of good deals towards AT lowers the performance of human investors, who in turn request higher interest rates as compensation. Our findings align with the theoretical predictions of Rock's (1986) model on investor information heterogeneity.

Platform affiliation brings loan origination fees into AT's investment decisions, potentially conflicting with the goal of maximizing users' investment returns. Evidence on AT's moral hazard shows it facilitates the financing of bad loans by filling their unfunded amounts, particularly when AT has a small stake in the target loan.

With AT playing more active roles in the primary market, the findings reveal possible ramifications. By widening the information gap, AT exaggerates biased allocation, winner's curse, and the associated underpricing. Additionally, for underwriter-affiliated AT, it may automate the conflict of interest between the underwriter and investors. The results also shed light on markets other than primary issuance that share similar settings.

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Figure 1. Bidding and Screening on OML

The graph depicts the bidding and screening process of investors on the platform. Circles in the first row represent investors, and the third row represents loan applications. The lines with arrowheads connecting investors and loans represent the bids made by investors. A solid line indicates a bid placed through AT, while a dashed line indicates a human bid. The fourth row indicates the funding status of each loan, and for the funded loans, the last row shows their repayment records.

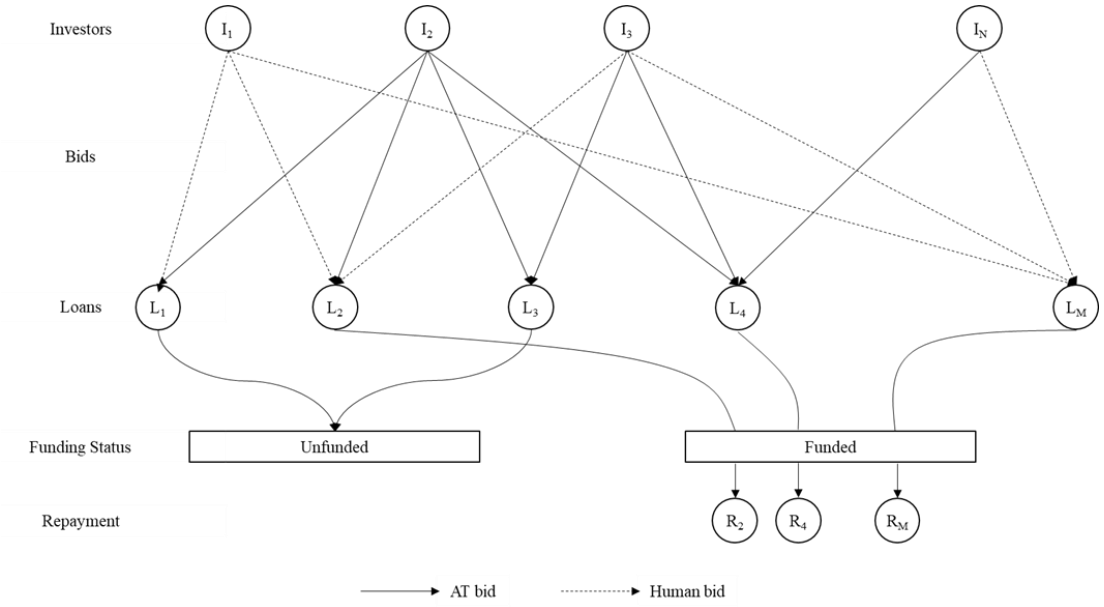


Figure 2. The Rise of AT

This graph illustrates the evolution of AT's investment on the platform. The solid and dashed lines depict the daily market share of AT, measured by the percentage of bids and bid amount, respectively. Each gray dot represents a loan, with the x-axis denoting its listing date and the y-axis representing the percentage amount funded by AT.

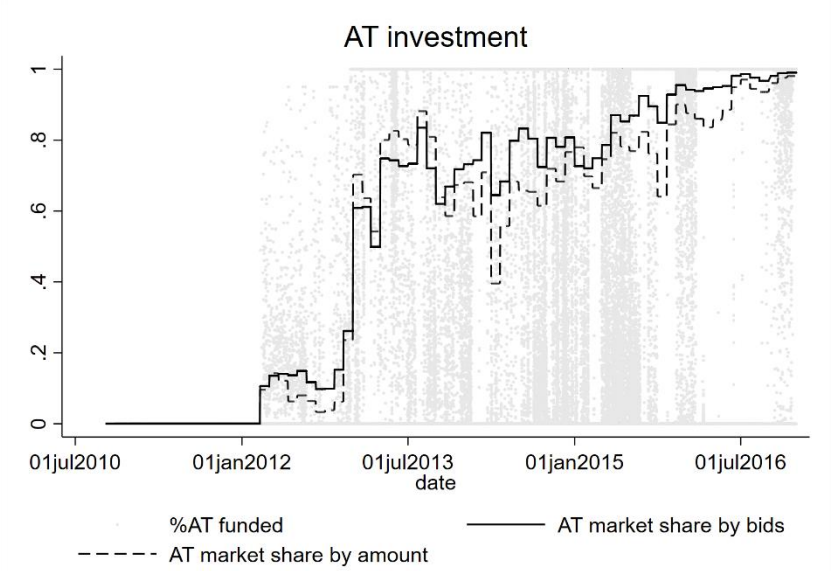


Figure 3. AT's Performance by Funding Period

This graph categorizes AT's bids into three groups. Bids arriving immediately after loan listing, within the first decile of human bid time (7.02 seconds), effectively preclude most human investors. Bids arriving after the ninth decile of loan funding time (840 seconds) belong to the close-to-end group. Bids falling between these two cutoffs are in the intermediate group. The solid line represents the average credit score of loans that the bids in each period go to, while the gray bar reflects the average default rate.

