ESSAYS ON THE WISDOM OF THE CROWD IN CROWDFUNDING

A Dissertation
Presented to
The Academic Faculty

by

Jiayu Yao

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
Scheller College of Business

Georgia Institute of Technology
August 2023

ESSAYS ON THE WISDOM OF THE CROWD IN CROWDFUNDING

Approved by:

Dr. Mingfeng Lin, Advisor
Scheller College of Business
Georgia Institute of Technology

Dr. Han Zhang
Scheller College of Business
Georgia Institute of Technology

Dr. D. J. Wu
Scheller College of Business
Georgia Institute of Technology

Dr. Xuan Wei
Antai College of Economics & Management
Shanghai Jiao Tong University

Dr. Sridhar Narasimhan
Scheller College of Business
Georgia Institute of Technology

Date Approved: [July 26, 2023]

ACKNOWLEDGEMENTS

As I stand at the precipice of concluding a significant chapter of my life, it is clear that this achievement has been shaped by the invaluable support and guidance of many around me.

First, I wish to convey my profound gratitude to my advisor Dr. Mingfeng Lin, whose wisdom and supervision have been the cornerstone of this research work. His rigorous guidance, insightful mentorship, generous encouragement, and incisive feedback have been crucial to my professional and personal development. His training enabled me to design meaningful research questions and construct robust arguments in support of my ideas. As I move forward on this academic journey, I aspire to establish myself as an extraordinary scholar following his example.

Next, I would like to express my gratitude to the members of my doctoral committee: Dr. D.J. Wu, Dr. Sridhar Narasimhan, Dr. Han Zhang, and Dr. Xuan Wei. My sincere appreciation goes to Dr. D.J. Wu, an inspiring coauthor and mentor, for his uplifting encouragement and robust support. My gratitude extends to Dr. Sridhar Narasimhan, who offered considerable assistance during my job search and was a reliable resource during my research and teaching experiences. I am thankful to Dr. Han Zhang for his comprehensive mentorship in constructing and executing high-quality research. Lastly, I express my thanks to Dr. Xuan Wei, a supportive coauthor and cherished friend, who has generously shared his professional experience and invaluable career advice.

My journey as a Ph.D. student has been blessed by an incredible group of people. My heartfelt thanks to all the other ITM faculty members, namely Dr. Marius Florin

Niculescu, Dr. Eric Overby, Dr. Lizhen Xu, Dr. Jeffrey Hu, and Dr. Saby Mitra, for their invaluable teachings and steadfast support. The Scheller staff Renee Jamieson, Shannon Smiths, and Ursula Reynolds played a significant role in managing my life as a Ph.D. student, and I express my sincere appreciation. I also extend my appreciation to my fellow Ph.D. students, including but not limited to: Zhanfei Lei, Hongchang Wang, Katja Siamionava, Yun Young Hur, Elizabeth Han, Chunghan Kang, Hao Hu, Ruiqi Zhu, Qixin Ye, Jie Zheng, and Jae Sang Rhee. Their company over the past five years have made my journey both rewarding and memorable. I would also like to acknowledge Dr. Kai Lu, whose relentless work ethic and expansive perspective during our research collaboration has been a constant source of inspiration.

I am deeply grateful to my friends around the world for being a sturdy pillar of support during this venture. Special thanks to Li Ding, Sen Zhou, Mingyi Bi, Yuqiao Chen, Haoye Sun, Ruolan Yang, Chi Zhang, Yash Manoj Melwani, Shivani Patel, Tejas Sathe, Priyanka Padmanabhan, Sagar Shah, Yamini Panchal, and Nidhi Kudiri. Their companionship has been a beacon of light during both the rewarding and challenging times over the past five years.

Finally, I reserve my deepest appreciation for my family. I acknowledge my parents, Shiwu Yao and Chunyan Zhang, whose unconditional love made all of this possible. My gratitude for my husband, Ben Vijayakumar, is boundless; his constant love and care throughout my Ph.D. studies have served as my steadfast anchor. Without their enduring presence and unconditional support, I would not have been where I am today. For that, I will forever be thankful.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

OVERVIEW

This dissertation studies the wisdom of the crowd in the context of crowdfunding. Specifically, this dissertation investigates crowd behaviors in online crowdfunding and the impact of crowdfunding on entrepreneurial development.

In the second chapter, we examine how we can better extract the wisdom of the crowd through investment behaviors. Despite the popularity of the phrase "wisdom of the crowd," not all crowds are wise because not everyone in them acts in an informed, rational manner. Identifying informative actions, therefore, can help isolate the truly "wise" part of a crowd. Motivated by this idea, we evaluate the informational value of investors' bids using data from online, debt-based crowdfunding, where we were able to track both investment decisions and ultimate repayment statuses for individual loans. We propose several easily scalable variables derived from the heterogeneity of investors' bids in terms of size and timing. We first show that loans funded with larger bids relative to the typical bid amount in the market, or to the bidder's historical baseline, particularly early in the bidding period, are less likely to default. More importantly, these variables improve the predictive performance of state-of-the-art models that have been proposed in this context. Even during the fundraising process, these variables improve both funding likelihood and loan quality predictions. We discuss the implications of these variables, including loan pricing in secondary markets, crowd wisdom in different market mechanisms, and financial inclusion. Crowdfunding platforms can easily implement these variables to improve market efficiency without compromising investor privacy.

In the third chapter, we study the impact of peer behavior information display on decision-making in crowdfunding. Providing peer behavior information in online trading markets can offer retailer investors extra informational signals and help reduce information asymmetry. However, an excessive display of peer information may overwhelm inexperienced investors and induce herding behavior. To investigate the effect of displaying peer behavior on investor behaviors, we study how different displays of prior investors' actions influence subsequent investors' abandonment, decision time, investment willingness, and risk preference. We examine three prevalent yet competing designs that are at different levels of aggregation: no display of peer investment history, aggregated display of peer investment history, and detailed display of peer investment history. Our results from two controlled experiments and a field study using a crowdfunding platform's peer information display change reveal a few key insights. When presented with detailed history, investors not only demonstrate a lower acceptance of the design but also take longer decision time, whereas the inclusion of aggregated history maintains a high acceptance and does not extend the decision time compared to not displaying any history. While the total investment amount of investors remains constant across different displays, their risk allocation is influenced more when the prior investments are displayed in an aggregated form. Overall, our findings highlight the saliency of aggregated display and draw attention to the potential information overwhelm caused by over-detailed displays. This chapter offers valuable implications for the design of online crowd-based platforms.

In the fourth chapter, we study whether and how the wisdom of crowds in reward-based crowdfunding helps entrepreneurial developments. Although crowdfunding has received significant attention from researchers during the past decade, little research has focused on the projects' post-crowdfunding outcomes despite its importance to entrepreneurs. Furthermore, while crowdfunding literature predominantly studies the exchange of financial resources between project creators and backers, they provide scarce evidence on the non-financial value of crowdfunding achieved by early customers' evolvement. Our study aims to fill this gap by studying if features from crowdfunding projects can predict entrepreneurs' mass market potential. Further, we examine if and how market reactions, especially their non-financial aspects, contribute to the prediction of mass market potential. We build classification and interpretable machine learning models to predict and explain entrepreneurs' market success using project and crowd factors of entrepreneurs' crowdfunding campaigns. Our results suggest that crowd features, especially the non-financial features, play an important role in predicting mass market launch and market evaluation. The analyses of non-financial features suggest that crowdfunding success does not always translate into mass market success. When products are very mature and receive predominately comments about shipping, or the comment sentiment is over optimism, even successful crowdfunding was successful, the creator need to be cautious about the future development of projects. On the other hand, if supported by enough backers and received more positive comments, even failed crowdfunding projects can contain seeds indicating mass market success. Altogether, the dissertation contributes to a better understanding of crowd intelligence in crowdfunding and its value.