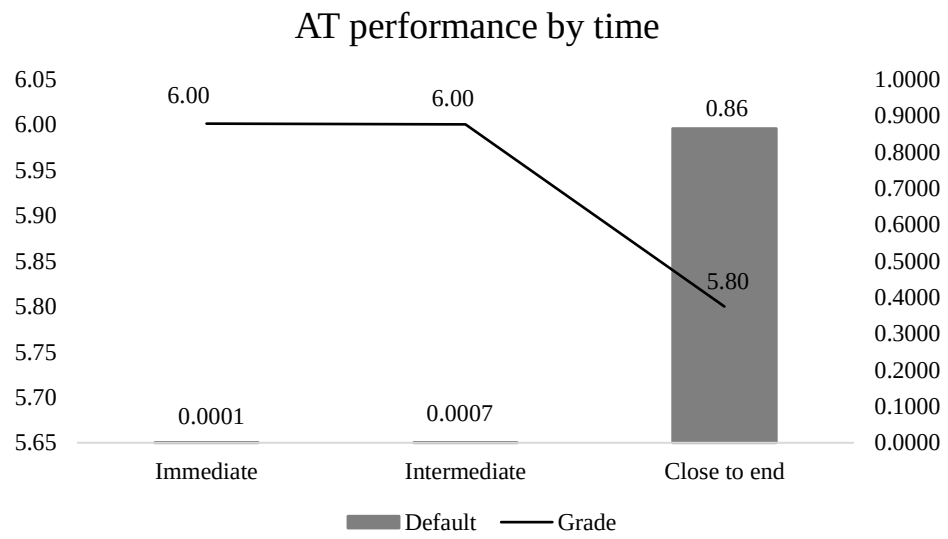
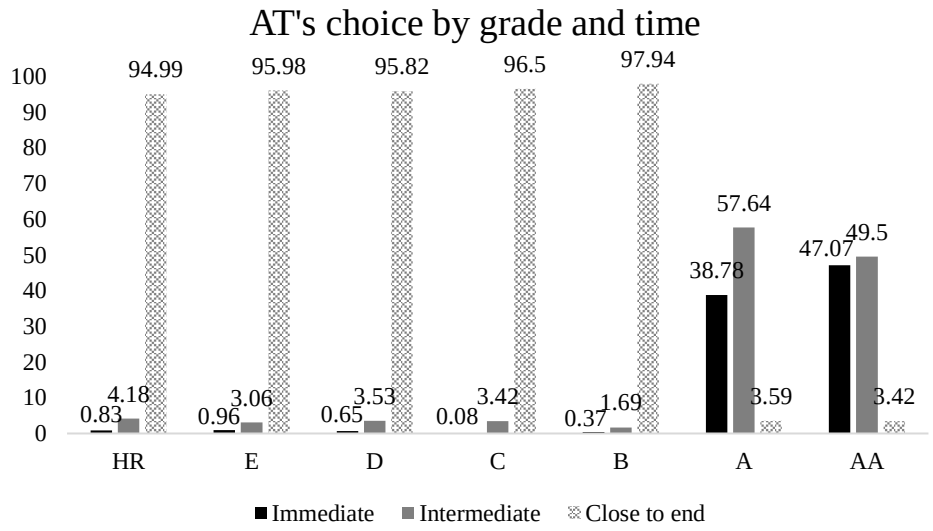


Figure 4. AT's Investment Choice by Funding Period

This graph categorizes AT's bids into three groups. Bids arriving immediately after loan listing are within the first decile of human bid time (7.02 seconds), precluding most human investors. Bids arriving after the ninth decile of loan funding time (840 seconds) belong to the close-to-end group. Bids falling between these two cutoffs are in the intermediate group. Panel A separately plots the distribution of AT's investment amount across the three funding periods for loans with different credit grades. In Panel B, within each credit grade, loans with a credit score equal to or above the median are classified as High Score Loans, while those below the median are classified as Low Score Loans. The left part of Panel B separately plots the distribution of AT's investment in high and low-score loans. The right part of Panel B separately plots the distribution for repaid and default loans. The black, gray, and shaded bars represent the percentage of AT's bid amount in the immediate, intermediate, and close-to-end stages.

Panel A. AT's Investment Choice by Credit Grade and Funding Period



Panel B. AT's Investment Choice by Loan Quality and Funding Period

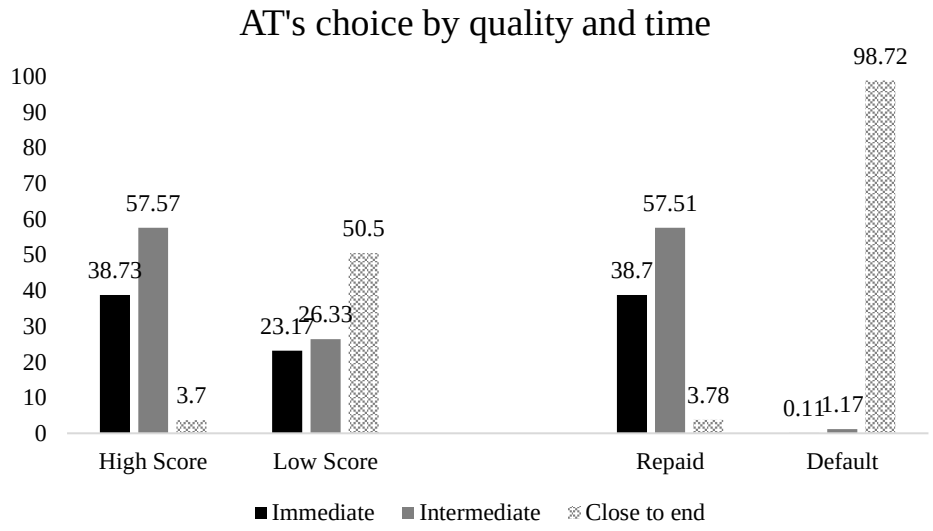


Figure 5. AT's Investment Strategies at Different Stages
The table displays the regression coefficients (represented by dots) and the 90% confidence intervals (represented by error bars) for *%AT_Q1* to *%AT_Q4* in Table 8.

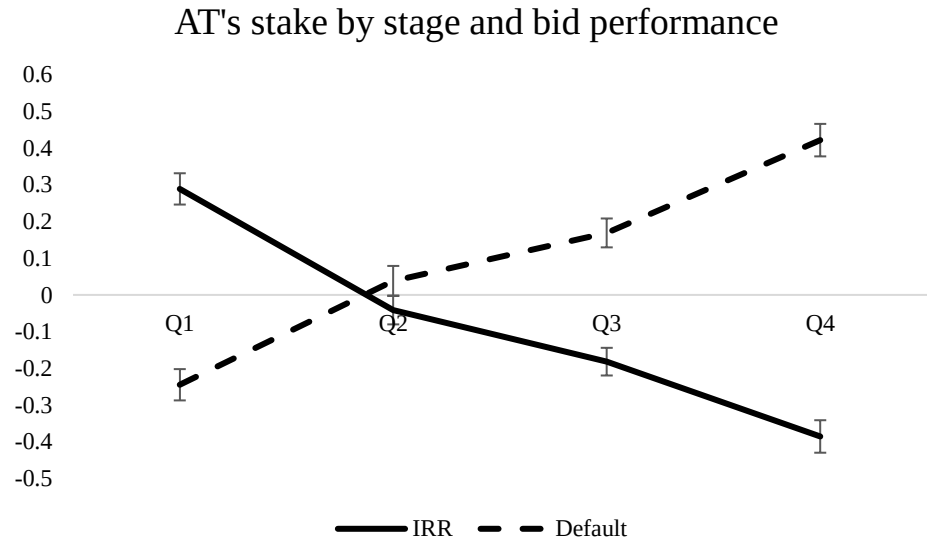


Table 1. Summary Statistics

Panel A presents the loan-level summary statistics of key variables, dividing the loan sample into two groups: loans funded solely by human investors (Human) and loans receiving AT investment (AT). Panel B presents the bid-level summary statistics, categorizing bids as either human-placed or AT-placed. In both panels, we report the number of observations, means, standard deviations, medians, minimums, maximums, and differences in means, along with t-test significance. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are in Appendix C.