CHAPTER 1. INTRODUCTION

This dissertation investigates the wisdom of the crowd in online crowdfunding. The wisdom of the crowd refers to the idea that a large group of non-experts can be collectively more intelligent than a few experts (Surowiecki, 2005). While each individual's judgment is biased, aggregate judgments tend to be surprisingly accurate, with errors associated with individual judgments canceling out. However, the crowd is not always wise. In reality, we observe both crowds' irrational behaviors such as the fluctuations in stock markets and financial technology (Fintech) markets and occasionally extreme unwise behaviors such as the Dutch Tulipomania of 1634-7. Therefore, crowds are neither always prudent nor always prescient. Motivated by the heterogeneous performance of crowds, this dissertation intends to study how to extract the wisdom from the crowd better and whether crowds can utilize embedded intelligence.

Crowdfunding provides an ideal context for studying the wisdom of the crowd. Crowdfunding facilitates the funding of a project, venture, or personal loan by soliciting contributions from a large number of people (Mollick 2014). By matching borrowers and lenders directly, crowdfunding provides an important platform for alternative finance. As of 2020, crowdfunding has become the most popular channel for individuals to raise money, with over 34 billion USD raised globally.[1] Crowdfunding has redefined financial behaviors and revolutionized traditional industries such as banking and retail. Therefore, we seek to understand the individual investor behavior in these financial platforms,

[1] Numbers from Fundly.com (https://blog.fundly.com/crowdfunding-statistics). Accessed August 2022.

whether valuable information can be extracted from their behaviors, and consequently the implications for platform design change.

The following chapters will investigate the wisdom of crowds in crowdfunding from multiple angles. Specifically, Chapter 2 will study how to improve the wisdom of the crowd. This chapter will identify the informational value of investors' bids in peer-to-peer lending and propose easily scalable variables derived from investment heterogeneity in size and timing. Chapter 3 will continue to examine whether and how crowds can utilize the wisdom embedded in the crowds. This chapter will study the impact of peer behavior information display on lender decision-making in peer-to-peer lending. Chapter 4 will examine the crowd value of crowdfunding beyond its primary financial value. This chapter will investigate how crowds provide early feedback to entrepreneurs through the interactions on rewards-based crowdfunding. These studies will not only contribute to the literature on crowdfunding and the wisdom of the crowd, but they will also deepen our understanding about individual behaviors in online markets, design of online platforms, and impact of Fintech.

CHAPTER 2. REVEALED WISDOM OF THE CROWD: BIDS PREDICT LOAN QUALITY

2.1 Introduction

The crowd is a fascinating phenomenon. A group of many individuals, each with their own intelligence, flaws, incentives, biases, and preferences, can collectively predict changes in the stock market, who will win the next election, and create an encyclopedia that eclipsed the professionally-edited Britannica. However, the crowd is not always wise. While extreme events such as the Dutch Tulipomania of 1634-7 are not frequent, a casual look at the stock market and other online markets, especially financial technology (fintech) markets, reveals that crowds are neither always prudent nor always prescient. While one may be satisfied that crowds are more often correct than incorrect, there is clearly a need to better understand and unpack the actions of individuals in the crowd, particularly if it helps to identify a part of the crowd that is wiser than the rest. This would produce a deeper understanding of the boundaries of crowd wisdom and reduce the likelihood of future incidents of crowd irrationality.

The crowd is neither a monolithic nor stable entity. Naturally, it has members who are better at prediction than others, either through access to better/more information or better ability to interpret the same public information, as well as those who occasionally blindly follow the actions of others (i.e., social learning). The actions of the first group should be more informative than the latter. Consequently, if we can distinguish between them, we may be able to derive higher levels of crowd intelligence. The challenge clearly lies in the fact that the smart crowd members are not easy to identify. They almost never have conspicuous labels attached to them, and their decision processes or judgments are rarely known. Existing studies have generally examined crowd heterogeneity in terms of demographic variables such as gender, which is static and often sensitive; or experience, which can be slow to change as investors learn from the outcome of past decisions. Our goal is to identify crowd heterogeneity based on information that is less sensitive than demographics, more timely than experience, and therefore more informative. Inspired by revealed preference theory, we infer investors' judgment through their actions.

More specifically, we propose several new variables derived from investor actions and show that they not only correlate significantly with investment quality but also improve the performance of predictive models. Since these variables are derived from revealed preference theories, we call them revealed wisdom of the crowd (RWOC) variables. The RWOC variables capture the relative amount of each bid compared to other bids on the market as well as to other bids from the same investor. They also capture the bid timing during the funding process.

We choose online debt-crowdfunding (also known as peer-to-peer lending), particularly Prosper.com, as the empirical context to test the predictive value of these new variables. On these platforms, one can invest in fractions of loans posted by individual borrowers who are verified by the platform, but remain anonymous on the site for privacy reasons. This context has many advantages over other types of crowdfunding. Most importantly, these loans are fixed-income assets with a predetermined repayment date, allowing us to objectively assess the wisdom of investing in them.

To this end, we follow the call of Shmueli and Koppius (2011) and Hofman et al. (2021) to integrate descriptive and predictive modeling. We first propose a series of relationships between the RWOC variables and loan quality and test them using data from Prosper.com. Notably, we find that while the number of investors (size of crowd) is not statistically associated with loan performance, this pattern is due to the mixed effects of signals and noise. The total number of large bids (compared to the rest of the market or an investor's own historical baseline) is significantly associated with a lower likelihood of default, especially when the large bids are placed early in the funding process. In contrast, the number of minimum bids (investors participate only to diversify portfolio rather than carefully evaluating loans) does not contain much useful information.

We then draw on the existing literature—including several papers that have used predictive models on data from Prosper.com (Fu et al. 2021, Iyer et al. 2016)—to build predictive models with RWOC variables as new features for predicting loan quality. We show that, after adding RWOC variables, the models improve by 21.19% in ROC-AUC. We further show that these performance improvements do not arise from alternative explanations such as the presence of expert investors. These results show that RWOC variables contain the truly informative part of the crowd actions, or the real "wisdom of the crowd."

One concern is that our analyses require the full bidding history, which will only be available after a loan has been funded. To address this, we show that RWOC variables have predictive efficacy during the funding process. RWOC variables based on early bids could be used to predict funding likelihood and speed of a loan request, as well as loan quality if funded.

Our approach also provides useful insights into the issue of financial inclusiveness, which is an essential aspect of crowdfunding's societal value proposition. We show that the predictive improvement is larger for borrowers who tend to have less access to capital: women and those with lower credit grades. This means that if a marketplace can implement RWOC variables and make them available to investors, it may help bridge gaps in capital access.

Our study has both theoretical and practical implications. Theoretically, it highlights the importance of opening the black box of the crowd to examine individual members before aggregating their actions. Instead of generalizing that a crowd is wise or irrational, separating signal from noise in a crowd is important. Practically, our study shows that, first, we can still strike a balance between leveraging the crowd's wisdom and preserving investor privacy. Platforms can easily replicate our approach to help investors make better decisions without compromising their privacy. In fact, using RWOC variables represents a much more efficient way for investors to process information contained in the full bidding history and thereby to improve market efficiency. Second, our approach suggests that for assets that have gone through market matching, that matching process contains valuable information that has been generally ignored to date. For assets with resale opportunities (such as the secondary market for loans), RWOC variables can help investors better price them on the secondary market. We conclude by discussing the generalizability of our findings under different market mechanisms and types of crowdfunding, as well as their implications for future research on participation thresholds on these online platforms and retail investor protection.