Panel A. Loan Level

	Human						AT						Diff
	Obs	Mean	SD	Median	Min	Max	Obs	Mean	SD	Median	Min	Max	Diff
IRR	56479	5.67	24.25	12.00	-100.00	24.40	162398	11.61	2.59	11.40	-100.00	24.00	-5.94***
Default	56479	7.30	26.01	0.00	0.00	100.00	162398	0.06	2.53	0.00	0.00	100.00	7.23***
Time	56477	1800.83	11109.23	145.00	0.00	410249.00	162388	1453.21	10089.10	9.00	0.00	603037.00	347.6***
CreditGrade	56479	4.20	2.20	6.00	1.00	7.00	162398	5.98	0.30	6.00	1.00	7.00	-1.78***
CreditScore	56479	138.15	57.06	180.00	0.00	245.00	162398	179.63	6.96	180.00	0.00	245.00	-41.49***
Education	56479	2.06	0.77	2.00	1.00	4.00	162398	2.03	0.73	2.00	1.00	4.00	0.02***
Income	56479	3.40	1.28	3.00	1.00	6.00	162398	3.45	1.22	3.00	1.00	6.00	-0.06***
Age	56479	36.30	8.21	35.00	21.00	73.00	162398	37.89	8.52	37.00	20.00	65.00	-1.60***
Married	56479	0.68	0.47	1.00	0.00	1.00	162398	0.71	0.45	1.00	0.00	1.00	-0.03***
Female	56479	0.21	0.41	0.00	0.00	1.00	162398	0.29	0.45	0.00	0.00	1.00	-0.08***
House	56479	0.50	0.50	1.00	0.00	1.00	162398	0.51	0.50	1.00	0.00	1.00	0.00
Mortgage	56479	0.28	0.45	0.00	0.00	1.00	162398	0.33	0.47	0.00	0.00	1.00	-0.04***
FirstTime	56479	0.66	0.47	1.00	0.00	1.00	162398	0.96	0.20	1.00	0.00	1.00	-0.29***
Interest	56479	12.07	1.53	12.00	7.00	24.40	162398	11.66	1.24	11.40	8.00	24.00	0.41***
LogAmount	56479	10.33	0.92	10.43	8.01	14.91	162398	10.97	0.54	11.00	8.01	13.12	-0.64***
Maturity	56479	20.01	11.13	18.00	1.00	48.00	162398	29.38	8.41	36.00	3.00	48.00	-9.37***

Panel B. Bid Level

	Human						AT						Diff
	Obs	Mean	SD	Median	Min	Max	Obs	Mean	SD	Median	Min	Max	Diff
IRR	1945610	8.06	19.44	12.00	-100.00	24.40	11217985	11.23	2.03	10.80	-100.00	24.00	-3.17***
Default	1945610	4.61	20.98	0.00	0.00	100.00	11217985	0.03	1.83	0.00	0.00	100.00	4.58***
BidTime	1945610	7463.11	27484.07	293.00	0.00	603037.00	11217985	500.71	5016.49	14.00	0.00	597891.00	6962.40***
CreditGrade	1945610	4.89	1.88	6.00	1.00	7.00	11217985	5.99	0.18	6.00	1.00	7.00	-1.10***
CreditScore	1945610	154.30	48.32	180.00	0.00	245.00	11217985	179.89	4.40	180.00	0.00	245.00	-25.59***
Education	1945610	2.01	0.77	2.00	1.00	4.00	11217985	2.16	0.74	2.00	1.00	4.00	-0.14***
Income	1945610	3.78	1.37	4.00	1.00	6.00	11217985	3.57	1.20	3.00	1.00	6.00	0.21***
Age	1945610	38.33	8.52	37.00	21.00	73.00	11217985	38.30	8.54	37.00	20.00	65.00	0.04***
Married	1945610	0.74	0.44	1.00	0.00	1.00	11217985	0.72	0.45	1.00	0.00	1.00	0.02***
Female	1945610	0.24	0.43	0.00	0.00	1.00	11217985	0.31	0.46	0.00	0.00	1.00	-0.07***
House	1945610	0.50	0.50	1.00	0.00	1.00	11217985	0.58	0.49	1.00	0.00	1.00	-0.08***
Mortgage	1945610	0.28	0.45	0.00	0.00	1.00	11217985	0.38	0.48	0.00	0.00	1.00	-0.09***
FirstTime	1945610	0.76	0.43	1.00	0.00	1.00	11217985	0.96	0.21	1.00	0.00	1.00	-0.19***
Interest	1945610	12.09	1.41	12.00	7.00	24.40	11217985	11.25	1.20	10.80	8.00	24.00	0.84***
LogAmount	1945610	10.91	0.88	11.00	8.01	14.91	11217985	11.28	0.54	11.30	8.01	13.12	-0.37***
Maturity	1945610	21.46	10.90	18.00	1.00	48.00	11217985	31.56	8.06	36.00	3.00	48.00	-10.10***

Table 2. The Rise of AT and Corner Solution

This table examines AT's expansion through external versus internal margins. The focal variable, *MktShare*, is the daily market share of AT, calculated as the percentage amount funded by AT on a given day. Specifications (1) to (3) focus on the extensive margin by investigating whether AT expands by purely funding more loans. The sample includes all loans, and the dependent variable, *Pure AT*, indicates if a loan is purely funded by AT. Specifications (4) to (6) focus on the intensive margin by investigating whether AT expands through evenly increasing its position in all loans. The sample includes loans that are not fully funded by AT, and the dependent variable is the percentage amount funded by AT for each loan. The table reports OLS regression coefficients with standard errors clustered at the loan listing date in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

Y=	All loans			Loans not purely funded by AT		
	Pure AT			%AT		
	(1)	(2)	(3)	(4)	(5)	(6)
MktShare	0.659***	0.445***	0.444***	0.007	-0.009	-0.009
	(0.049)	(0.039)	(0.039)	(0.011)	(0.010)	(0.010)
Married			-0.003			-0.004**
			(0.002)			(0.002)
Female			0.006***			0.001
			(0.002)			(0.002)
House			0.014***			-0.007***
			(0.003)			(0.002)
Mortgage			-0.031***			-0.012***
			(0.004)			(0.003)
FirstTime			0.002			-0.002
			(0.003)			(0.002)
Interest		-0.005	-0.005		-0.006***	-0.005***
		(0.003)	(0.003)		(0.001)	(0.001)
LogAmount		-0.020***	-0.025***		0.020***	0.018***
		(0.003)	(0.003)		(0.002)	(0.002)
Maturity		0.008***	0.009***		0.001***	0.002***
		(0.001)	(0.001)		(0.000)	(0.000)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	No	Yes	Yes	No	Yes	Yes
Education FE	No	No	Yes	No	No	Yes
Income FE	No	No	Yes	No	No	Yes
Age FE	No	No	Yes	No	No	Yes
Constant	0.192***	0.387***	0.432***	0.074***	-0.083***	-0.062***
	(0.037)	(0.059)	(0.057)	(0.008)	(0.019)	(0.020)
Observations	218,889	218,889	218,885	71,184	71,184	71,181
R-squared	0.168	0.381	0.382	0.108	0.177	0.180