2.2 Empirical Context

We use data from debt-based crowdfunding, also known as "peer-to-peer lending" or P2P lending, which allows individuals to obtain unsecured personal loans from others. As of 2023, P2P lending has been the largest crowdfunding type, with a global market valued at 143.64 billion USD.[2] Given the market size, even tiny improvements in loan-quality prediction can be highly useful for stakeholders.

Data from debt crowdfunding offer unique advantages over prediction markets and other types of crowdfunding. Prediction markets typically focus on one-off events, which are unique and almost impossible to repeat (e.g., whether a candidate would win a certain election in a given year). In contrast, debt crowdfunding data offer many more comparable observations, enabling us to evaluate the wisdom of the crowd. Relative to donation- and rewards-based crowdfunding, in which donors and backers are likely to be, at least partially driven by altruistic rather than economic motives (Dai and Zhang 2019, Hong et al. 2018, Simpson et al. 2021, Song et al. 2021), investors in debt crowdfunding have clearer incentives to evaluate loans and invest only in those that will preserve their funds and generate returns. Compared to equity crowdfunding in which investors are typically allowed to change their minds and withdraw their investments within a certain period (e.g., the "cooling off" period in Crowdcube) (Agrawal et al. 2014, Donovan 2021), debt crowdfunding typically does not allow bid withdrawal. Each bid, therefore, should represent more serious consideration and commitment and is more likely to be economically informative. Furthermore, the investment decision quality in debt

[2] Numbers from Peer-to-Peer (P2P) Lending Global Market Report 2023 (https://www.researchandmarkets.com/reports/5766977).

crowdfunding is more straightforward to evaluate because when loans mature, one can unequivocally gauge whether each investor's decision to bid is economically justified. In contrast, firms in equity crowdfunding have an infinite time horizon, as they can be profitable one year and nearly bankrupt the next.

We use data from Prosper.com, one of the largest online P2P lending platforms in the United States. The Prosper transaction process involves several steps.[3] First, borrowers create accounts on the website after verifying personal financial information. Second, they post a loan request, called a "listing," with the requested amount, interest rate[4], loan purpose, campaign duration, and credit information about the loan and the borrower. Meanwhile, lenders can browse all available listings on the website and choose to bid on any they find interesting. In keeping with the literature (Iyer et al. 2016, Lin and Viswanathan 2016, Zhang and Liu 2012), "bid" in this context refers to an offer of an investment from a lender. An individual lender can bid as little as $25 (the minimum required by Prosper.com) or as much as the entire requested amount. Once placed, bids cannot be withdrawn. A listing closes successfully when 100% of the requested amount is received before expiration; otherwise, bids are refunded to lenders. Successful listings are further reviewed by Prosper.com staff members. Once approved, a listing becomes an issued loan. The borrower then receives the funds minus platform service fees. The borrower makes monthly repayments for the principal and interest, which the platform distributes proportionally to each investor. If a monthly payment is delayed by two or more months or the borrower stops payment, the account is sent to a collection agency. If

---

[3] For more details about crowdfunding transactions, see Wang and Overby (2020) and Wei and Lin (2017).
[4] Since 2011, Prosper.com has implemented a fixed interest rate model in which the platform determines the interest rate, and this rate does not change after the listing is posted.

the loan is still not fully repaid after the collection agency's efforts, it is treated as a loss. Lenders are explicitly informed that their investments are not guaranteed. The risk inherent in these lending decisions, therefore, provides another reason why this market serves as an interesting and useful context to study crowd decisions under uncertainty.

We highlight another two important Prosper features. First, borrowers cannot selectively repay some lenders but not others. Technically, all loans are made by WebBank, a Utah-chartered Industrial Bank. Borrowers obtain loans from the bank, while lenders receive loan shares. Second, during our study period, lenders could observe the bid history for each listing during the funding process: who bid how much and when. Through the platform's public data export or application programming interface (API), lenders also had access to other raw data, including lenders' investment history and monthly loan payoffs. However, not all lenders would be willing or able to digest and/or properly interpret these data.

2.3 Literature Review and RWOC Variables

Our study draws on and contributes to multiple research disciplines, including economics, behavioral finance, and information systems. In this section, we first review the literature on the wisdom of the crowd. Then we review how the literature has been applied in the context of crowdfunding, since crowdfunding platforms ultimately depend on the crowd's collective intelligence to identify worthy investment opportunities. Finally, we build on recent studies of crowd heterogeneity, moving from individual-based to action-based differences to better extract crowd wisdom.

2.3.1 Wisdom of the Crowd

The key idea behind this notion is that a large group of nonexperts can be collectively more intelligent than a few experts (Surowiecki, 2005). While each individual's judgment may be biased, aggregate judgments tend to be surprisingly accurate, with errors associated with individual judgments canceling out. In other words, the key feature of this literature is the aggregate behavior of a crowd, rather than the uniqueness of each member within it.

A prime example of the wisdom of the crowd is crowdsourcing, which harnesses large networks of potential contributors to solve challenging problems. It has not only received much scholarly attention (e.g., Greenstein and Zhu 2018, Lee et al. 2018, Lukyanenko et al. 2019, Majchrzak and Malhotra 2016, Wang et al. 2017) but also been used by many companies and institutions to collect ideas for new products and services. This is part of the "open innovation" movement and has been widely recognized as an approach to fostering innovation in an economical and efficient manner (Bayus 2013, Boudreau et al. 2011). The winning solution in crowdsourcing typically comes from a particular team or a member of the crowd. In other words, it only requires one team to come up with the best solution, so there is no need for a crowd consensus. In crowdsourcing contests, there is little emphasis on the solutions that were not chosen; information in the forsaken solutions is typically ignored.

Prediction markets and prediction polls are also valuable applications of crowd wisdom. In the former, where participants are motivated by potential profits, members buy or sell token stocks based on the information they possess or receive over time. The aggregated result, as reflected in the price of that "stock," often provides accurate predictions of future events (Chen et al. 2014, Da and Huang 2019, Spann and Skiera 2003). In the latter (Atanasov et al. 2017), forecasters are asked to assign probabilistic judgments of the likelihoods of future event, either independently or interactively (e.g., engaging in discussions before making predictions). What makes both different from crowdsourcing is that the wisdom of the crowd in prediction markets and polls is based on the *aggregate* decisions of its members, with each influencing the final result.

Crowdfunding is an especially interesting and complex example of the wisdom of the crowd due to its financial nature. Investors in crowdfunding have a strong incentive to fund "right" projects and weed out inferior ones. Each project must convince a sufficient number of backers to become successful. Many members of the crowd often participate repeatedly in the market, and each person's investment could be dramatically different (i.e., different weights in the total investment) based on their personal interpretations of the investment opportunity.

2.3.2 Wisdom of the Crowd in Crowdfunding

Crowdfunding has become an essential method of raising capital for both individuals and businesses. It harnesses the broad reach of the Internet to allow many investors to contribute to one individual or business. Along with the rapid growth of crowdfunding, academic research on this phenomenon has blossomed. Our goal is not to be exhaustive in reviewing this literature (Agrawal et al. 2014 and Moritz and Block 2016 offer excellent reviews) but to focus on research that directly informs our study.