Table 3. Biased Loan Share Allocation

This table contrasts AT and human bids using the full bid-level sample, with the focal variable being the *AT* dummy indicating whether a bid is placed by AT or a human. Specifications (1) to (3) measure bid performance by its *IRR*, and specifications (4) to (6) use the *default* indicator. The table reports OLS regression coefficients along with standard errors clustered at the investor level in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

Y=	IRR			Default		
	(1)	(2)	(3)	(4)	(5)	(6)
AT	3.518***	0.238***	0.124***	-3.774***	0.081***	-0.156***
	(0.037)	(0.015)	(0.015)	(0.043)	(0.016)	(0.016)
Borrower Char.	No	No	Yes	No	No	Yes
Loan Char.	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	No	Yes	Yes	No	Yes	Yes
Education FE	No	No	Yes	No	No	Yes
Income FE	No	No	Yes	No	No	Yes
Age FE	No	No	Yes	No	No	Yes
Constant	7.759***	10.557***	15.112***	3.928***	0.640***	-16.784***
	(0.031)	(0.013)	(0.254)	(0.037)	(0.014)	(0.264)
Observations	13,128,357	13,128,357	13,128,357	13,128,357	13,128,357	13,128,357
R-squared	0.077	0.290	0.298	0.084	0.328	0.336

Table 4. AT's Information and Speed Advantage

This table examines AT's information and speed advantage over human investors. The dependent variable in specifications (1) and (2) is the *credit score* of a loan that a bid goes to. Specifications (3) and (4) revisit the differences in *IRR* and *default* rate between AT bids and human bids, but additionally control for credit score. Specifications (5) and (6) measure investment speed by bid time, calculated as the difference in seconds between each bid and loan listing time. The table uses all bids, and the focal variable is an *AT* dummy indicating if a bid is placed by AT. Specifications (1), (2), (5), and (6) report Poisson regression coefficients, and specifications (3) and (4) present OLS regression coefficients. Standard errors in parentheses are clustered at the investor level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

	Poisson		OLS		Poisson	
Y=	Credit Score		IRR	Default	BidTime	
	(1)	(2)	(3)	(4)	(5)	(6)
AT	0.077***	0.002***	-0.000	-0.010	-2.068***	0.038
	(0.001)	(0.000)	(0.012)	(0.012)	(0.020)	(0.064)
AT*Credit Score						-0.012***
						(0.000)
Credit Score			0.512***	-0.601***		0.001***
			(0.004)	(0.005)		(0.000)
Borrower Char.	Yes	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	No	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.631***	5.251***	-80.548***	95.462***	5.024***	4.876***
	(0.005)	(0.002)	(0.849)	(0.945)	(0.072)	(0.073)
Observations	13,128,304	13,128,304	13,128,357	13,128,357	13,128,323	13,128,323
R-squared			0.502	0.578		
Pseudo R-sq	0.135	0.265			0.624	0.626

Table 5. AT and Human Investors' Performance

This table examines the impact of the rise of AT on the performance of human bids. The sample includes bids placed by humans. Specifications (1)-(3) and (4)-(6) analyze bid performance based on the loan's IRR and default status, respectively. The focal variable is the daily market share of AT. The table reports OLS regression coefficients along with standard errors clustered at the investor level in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

Y=	IRR			Default		
	(1)	(2)	(3)	(4)	(5)	(6)
MktShare	-1.801***	-0.153**	-0.130*	2.133***	0.423***	0.371***
	(0.093)	(0.074)	(0.073)	(0.103)	(0.080)	(0.078)
Borrower Char.	No	No	Yes	No	No	Yes
Loan Char.	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	No	Yes	Yes	No	Yes	Yes
Education FE	No	No	Yes	No	No	Yes
Income FE	No	No	Yes	No	No	Yes
Age FE	No	No	Yes	No	No	Yes
Constant	9.114***	30.297***	25.238***	3.374***	-33.725***	-27.478***
	(0.055)	(0.482)	(0.506)	(0.061)	(0.490)	(0.506)
Observations	1,919,610	1,919,610	1,919,610	1,919,610	1,919,610	1,919,610
R-squared	0.066	0.279	0.294	0.073	0.321	0.337

Table 6. Human Performance Change around AT's Introduction (Event study)
This table examines the changes in the investment performance of human investors following the introduction of AT on the platform. The month of AT's introduction (March 2012) is normalized to 0 and excluded from the analysis. Panel A and Panel B use a sample of human bids placed in the 9, 6, and 12 months before and after the introduction of AT. Panel A presents the unconditional changes in the IRR and default rate of human bids. Panel B reports regression results with a full set of control variables. The focal variable is *Post*, indicating if a loan is listed after the introduction of AT. Panel C restricts the sample to bids from human investors who did not switch to using the AT service in the year following AT's introduction. Panel D compares the average credit grade and credit score of all funded loans around the introduction of AT. Panels B and C report OLS regression coefficients, with standard errors clustered at the investor level in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

Panel A. Performance Changes of Human Bids (Unconditional)

		Before		After		Diff
		Mean	SD	Mean	SD	
[-9m,+9m]	IRR	11.474	15.467	7.257	23.839	4.217***
	Failure	3.427	18.193	7.218	25.879	-3.791***
[-6m,+6m]	IRR	11.427	15.689	6.360	25.894	5.066***
	Failure	3.629	18.701	8.600	28.037	-4.972***
[-1y,+1y]	IRR	11.481	15.664	7.853	22.432	3.628***
	Failure	3.408	18.144	6.235	24.180	-2.827***

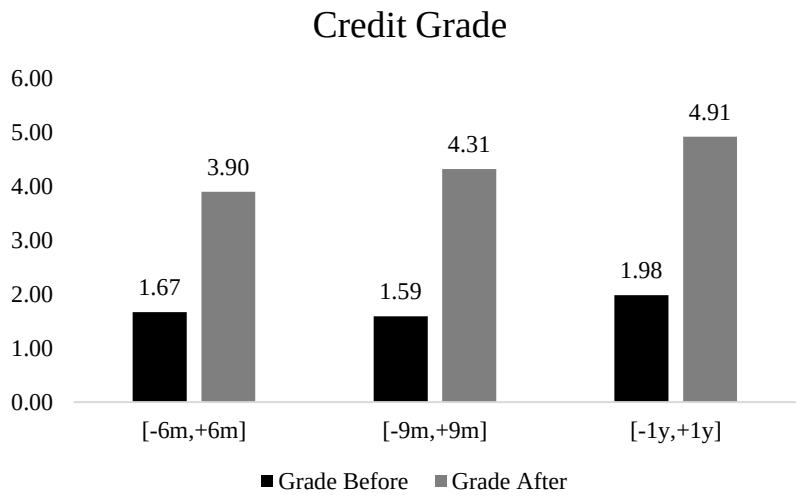
Panel B. Performance Changes of Human Bids (Regression)