A majority of research in crowdfunding, consistent with other literature on the wisdom of the crowd, examines how investors as a group interpret information about borrowers or fundraisers. Studies across many types of crowdfunding, including rewards-based, equity, and debt, suggest a remarkable level of wisdom in the financial decisions made by the crowd of small investors. In rewards crowdfunding, Mollick and Nanda (2016) find that crowd choices of projects on Kickstarter.com are similar to those of experts. In equity crowdfunding, Kim and Viswanathan (2019) have shown that early investors with work experience in related areas tend to select better projects; interestingly, the crowd can take advantage of that information by following their lead. In debt crowdfunding, where loan quality can be more objectively determined ex-post, there is also evidence that crowds perform remarkably well. Iyer et al. (2016) report that Prosper.com investors utilize multiple sources of information about borrowers, including unstructured and non-standard information, to predict their default likelihoods. This evidence suggests that the crowd, *as a whole*, is remarkably sophisticated.

There is also evidence of failures of collective intelligence. For example, Hildebrand et al. (2017) document adverse incentives in debt crowdfunding, finding that group leader bids are wrongly perceived as signals of high loan quality. Using data from LendingClub.com, Vallee and Zeng (2009) show that sophisticated investors perform better than retail investors, though this difference is attenuated when the platform makes less borrower information available. Leveraging a unique period of mispricing on Prosper.com, Lin et al. (2022) report that retail investors perform only slightly worse than expert investors. Fu et al. (2021) propose a machine learning algorithm that outperform crowd predictions using data from Prosper.com.

Multiple studies have documented how investors react, correctly or incorrectly, to borrowers' demographic information, including race (Younkin and Kuppuswamy 2018), gender (Bapna and Ganco 2021, Ewens and Townsend 2020), appearance (Duarte et al.

2012), location (Agrawal et al. 2015, Burtch et al. 2014, Lin and Viswanathan 2016), as well as borrowers' social features such as social networks (Lin et al. 2013, Liu et al. 2015), social capital (Hasan et al. 2020), and text descriptions (Gao et al. 2022, Herzenstein et al. 2011). A common theme in these studies is that there exists a typical investor in the crowd who represents all investors. The crowd is treated as a collective that interprets available information about borrowers. However, each investor is unique and acts differently when faced with different investment opportunities. For example, suppose investor A almost always invests the bare minimum required by the platform ($25) in each loan but invests $100 in borrower X. In that case, this increased investment indicates strong confidence in this particular borrower. In contrast, investor B might always invest $200 in each loan but only invest $100 in borrower Y. Even though both X and Y receive $100, do these investments indicate different opinions on behalf of the crowd, and can such a difference be captured systematically to make the market more efficient? We hypothesize that such differences can and should be captured to better predict loan quality and reduce information asymmetry. To our knowledge, the literature published to date has not addressed this possibility.

2.3.3 Value of Action Heterogeneity

The idea that actions reflect preferences and opinions was first formalized in revealed preference theory (Samuelson 1938). For decades, marketers have carefully studied consumer purchase behaviors, even highly aggregated ones, to infer preferences and opinions (e.g., Berry et al. 1995). In the Internet age, practitioners and marketers pay close attention to online consumer behavior and then use this information to do market segmentation (referred to as “behavioral targeting”). This practice is now an industry standard (e.g., Chen and Stallaert 2014, Choi et al. 2020, Trusov et al. 2016).

Our study also draws on other streams of literature on heterogeneity. Specifically, it is highly consistent with long-standing findings in the open-innovation literature (i.e., crowdsourcing). Jeppesen and Lakhani (2010) championed the value of the broadcast search—that is, by sending a problem to a more diverse group of experts, an organization is more likely to find a solution for it. Due to the use of bidding in our context, our study is also informed by research on auctions, particularly those on strategic bidding (e.g., Bapna et al. 2003). While these auctions we study are different from those for selling merchandise, “jump bidding” or its converse, “sniping” behavior, documented in the literature suggests that large-size bids placed earlier (or later in the case of “sniping”) reveal useful information that strategic bidders can exploit. This inspires us to consider both bid size and timing. Meanwhile, we contribute to the auction literature by using data from a context allowing us to directly link bidding behaviors to the ex-post quality of the product (loan repayment) to measure bid informational values.

The heterogeneity we focus on builds on, but also differs from, expertise heterogeneities recently studied. In those studies, experts within a crowd are nearly always better in evaluating identical objective information about fundraisers. For example, Kim and Viswanathan (2019) report on investor differences regarding their prior work experience in software development. Such differences are conspicuous and observable by other crowd members, and the experts are better at identifying higher-quality investments. The differences we examined are broader and not attached to specific individuals; we hypothesize that there can be economically meaningful information extracted from the actions of *every* investor.

2.4 Descriptive Model of RWOC Variables and Loan Quality

The primary goal of our study is to identify new variables that improve predictive performance. Before constructing our models, we first follow the suggestions from Hofman et al. (2021) and Shmueli and Koppius (2011) to conduct descriptive analyses and provide initial evidence on of the RWOC variables. In this section, we draw on the literature that leads us to propose the RWOC variables and investigate the relationships between them and loan quality using data from Prosper.com.

2.4.1 RWOC Variables

Investment actions can be characterized in two complementary ways: (A) amount (how much investors place their bids) and (B) timing (when investors place their bids) (Burtch et al. 2013, Grenadier and Wang 2005, Jiang et al. 2020). When an investor chooses an opportunity, their evaluation of it should be reflected in both dimensions. We therefore construct the RWOC variables from these dimensions.

2.4.1.1 Investment Size

Absolute Investment Amounts. On Prosper.com, investors can choose to invest partially in a loan for a minimum of $25, or to purchase an entire loan, which is obviously riskier due to lack of diversification. Consistent with the marketing literature on purchase quantity models (e.g., Krishnamurthi and Raj 1988), investment size reflects investors’ assessments of the borrower’s creditworthiness. A small investment suggests that the lender either does not find the borrower trustworthy or does not scrutinize the loan carefully—that is, the investor does not care about the specific loan enough to examine it closely, simply trusts the platform's decision to list it, and is investing to diversify their portfolio (Herzenstein et al. 2011). Hence, minimum bids reveal very little information about an investor's evaluation of the loan beyond the static borrower information provided. In contrast, large investments, especially those significantly greater than the platform minimum, are more likely to reflect positive evaluations of the borrower's creditworthiness. Otherwise, investors have no incentive to place more funds at risk with a single loan. The relationship between bid amount and knowledge is documented in the literature. Kim and Viswanathan (2019) show that expert investors with more knowledge place larger bids. All else equal, a higher-quality listing should be able to convince more investors to place larger bids[5]. Therefore, there should be a positive correlation between the number of large bids and the quality of the loan.

One possible counterargument is that since loan amounts are fixed prior to the start of funding, larger bids must mathematically lead to a smaller number of investors. Yet, a typical conclusion of the crowd wisdom literature is that if something can convince a larger number of people to believe in it, it should be of higher quality (Mannes 2009). Because total loan amounts are predetermined, those that convince larger numbers to invest should be of higher quality. All else equal, there could also be a positive

[5] As a quantitative example, assume that all investors have the same portfolio and budget and a minimum bid of $25, we compare two hypothetical loans that are both funded with $5,000 in total. The first loan (A) is funded by 200 investors with minimum bids of $25. The second loan (B) is funded by 5 investors at $1,000 each. This suggests that investors in Loan B demonstrate a much higher degree of confidence in their evaluations than investors in Loan A; therefore, Loan B is more likely to be a good investment because its investors would not have invested so much if they lacked confidence in its quality. Investors in Loan A, however, all simply meet the minimum investment threshold (which is more likely to be caused by a desire to diversify their portfolios), so their investment decisions neither reflect nor instill much confidence.

relationship between the number of bids (and equivalently, a smaller number of large bids) a listing receives and loan quality. Hence, the contrast between the number of larger bids and the size of the crowd attracted (larger number of smaller bids) represents an interesting tension driven by the fixed-loan-size feature of debt-crowdfunding that has not been previously addressed in the crowd wisdom literature.

Relative Investment Amounts. We focus on absolute bid dollar values in the above. However, due to budget constraints and risk preferences, what one investor views as a large investment may be tiny for another. This heterogeneity means that investments of the same absolute dollar amount should reflect different confidence levels from different investors. If we track each investor's pattern over time, we can establish baselines to measure relative values.[6] Even when the bids contribute the same dollar amount to the loan, they can reflect dramatically different opinions. We therefore conclude that a bid contains significant informational value when it exceeds *a particular investor's typical investment amount* (henceforth, "above-normal bid"). Regardless of the absolute amount, it indicates a positive evaluation that should be economically significant (Bower 2015). Evaluating bid informational value based on investors' historical behavior is logically consistent with Bansal and Gutierrez (2020) and Budescu and Chen (2015), who consider the historical performance of individual subjects before aggregating their forecasts. We therefore hypothesize that, all else equal, there is a positive relationship between the number of above-normal bids a listing receives and loan quality.

[6] For example, for a wealthy investor with a million-dollar portfolio who typically invests $500 in each loan, a $500 bid may reflect little confidence and therefore does not carry too much useful information. In contrast, a $500 bid from a less-wealthy investor who almost always bids the platform minimum of $25 for other loans will reflect remarkably high confidence.

2.4.1.2 Investment Timing

Besides investment amounts, the other important aspect of investment decisions is their timing, which also reflects an investor's evaluation of loan quality. The norm in debt crowdfunding is that borrower information is available to potential investors at the beginning of a listing funding process and does not change during the process.[7] If such information is sufficient to convince investors, they should be motivated to invest immediately, because loan values are fixed; this is different from rewards crowdfunding where overfunding is possible.

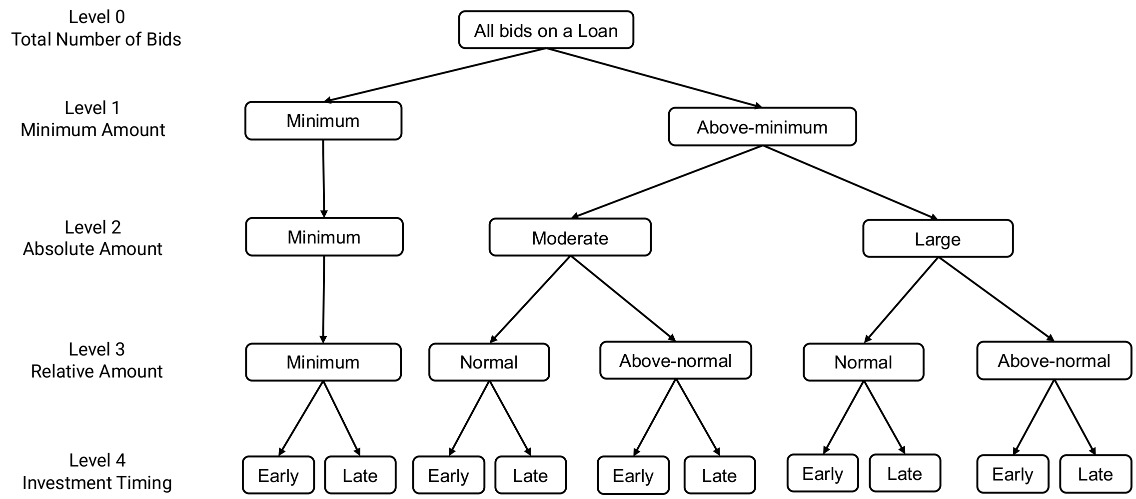
Once a listing reaches its required funding amount, no further investments are possible. Thus, there is no upside for lenders who are confident in the listing to wait, as they might miss the opportunity. This is consistent with the psychology and decision science literature; for example, subjects' response time to a stimulus reveals the strength of preference or belief beyond that revealed by choice outcomes (Frydman and Krajbich 2022, Konovalov and Krajbich 2017). The finance literature also documents that investors with sufficient confidence or experience in evaluating borrower quality are more likely to bid early and rapidly (e.g., Jiang et al. 2020, Kim and Viswanathan 2019, Vallee and Zeng 2019). The model proposed by Holden et al. (2020) suggests that early lenders are more likely to be informed lenders. Following the logic of absolute investment amount, we expect to observe more large bids in the *earlier* stage of funding process for higher-quality loans. [8]

[7] In rewards and equity crowdfunding, fundraisers can often respond to questions from potential funders or make changes during the fundraising process; this is generally not the case in debt crowdfunding.
[8] To use a more quantitative example, suppose there are two loans (C and D) that are otherwise similar—including the individual bids—with the only difference in bid sequence: C and D have the same loan amount and both were funded by one large ($1000) and 20 small ($25) bids. The only difference is that the $1000 bid began the bidding for C, whereas for D the $1000 completed the bidding. H3a predicts that C will be of higher quality than D.

Despite the argument presented above, there may still be incentives for investors to delay placing bids, even if they feel confident about the loan. Late investors can receive more cues from peer investors (e.g., social learning; Bikhchandani et al. 2021). Prior papers also document a rational herding effect in P2P lending (Zhang and Liu, 2012). Lenders may benefit from confirming their independent evaluations by observing peer behavior and therefore strategically delay their own bids (Burtch et al. 2016, Jiang et al. 2022, Kim and Viswanathan 2019, Liu et al. 2015, Müller-Trede et al. 2018). In this scenario, we hypothesize that more large bids are placed *later* in the funding process for higher-quality loans.

2.4.2 Empirical Strategy

To test the relationship between bid heterogeneity that we propose above and loan quality, we sequentially classify bids as shown in Figure 2-1. The top level (Level 0) represents the total number of bids in a loan. Level 1 separates bids that are equal to Prosper's minimum ($25) from those above the minimum. We call the latter "above-minimum bids." Level 2 further classifies the above-minimum bids as moderate or large relative to all other bids in the market around the same time (details in §4.3). On Level 3, we further distinguish bids using individual lenders' bidding histories, i.e., whether the moderate/large bids were typical or atypical. Finally, on Level 4, we focus on bid timing to subdivide each Level 3 class into early and late. Importantly, on each level, the total numbers of all bid types sum up to the total number of bids for the loan; each level indicates different ways of classifying these bids.



Notes. Level 1 separates bids into minimum and above-minimum. Level 2 further classifies above-minimum bids as either moderate or large. Level 3 distinguishes within the moderate and large bids into normal or above-normal classes using individual lenders' histories. Level 4 divides each bid type in Level 3 into early and late classes. For each level, all bid types sum up to total bids. To test the relationships specified in our hypotheses, we sequentially test the relationships between bid-type variables and loan quality. Details follow our variable descriptions.

Figure 2-1. Hierarchical Bid Classification

2.4.3 Data and Variables

Our raw dataset includes all loan requests (funded and unfunded) posted on Prosper.com between January 2011 and December 2012, information available to lenders about borrowers and loan requests, bids placed on those loans (including their timing and amount as well as the investor who placed it), and the ex-post monthly repayment histories of funded loans. We select this time window because the primary features on Prosper.com were highly consistent and stable throughout it.[9] In our primary analysis, we

[9] Prosper.com shifted from an auction model to a fixed-rate model on December 19th, 2010. Beginning in January 2013, Prosper.com experienced a series of management team changes, new investments, and feature modifications. We therefore limit the time window to the 24 months between January 2011 and December 2012. During our study period, the platform used posted-price format only.

focus on funded loans since unsuccessful listings do not become loans and therefore do not have any quality data (see §2.2.2).