Y=	IRR			Default		
	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-3.701***	-1.721***	-3.370***	3.876***	1.913***	3.537***
	(0.192)	(0.230)	(0.179)	(0.221)	(0.259)	(0.187)
Month	0.108***	-0.257***	0.071***	-0.222***	0.126***	-0.173***
	(0.022)	(0.035)	(0.017)	(0.025)	(0.039)	(0.017)
Borrower Char.	Yes	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.199***	10.749***	15.303***	-17.179***	-14.846***	-18.773***
	(0.652)	(0.791)	(0.666)	(0.654)	(0.772)	(0.645)
Observations	279,787	225,433	333,955	279,787	225,433	333,955
R-squared	0.303	0.320	0.296	0.357	0.373	0.348

Panel C. Performance Changes of Human Bids (Subsample Regression)

Y=	IRR			Default		
	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-3.181***	-0.961***	-3.372***	3.929***	2.093***	3.982***
	(0.196)	(0.237)	(0.169)	(0.225)	(0.268)	(0.194)
Month	0.067***	-0.350***	0.090***	-0.259***	0.063	-0.248***
	(0.024)	(0.039)	(0.018)	(0.027)	(0.041)	(0.019)
Borrower Char.	Yes	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	20.785***	18.648***	22.536***	-27.791***	-26.380***	-28.896***
	(0.672)	(0.776)	(0.647)	(0.728)	(0.854)	(0.689)
Observations	199,491	171,060	233,253	199,491	171,060	233,253
R-squared	0.271	0.283	0.265	0.332	0.343	0.326

Panel D. Loan Quality Changes



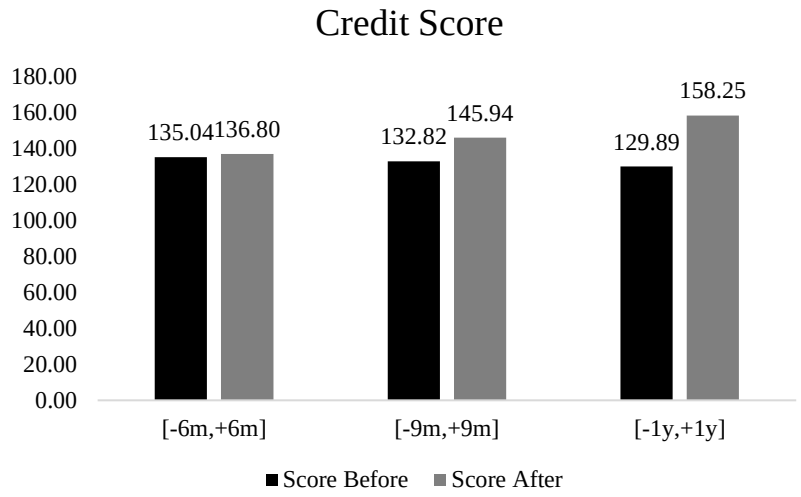


Table 7. Changes in Human Belief

This table examines the changes in the posterior belief of human investors about investment performance associated with the rise of AT. The dependent variable is the interest rate of the loan that a bid goes to. Specification (1) uses a sample of all human bids, with the focal variable being AT's daily market share. Specifications (2) to (7) replicate the event study presented in Table 6. Specifications (2) to (4) use all human bids around the introduction of AT, and specifications (5) to (7) restrict the sample to bids from human investors who did not switch to using the AT service in the year following AT's introduction. The table reports OLS regression coefficients along with standard errors clustered at the investor level in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

	Human Bids	Human Bids Around AT's introduction			Non-Switchers' Bids Around AT's introduction		
	All	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]
Y=Interest	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MktShare	0.069***						
	(0.005)						
Post		0.241***	0.076**	0.323***	0.268***	0.060*	0.336***
		(0.027)	(0.030)	(0.026)	(0.030)	(0.032)	(0.031)
Month		-0.105***	-0.071***	-0.113***	-0.107***	-0.066***	-0.114***
		(0.005)	(0.006)	(0.004)	(0.006)	(0.007)	(0.005)
Borrower Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	10.407***	12.023***	12.150***	12.139***	11.560***	11.711***	11.798***
	(0.038)	(0.125)	(0.140)	(0.116)	(0.139)	(0.154)	(0.141)
Observations	1,919,610	279,787	225,433	333,955	199,491	171,060	233,253
R-squared	0.760	0.559	0.546	0.553	0.497	0.493	0.489

Table 8. AT's Investment Strategies at Different Stages

This table uncovers the moral hazard in AT investment by showing how AT switches from cherry-picking good loans at early stages to facilitating bad loans at late stages. The table uses all bids that go to hybrid-funded loans. The funding process of each hybrid-funded loan is equally partitioned into four stages by the amount funded, and the AT bid ratio is calculated within each stage (*%AT_Q1* to *%AT_Q4*). The table regresses bid performance against *%AT_Q1* to *%AT_Q4* separately, while controlling for the full set of control variables. Panel A and Panel B proxy bid performance by *IRR* and *Default*, respectively. The table reports OLS regression coefficients along with standard errors clustered at the investor level in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

Panel A. IRR

Y=IRR	(1)	(2)	(3)	(4)	(5)
%AT_Q1	0.289***				
	(0.026)				
%AT_Q2		-0.041*			
		(0.024)			
%AT_Q3			-0.182***		
			(0.023)		
%AT_Q4				-0.386***	-1.176***
				(0.027)	(0.069)
%AT_Q4 * %AT					1.484***
					(0.091)
%AT					-0.429***
					(0.052)
Borrower Char.	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Constant	30.070***	30.137***	30.288***	30.525***	30.831***
	(0.715)	(0.717)	(0.718)	(0.719)	(0.721)
Observations	1,058,590	1,058,590	1,058,590	1,058,590	1,058,590
R-squared	0.372	0.372	0.372	0.372	0.373

Panel B. Default

Y=Default	(1)	(2)	(3)	(4)	(5)
%AT_Q1	-0.245***				
	(0.026)				
%AT_Q2		0.038			
		(0.025)			
%AT_Q3			0.169***		
			(0.024)		
%AT_Q4				0.422***	1.357***
				(0.027)	(0.070)
%AT_Q4 * %AT					-1.800***
					(0.097)
%AT					0.570***
					(0.057)
Borrower Char.	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Constant	-33.873***	-33.931***	-34.070***	-34.357***	-34.736***
	(0.766)	(0.768)	(0.770)	(0.772)	(0.775)
Observations	1,058,590	1,058,590	1,058,590	1,058,590	1,058,590
R-squared	0.432	0.432	0.432	0.432	0.432

Table 9. Interest Rate Bin Fixed Effects

This table replicates the baseline results by replacing the interest rate control with its bin fixed effects. The interest rates in our sample range from 7% to 24.4%, and we divide them into 35 bins of 0.5%. Panel A replicates the results in Table 2 on AT's expansion through the extensive margin. Panel B replicates the results in Tables 3 and 4 on AT's information and speed advantages, and its superior performance. Panel C replicates the event study results in Table 6, Panel B, on human performance changes around AT's introduction. Panel D replicates the results in Table 8 on AT's investment strategy changes over funding stages. It presents the results in the format of Graph 5.

Panel A. The Rise of AT and Corner Solution

	All loans		Loans not purely funded by AT	
Y=	Pure AT		%AT	
	(1)	(2)	(3)	(4)
MktShare	0.448***	0.448***	-0.014	-0.014
	(0.039)	(0.039)	(0.010)	(0.010)
Borrower Char.	No	Yes	No	Yes
Loan Char.	Yes	Yes	Yes	Yes
Interest bin FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
CreditGrade FE	No	Yes	Yes	No
Education FE	No	No	Yes	No
Income FE	No	No	Yes	No
Age Fe	No	No	Yes	No
Constant	0.249***	0.262***	-0.153***	-0.139***
	(0.042)	(0.043)	(0.018)	(0.020)
Observations	218,886	218,882	71,181	71,178
R-squared	0.388	0.389	0.204	0.206

Panel B. Information Advantage, Speed Advantage, and Superior Performance

	IRR		Default		Credit Score	BidTime	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AT	0.181***	0.013	-0.240***	-0.044***	0.002***	-2.061***	-0.000
	(0.015)	(0.012)	(0.017)	(0.012)	(0.000)	(0.020)	(0.063)
AT*Credit Score							-0.012***
							(0.000)
Credit Score		0.512***		-0.600***			0.001***
		(0.004)		(0.005)			(0.000)
Borrower Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interest bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.128***	-73.724***	-6.545***	99.905***	5.185***	0.719***	0.604***
	(0.134)	(0.795)	(0.146)	(0.903)	(0.001)	(0.053)	(0.057)
Observations	13,128,357	13,128,357	13,128,357	13,128,357	13,128,304	13,128,323	13,128,323
R-squared	0.300	0.503	0.339	0.579			0.633
Pseudo R-sq					0.265	0.632	

Panel C. Human Performance Change around AT's Introduction (Event study)

Y=	IRR			Default		
	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]	[-9m,+9m]	[-6m,+6m]	[-1y,+1y]
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-3.835***	-1.889***	-3.877***	3.685***	1.821***	3.902***
	(0.195)	(0.238)	(0.181)	(0.215)	(0.262)	(0.183)
Month	0.159***	-0.205***	0.181***	-0.214***	0.119***	-0.249***
	(0.023)	(0.037)	(0.018)	(0.024)	(0.039)	(0.017)
Borrower Char.	Yes	Yes	Yes	Yes	Yes	Yes
Loan Char	Yes	Yes	Yes	Yes	Yes	Yes
Interest bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	24.713***	25.434***	26.581***	-15.148***	-16.660***	-16.378***
	(0.613)	(0.719)	(0.551)	(0.647)	(0.823)	(0.592)
Observations	279,787	225,433	333,955	279,787	225,433	333,955
R-squared	0.311	0.328	0.305	0.365	0.381	0.357

Panel D. AT's Investment Strategies at Different Stages

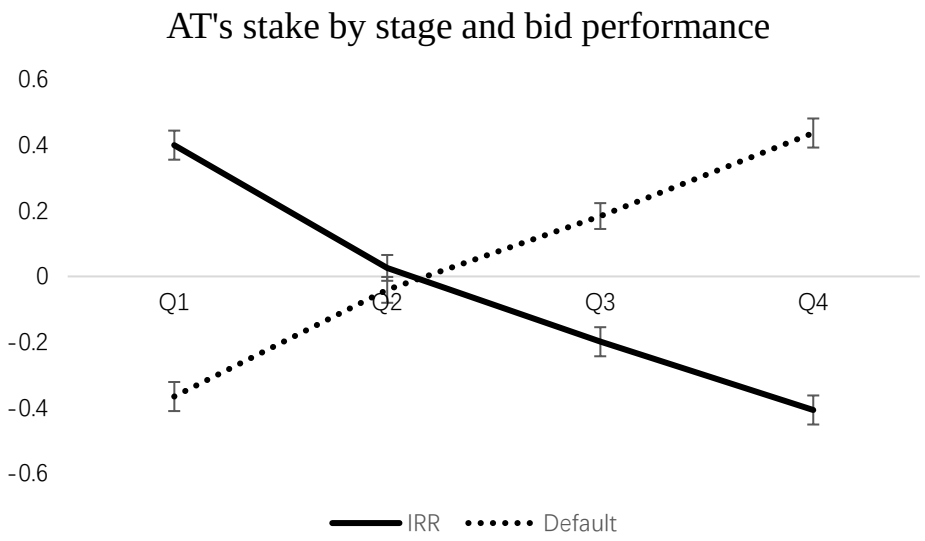


Table 10. AT's Investment Strategies at Different Stages (Robustness)

This table replicates the results in Table 8 on AT's investment strategy changes over funding stages. For each specification, it includes the AT-funded ratio of the targeted loan (%AT).