Our dataset excludes loans wholly funded by a single lender, as such loans have no lender heterogeneity data; there are only 573 such loans in the dataset (less than 2%). Below we discuss the primary variables of interest, each defined at the loan level for a specific level of analysis. Table 2-1 provides definitions of all variables.

Table 2-1. Variables Definitions

Variable name	Description
	Panel A: Loan quality
Default percentage	Default amount/loan amount * 100. (0 if fully paid.)
Default indicator	Dummy variable that is 1 if the loan is defaulted; 0 if fully paid.
ROI	Return on investment, calculated by (paid principal + paid interest)/loan amount.
	Panel B: Bid variables
#Bids	Number of bids for the loan.
#Minimum bids	Number of $25 bids, the minimum allowed.
#Above-minimum bids	Number of bids over $25.
#Moderate bids	Number of bids > $25, but < the weekly mean + 3* standard deviations of all the loans in the week.
#Large bids	Number of bids ≥ weekly mean + 3* standard deviations of all the loans in the week.
#Normal moderate bids	Number of moderate bids whose amounts are no more than the mode of the lender’s previous bids.
#Above-normal moderate bids	Number of moderate bids whose amounts are more than the mode of the lender’s previous bids.
#Normal large bids	Number of large bids whose amounts are no more than the mode of the lender’s previous bids.
#Above-normal large bids	Number of large bids whose amounts are more than the mode of the lender’s previous bids.
#Early minimum bids	Number of minimum bids that are placed within the first half of the loan requested amount.
#Late minimum bids	Number of minimum bids that are placed within the latter half of the loan requested amount.
#Early normal moderate bids	Number of moderate bids that are lower than the lender’s investment mode and placed within the first half of the loan requested amount.

Table 2-1. Continued

#Late normal moderate bids	Number of moderate bids that are lower than the lender's investment mode and placed within the latter half of the loan requested amount.
#Early above-normal moderate bids	Number of moderate bids that are higher than the lender's investment mode and placed within the first half of the loan requested amount.
#Late above-normal moderate bids	Number of moderate bids that are higher than the lender's investment mode and placed within the latter half of the loan requested amount.
#Early normal large bids	Number of large bids < lender's investment mode placed within the first half of the loan requested amount.
#Late normal large bids	Number of large bids < lender's investment mode placed within the second half of the loan requested amount.
#Early above-normal large bids	Number of large bids > lender's investment mode placed within the first half of the loan requested amount.
#Late above-normal large bids	Number of large bids > lender's investment mode placed within the latter half of the loan requested amount.
Panel C: Control variables	
Category	The category of this loan: business, individual debt consolidation, or others.
Funded amount (log)	Amount funded of the loan (log).
Term	Loan repayment length: 12, 36, or 60 months.
Interest rate	The interest rate of the loan.
Credit grade	Credit grade of the borrower at the time of listing was created: AA, A, B, C, D, E, and HR.
Partial Funding Allowance	Whether the loan is allowed to be funded at 70% or higher of the required amount; if not, the loan needs to raise 100% of the required amount to be considered as funded.
Estimated return	Estimated annualized return on the loan.
Estimated loss	Estimated annualized loss rate on the loan.

Loan quality: A key benefit of studying debt crowdfunding is that loans have an unequivocal measure of quality at their maturity. Since they are repaid monthly, we calculate the outcome as the proportion of principal that the borrower fails to repay (i.e., the ratio of the default amount to the total loan amount). We call this metric "loan default percentage" for consistency with the literature (e.g., Iyer et al. 2016, Lin and Viswanathan 2016). This value is zero if a loan is fully repaid, and lower percentages suggest higher quality. The robustness checks in §4.5 provide additional results from alternative outcome variables (i.e., a binary default indicator, and return on investment).

Absolute bid amount: Levels 1 and 2 differentiate bids by dollar amount. If the bid is equal to the minimum required by Prosper.com ($25), we consider it a *minimum bid*. We count the number of minimum bids for each loan to generate the variable *#minimum bids.* The difference between total bids and *#minimum bids* is defined as *#Above-minimum bids.* For Level 2, to differentiate between moderate and large bids, we calculate the mean and the standard deviation for all bids placed in the entire market during the week of the bid. If the bid amount is larger than the sum of the mean and 3 times the standard deviation, we define it as a *large bid* (also known as the "three-sigma rule"). Over 2% of lenders made such unusual bids at least once in our sample period. Otherwise, if a bid is larger than the minimum but smaller than the mean plus 3 times the standard deviations[10], we define it as a *moderate bid*. We count the total number of moderate and large bids for each loan to generate *#Moderate bids and #Large bids*.

Relative amount: On Level 3, we compare each bid with the mode of all bids from the same lender. We treat each investor's *mode* as the typical bid that they place on loans.[11] If a bid is less than or equal to the mode, we define it as a *normal bid*; otherwise, an *above-normal bid*. We count such bids for each loan to generate *#Above-normal bids*.

Investment timing: We split the funding process into *early* and *late* halves of loan funding duration. Level 4 of Figure 2-1 shows how all bid types on Level 3 are temporally divided.

[10] Results are highly consistent when we use the mean plus two standard deviations.
[11] Results are highly consistent when we use the median investment amount.

Control variables: We incorporate all available loan and borrower characteristics provided by Prosper for lenders, such as requested amount, interest rate, term, category, campaign duration, credit grade, income level, employment status, and home ownership. In addition, we have generated some derived features, such as description length and quarterly fixed effects.

Table 2-2 presents summary statistics. Our sample contains 29,900 loans funded by 2,494,942 bids. The average loan size is $7,458 (range $2,000 to $25,000). All loans in the dataset include at least one above-minimum bid, with 15,375 (51.42%) including one or more large bids. Those with at least one large bid receive $9,060 and 69 bids on average, while those without any large bids receive $5,863 and 98 bids on average. In terms of the relative bids, 60.92% of the large bids are larger than the lenders' mode, while 42.11% of the moderate bids are larger than the mode. In other words, not all large bids are unusual for the lenders who placed them, highlighting the value of relative bid amount. Finally, 33.24 % and 66.76% of the bids are placed in the early and late stage.

Table 2-2. Descriptive Statistics

Variable name	Mean	SD	Min.	Max.	Median
		Panel A: Loan quality			
Default percentage	0.14	0.31	0.00	1.00	0.00
Default indicator	0.23	0.42	0.00	1.00	0.00
ROI	1.15	0.39	0.00	2.13	1.21
		Panel B: Variables about bid types			
#Bids	83.44	84.65	2.00	656.00	56.00
#Minimum bids	42.60	47.64	0.00	462.00	28.00
#Above-minimum bids	40.84	38.63	1.00	291.00	28.00
#Moderate bids	40.18	38.63	0.00	291.00	28.00
#Large bids	0.66	0.81	0.00	8.00	1.00
#Normal moderate bids	21.78	22.84	0.00	182.00	14.00
#Above-normal moderate bids	18.41	18.23	0.00	157.00	13.00
#Normal large bids	0.25	0.50	0.00	5.00	0.00
#Above-normal large bids	0.40	0.67	0.00	8.00	0.00