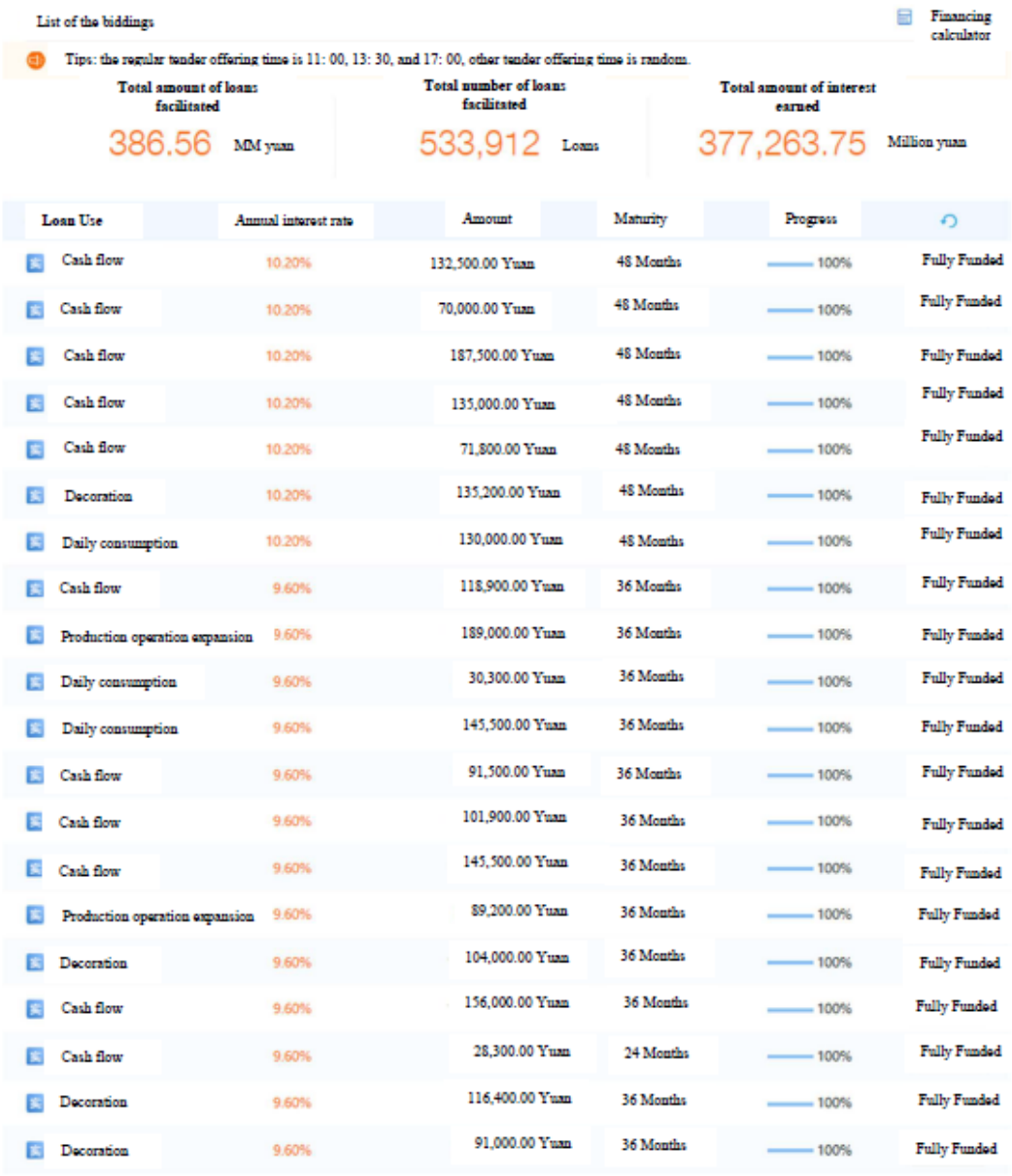
Panel A. IRR

Y=IRR	(1)	(2)	(3)	(4)
%AT_Q1	0.521***			
	(0.038)			
%AT_Q2		0.095*		
		(0.055)		
%AT_Q3			-0.302***	
			(0.046)	
%AT_Q4				-0.490***
				(0.036)
%AT	-0.566***	-0.255***	0.224***	0.227***
	(0.044)	(0.072)	(0.057)	(0.038)
Borrower Char.	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Constant	30.384***	30.246***	30.257***	30.491***
	(0.720)	(0.716)	(0.718)	(0.719)
Observations	1,058,590	1,058,590	1,058,590	1,058,590
R-squared	0.372	0.372	0.372	0.372

Panel B. Default

Y=Default	(1)	(2)	(3)	(4)
%AT_Q1	-0.472***			
	(0.038)			
%AT_Q2		-0.145***		
		(0.054)		
%AT_Q3			0.224***	
			(0.046)	
%AT_Q4				0.525***
				(0.036)
%AT	0.553***	0.345***	-0.103*	-0.225***
	(0.045)	(0.071)	(0.059)	(0.039)
Borrower Char.	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
CreditGrade FE	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Constant	-34.180***	-34.078***	-34.056***	-34.323***
	(0.772)	(0.768)	(0.770)	(0.772)
Observations	1,058,590	1,058,590	1,058,590	1,058,590
R-squared	0.432	0.432	0.432	0.432

Appendix A. Screenshots of the Investment Page
Panel A. Entry Page



List of the biddings

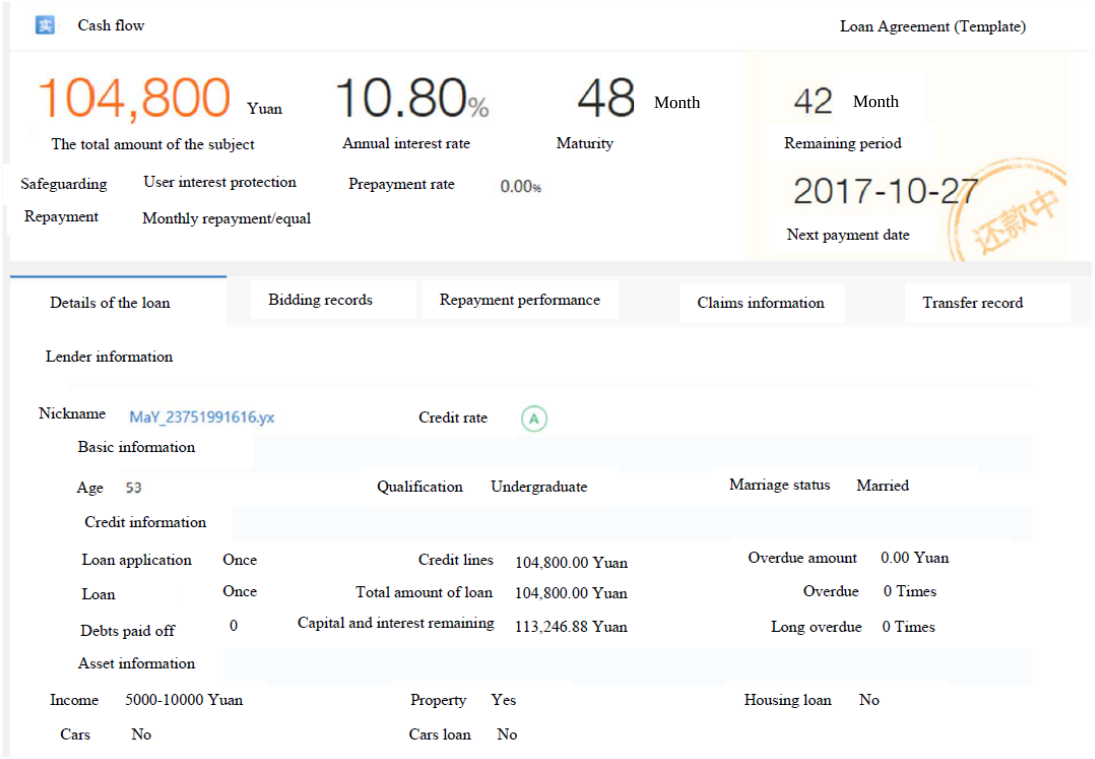
Financing calculator

Tips: the regular tender offering time is 11: 00, 13: 30, and 17: 00, other tender offering time is random.

Total amount of loans facilitated	Total number of loans facilitated	Total amount of interest earned
386.56 MM yuan	533,912 Loans	377,263.75 Million yuan

Loan Use	Annual interest rate	Amount	Maturity	Progress	
Cash flow	10.20%	132,500.00 Yuan	48 Months	100%	Fully Funded
Cash flow	10.20%	70,000.00 Yuan	48 Months	100%	Fully Funded
Cash flow	10.20%	187,500.00 Yuan	48 Months	100%	Fully Funded
Cash flow	10.20%	135,000.00 Yuan	48 Months	100%	Fully Funded
Cash flow	10.20%	71,800.00 Yuan	48 Months	100%	Fully Funded
Decoration	10.20%	135,200.00 Yuan	48 Months	100%	Fully Funded
Daily consumption	10.20%	130,000.00 Yuan	48 Months	100%	Fully Funded
Cash flow	9.60%	118,900.00 Yuan	36 Months	100%	Fully Funded
Production operation expansion	9.60%	189,000.00 Yuan	36 Months	100%	Fully Funded
Daily consumption	9.60%	30,300.00 Yuan	36 Months	100%	Fully Funded
Daily consumption	9.60%	145,500.00 Yuan	36 Months	100%	Fully Funded
Cash flow	9.60%	91,500.00 Yuan	36 Months	100%	Fully Funded
Cash flow	9.60%	101,900.00 Yuan	36 Months	100%	Fully Funded
Cash flow	9.60%	145,500.00 Yuan	36 Months	100%	Fully Funded
Production operation expansion	9.60%	89,200.00 Yuan	36 Months	100%	Fully Funded
Decoration	9.60%	104,000.00 Yuan	36 Months	100%	Fully Funded
Cash flow	9.60%	156,000.00 Yuan	36 Months	100%	Fully Funded
Cash flow	9.60%	28,300.00 Yuan	24 Months	100%	Fully Funded
Decoration	9.60%	116,400.00 Yuan	36 Months	100%	Fully Funded
Decoration	9.60%	91,000.00 Yuan	36 Months	100%	Fully Funded

Panel B. Loan Information



Panel C. Bidding Records



Rank	Bidder	Amount	Time
1	W***5	500.00 Yuan	2017-03-27 20:11
2	L***8	500.00 Yuan	2017-03-27 20:11
.....	.....	.....	.....
40	英***花	50.00 Yuan	2017-03-27 20:11
41	s***i	800.00 Yuan	2017-03-27 20:11
42	L***8	50.00 Yuan	2017-03-27 20:11
43	c***5	250.00 Yuan	2017-03-27 20:11
44	b***a	100.00 Yuan	2017-03-27 20:11
45	神***说	350.00 Yuan	2017-03-27 20:11
46	玉***r	1500.00 Yuan	2017-03-27 20:11

Appendix B. Biased Loan Share Allocation (Loan Level)

This table provides loan level evidence on the biased allocation of good issues towards AT. The sample includes all loan applications. The dependent variables are percentage amount funded by AT for each loan (*%AT*) in specifications (1) and (2), and a dummy variable indication if a loan is purely funded by AT (*Pure AT*) in specifications (3) and (4). The focal variable is loan quality proxy, *Credit Score*. The table reports OLS regression coefficients along with standard errors clustered at the investor level in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions are provided in Appendix C.

Y=	%AT		Pure AT	
	(1)	(2)	(3)	(4)
Credit Score	0.004***	0.001***	0.004***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Char.	Yes	Yes	Yes	Yes
Loan Char.	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
CreditGrade FE	No	Yes	No	Yes
Education FE	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Constant	-0.220***	0.517***	-0.138***	0.573***
	(0.048)	(0.052)	(0.052)	(0.054)
Observations	218,869	218,869	218,885	218,885
R-squared	0.374	0.395	0.342	0.361

Appendix C. Variable Definitions

Variable	Definition
IRR	The annualized internal rate of return for each loan.
Default	A dummy variable equals 100 if a loan defaults and 0 otherwise
Time	The funding time of each loan in seconds.
CreditGrade	A discrete variable equal to 1 if a loan's credit grade is HR (high risk), 2 if E, 3 if D, 4 if C, 5 if B, 6 if A, and 7 if AA.
CreditScore	The algorithm-calculated credit score from 0 to 245 for each loan. A higher score indicates better quality.
Education	A discrete variable equal to 1 if the borrower's degree is high school or below, 2 if associate's degree, 3 if bachelor's degree, and 4 if post-graduate degree or above.
Income	A discrete variable equal to 1 if the borrower's monthly income is below RMB2,000, 2 if between RMB2,000 and RMB5,000, 3 if between RMB5,000 and RMB10,000, 4 if between RMB10,000 and RMB20,000, 5 if between RMB20,000 and RMB50,000, and 6 if above RMB50,000.
Age	The age of the borrower.
Married	A dummy variable equals 1 if the borrower is married and 0 otherwise.
Female	A dummy variable equals 1 if the borrower is female and 0 if the borrower is male.
House	A dummy variable equals 1 if the borrower owns a house and 0 otherwise.
Mortgage	A dummy variable equals 1 if the borrower has a mortgage loan and 0 otherwise.
FirstTime	A dummy variable equal to 1 if the borrower is a first-time borrower on the platform and 0 otherwise.
Interest	The interest rate of each loan.
LogAmount	The logarithm of the requested loan amount.
Maturity	The maturity of each loan (in months).
BidTime	Time taken for each bid, calculated as the time difference in seconds between each bid and loan listing time.
Corner	A dummy variable equal to 1 if a loan is either purely funded by human investors or purely funded by AT, and 0 if hybrid funded by both human and AT.
Type	A categorical variable equal to 0 if a loan is purely funded by human investors, 1 if hybrid funded by both human and AT, and 2 if purely funded by AT.
PureAT	A dummy variable equals 1 if a loan is purely funded by AT, and 0 otherwise.
AT	A dummy variable equals 1 for algorithmic bids and 0 for human bids.
MktShare	The percentage amount funded by AT for each day.
Post	A dummy variable equals 1 if the bid is placed after the introduction of algorithmic investment in March 2012.
Month	The month that a bid is placed. March 2012 is normalized to 0.
%AT	The percentage amount funded by AT for each loan.
%AT_Q1	The percentage amount funded by AT for the first 25% amount of each loan.
%AT_Q2	The percentage amount funded by AT for the 25%-50% amount of each loan.
%AT_Q3	The percentage amount funded by AT for the 50%-75% amount of each loan.
%AT_Q4	The percentage amount funded by AT for the last 25% amount of each loan.