Table 2-2. Continued

#Early minimum bids	15.13	16.46	0.00	319.00	11.00
#Late minimum bids	27.48	38.76	0.00	436.00	14.00
#Early normal moderate bids	8.55	8.74	0.00	118.00	6.00
#Late normal moderate bids	13.23	18.00	0.00	163.00	6.00
#Early above-normal moderate bids	7.19	7.84	0.00	121.00	5.00
#Late above-normal moderate bids	11.22	13.67	0.00	152.00	6.00
#Early normal large bids	0.08	0.28	0.00	4.00	0.00
#Late normal large bids	0.17	0.43	0.00	5.00	0.00
#Early above-normal large bids	0.13	0.38	0.00	5.00	0.00
#Late above-normal large bids	0.28	0.55	0.00	6.00	0.00
Panel C: Control variables					
Funded Amount (log)	8.70	0.67	7.60	10.13	8.59
Interest Rate	0.22	0.08	0.05	0.33	0.23
Estimated Return	0.11	0.03	0.02	0.18	0.12
Estimated Loss	0.09	0.05	0.00	0.20	0.09
Prosper Score	6.12	2.20	1.00	10.00	6.00
Now Delinquent	0.42	1.24	0.00	27.00	0.00
Amount Delinquent	1190.00	7726.00	0.00	279970.00	0.00
Public Records Last 12 Months	0.01	0.13	0.00	4.00	0.00
Public Records Last 10 Years	0.28	0.63	0.00	12.00	0.00
Delinquencies Last 7 Years	3.89	9.43	0.00	99.00	0.00
Inquiries Last 6 Months	1.13	1.58	0.00	27.00	1.00
Credit Age (Years)	17.28	7.78	0.62	61.22	16.25
Current Credit Lines	9.49	5.40	0.00	59.00	9.00
Open Credit Lines	8.42	4.87	0.00	48.00	8.00
Total Credit Lines	6.45	4.34	0.00	47.00	6.00
Revolving Credit Balance (USD in thousands)	19.45	36.58	0.00	1073.00	8.79
Bankcard Utilization	0.53	0.32	0.00	2.23	0.55
Debt/Income Ratio	0.70	28.55	0.00	4404.00	0.20
Employment Duration (Month)	96.44	93.11	0.00	755.00	67.00
Campaign Duration (Days)	4.81	4.27	1.00	15.00	3.00
Description Length (Words)	235.20	252.90	0.00	4703.00	167.00

Notes. The sample includes 29,900 loans funded between January 2011 and December 2012. The table omits the categorical control variables, including Category, Credit Grade, Consumer Credit Score, Day of Week, Employment, Group Member, Have Listing Description, Home Ownership, Income Range, Partial Funding Allowance, Quarter, Term.

2.4.4 Models and Hypothesis Testing

Before delving into predictive models, we first present methods, primary results, and robustness checks for our explanatory model that tests the hypotheses. To examine how different bid types predict loan quality, we estimate the following specifications:

$$DefaultPercentage_i = \beta \times BidTypes_i^L + f\,(ListingInfo_i + BorrowerInfo_i + QuarterlyFEs_i) \quad (1)$$

where $BidTypes_i^L$ represents all the bid types on Level L of Figure 2-1 for Loan i; $L \in \{0,1,2,3,4\}$, corresponding to the five levels in Figure 2-1.[12] β is a vector of coefficients for different bid types, as shown in Figure 2-1; when negative, a particular type of bid is associated with a lower default percentage and therefore higher loan quality. Since our outcome variable of interest in the primary specification is *Default Percentage*, which ranges between 0 and 1, we use a fractional outcome regression (Lin and Viswanathan 2016, Pang 2017, Papke and Wooldridge 1996).

Table 2-3 reports our estimates. Each column reports the results of one of the bid hierarchy levels shown in Figure 2-1. Column 1 shows a non-significant relationship between the total number of bids in a loan and its default percentage. This suggests that

---

[12] For example, all the bid types on Level 3 are Minimum bids, Normal moderate bids, Above-normal moderate bids, Normal large bids, and Above-normal large bids. Then the specification for examining Level 3 is

$$DefaultPercentage_i = \beta_1 \times \#Minimum\ Bids_i + \beta_2 \times \#Normal\ Moderate\ Bids_i + \beta_3 \times \#Above\ Normal\ ModerateBids_i + \beta_4 \times \#Normal\ Large\ Bids_i + \beta_5 \times \#Above\ Normal\ Large\ Bids_i + f\,(ListingInfo_i + BorrowerInfo_i + QuarterlyFEs_i).$$

when we do not differentiate among bids, the number of bids (in a sense, the size of the crowd) that a loan receives does not provide extra information about loan quality beyond what has already been conveyed in the borrower and loan variables. In other words, bid numbers, a traditional measure of popularity, fail to offer informational value in the context of debt crowdfunding, where overfunding is not possible.

More interesting patterns emerge as we move down the hierarchy. Column 2 (Level 1) shows that *#Minimum Bids* is positively correlated with default percentage, whereas *#Above-minimum bids* is negatively correlated with loan quality. In other words, of the bids that a loan receives, only those larger than the platform-mandated minimum are predictive of high loan quality.

Column 3 (Level 2) further categorizes above-minimum bids between moderate and large bids. The coefficient for *#Minimum Bids* remains positive and significant. *#Moderate Bids* and *#Large Bids* are both negatively associated with default percentage, consistent with the result in Level 1. However, the coefficient (and also the related marginal effect) of *#Large Bids* is much larger than that of *#Moderate Bids*. These results support a positive relationship between the number of large bids and loan quality.

Level 3 in Column 4 further distinguishes bids by their *relative* values, i.e., whether they are greater than the mode of that lender's bids. Within both moderate and large bids, only above-normal bids are significantly correlated with a lower default percentage. In contrast, none of the normal bids (including minimum bids) has a statistically significant coefficient. Holding everything else at the median, each additional above-normal large bid produces a 0.84% reduction in default percentage, approximately $45 in default amount. Additionally, normal and above-normal large bids both have larger negative coefficients (in absolute value) than the corresponding types of moderate bids, consistent with our findings in Level 2. Therefore, our results support a positive relationship between the number of above-normal bids and loan quality.

With respect to investment timing, Level 4 categorizes all bid types in Level 3 into early and late stages. Most coefficient estimates for above-normal bids remain negative and significant (except Late above-normal large bids), but all such relations are stronger when the bids are placed in early than in the late half. For example, the coefficient for early above-normal large bids is more than two-fold greater than the coefficient for late above-normal large bids. Our calculation of the marginal effect shows that, holding all else at the median, each additional early above-normal large bid results in a 1.25% reduction in default percentage, approximately $68 in default amount. These results therefore support a positive relationship between early large bids and loan quality.

Table 2-3. Bid Types and Loan Quality

Dependent variable: Default percentage	(1) Level 0 Total number of bids	(2) Level 1 Minimum bids	(3) Level 2 Absolute amount	(4) Level 3 Relative amount	(5) Level 4 Investment timing
#Bids	0.050 (0.165)				
#Minimum bids		2.096*** (0.534)	2.000*** (0.536)	0.942 (0.606)	
#Above-minimum bids		-2.613*** (0.696)			
#Moderate bids			-2.782*** (0.703)		
#Large bids			-28.431** (13.082)		
#Normal moderate bids				0.965 (1.245)	
#Above-normal moderate bids				-4.970*** (0.927)	
#Normal large bids				-23.804 (17.093)	

Table 2-3. Continued

#Above-normal large bids				-36.983** (16.878)	
#Early minimum bids					4.081*** (1.188)
#Late minimum bids					-0.085 (0.742)
#Early normal moderate bids					0.871 (2.162)
#Late normal moderate bids					1.449 (1.556)
#Early above-normal moderate bids					-9.014*** (1.857)
#Late above-normal moderate bids					-3.714*** (1.287)
#Early normal large bids					-20.874 (28.543)
#Late normal large bids					-25.589 (19.916)
#Early above-normal large bids					-54.723** (25.489)
#Late above-normal large bids					-24.928 (19.077)
Observations	29,900	29,900	29,900	29,900	29,900
Loan information	YES	YES	YES	YES	YES
Borrower information	YES	YES	YES	YES	YES
Quarter dummies	YES	YES	YES	YES	YES

Notes. Coefficients are estimated using a fractional outcome regression model. For brevity, the table shows covariates only for variables of interest, with some covariates omitted. Numbers of bids are in thousands. Robust standard errors are in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

2.4.5 Robustness of the Explanatory Model

While the focus of our study is the value of the RWOC variables for predictive purposes, we still conduct an extensive set of robustness tests for our descriptive models' findings to rule out alternative explanations. First, various potential sources for endogeneity are unlikely to be a first-order concern in our study. (A) Reverse causality (i.e., borrower repayment affects bid distribution) is highly unlikely in our context because borrower repayment and bid distribution formed during the funding period are temporally disjointed. When the pre-set, 14-day funding period ends, Prosper.com staff begin to verify the loan. The repayment period (36 months) begins only after the verification is complete. As prior studies of the same market indicate, predicting loan quality is a non-trivial task (Iyer et al. 2016), even for institutional investors (Lin et al. 2022). Hence, lenders cannot fully foresee repayment and then decide whether or how much to invest. (B) Spurious correlation (i.e., an unobserved error term that correlates with bid distribution as well as borrower repayment) would be plausible if borrowers could observe bid distributions during bidding and then decide whether and how much to repay. This concern is also highly unlikely in our context because the repayment process of loans is entirely managed by the platform (in collaboration with WebBank). As such, borrowers cannot selectively repay lenders; rather, repayment is proportionally issued to each lender according to their proportion of the loan.

We then conduct a series of robustness tests. We conduct matching to verify our primary findings; rule out herding as an alternative explanation; rule out the possibility that borrowers repay due to lenders being friends and family or being local lenders; and rule out the possibility that the results are driven by expert (institutional) investors. Our results also hold when we use alternative measures of loan quality, including a binary indicator of loan default and the loan's overall return-on-investment, when we differentiate moderate and large bids based on another two thresholds, and when we redefine early bids as the bids placed on the first day or first two days.

2.5 Using RWOC Variables for Loan Quality Prediction

The descriptive analyses conducted above reflect the utility of RWOC variables and their within-sample predictive power. As our primary interest is whether incorporating these variables can help predict loan performance, this section demonstrates that including RWOC variables in the feature set improves predictive performance across a wide range of advanced prediction algorithms, as well as in published models that also seek to predict loan quality using Prosper.com data.

2.5.1 Predictive Analysis

2.5.1.1 Model Setup

In this section, we train a series of standard, supervised, machine-learning models to predict loan quality. Since a critical reflection of loan quality is default rate, the outcome variable of interest is a binary *Default Indicator*, one if the loan defaults and zero otherwise (Fu et al. 2021, Iyer et al. 2016).

Our goal is to study whether we can improve the performance of loan-quality prediction by incorporating RWOC variables as additional predictors. We first define three baseline features sets. The first feature set uses Consumer Credit Score and Prosper Score (henceforth Feature Set A), since they reflect the comprehensive evaluation of borrowers from consumer credit rating agencies and Prosper respectively. The second feature set includes all the observable borrower and loan characteristics on Prosper (henceforth Feature Set B). This baseline is consistent with the typical underwriting practice of basing loan decisions exclusively on borrower characteristics. Table 2-1 Panel C lists all the variables. Furthermore, we build a more demanding baseline that adds the total number of bids on a loan to Feature Set B, which corresponds to Level 0 in Figure 2-1 (henceforth Feature Set C). Feature Set C reflects the traditional belief of the crowd wisdom, taking the crowd as a whole and not considering differences among members.

We then construct a series of feature sets that incorporate RWOC variables. We first construct Feature Set D that adds the simple RWOC variables we use in the descriptive models (all bid variables on Level 4 of Figure 2-1 since Level 4 is the most comprehensive) to Feature Set B. This feature set allows us to evaluate the predictive power of intuitive RWOC variables. To further gauge the informativeness of RWOC variables, we perform feature engineering of the RWOC variables. Using these engineered features, we construct additional feature sets that capture different aspects of RWOC variables. Specifically, Feature Set E adds absolute investment amount related features, Feature Set F adds relative investment amount related features, and Feature Set G adds investment timing related features. Finally, we construct Feature Set H that encompass all the engineered RWOC features. Considering scenarios where investor history is unavailable (due to data absence or privacy concerns), we also construct an additional feature set, Feature Set I, which excludes relative bid amount features. By comparing the performance of models using baseline feature sets and those using RWOC feature sets under different algorithms, we can evaluate whether the RWOC variables improve loan quality prediction beyond what has been captured and fixed in borrower information known before the start of bidding.

We utilize four popular classification algorithms: the basic classification method, multinomial logistic regression (Logistic) (Cox 1958); two widely applied boosting methods, Light Gradient Boosting Machine (LightGBM) (Ke et al. 2017) and eXtreme

Gradient Boosting (XGBoost) (Chen and Guestrin 2016); and a deep-learning method, multilayer perceptron (MLP) (Haykin 1994). We use the same dataset used in the descriptive models (loans funded between January 2011 and December 2012) to train and test the predictive models. To reduce evaluation bias, we repeat five-fold cross-validation twice, using different random seeds at each iteration (James et al. 2013). The ideal hyperparameters of models are identified by hyperparameter tuning with the grid search method. The entire predictive modeling process is performed in Python using scikit-learn (Pedregosa et al. 2011), xgboost (Chen and Guestrin 2016), lightgbm (Ke et al. 2017), and tensorflow (Abadi et al. 2016) libraries.

It is worth noting that machine-learning methods are highly variable with different algorithms and datasets. Hence, our goal in this section is not to build sophisticated models with significantly better performance than those published in the literature (though §5.2 will show that our model does perform considerably better); instead, we are interested in whether adding RWOC variables to models trained on the same dataset can improve performance (Fu et al. 2021, Song et al. 2021).

2.5.1.2 Results

Table 2-4 presents the predictive performance of multiple algorithms using various feature sets. Following the literature (Padmanabhan et al. 2022), we evaluate two performance metrics. The first is the area under the receiver operating characteristic curve (ROC-AUC), which is a widely applied measure of predictive performance. ROC-AUC is particularly useful to represent how well a model can distinguish between classes (default or not) when there is no obvious cutoff for a probability from which one can consider an observation belongs to a class (Fu et al. 2021, Iyer et al. 2016). The AUC ranges from 0 to 1, and a higher AUC corresponds with better predictive performance. The second metric is the financial impact of improving predictive power produced by adding RWOC variables (Padmanabhan et al. 2022). Since the models aim to correctly classify repaid and defaulted loans, we measure financial impact by calculating investment losses from misclassified loans (Wang et al. 2017). Misclassification can be either false positive (classifying a repaid loan as defaulted) or false negative (classifying defaulted as repaid). Since the misclassification costs of these two cases are asymmetric[2], we follow Simester et al. (2020) to calculate the loss from a false positive as the loss of its interest, and the loss from a false negative as the loss of its principal. Table 2-4 reports the results.

Table 2-4. Predictive Performance of Default Indicator

Algorithm	Feature Set	(1) ROC-AUC	(2) Misclassification Cost
Logistic	(A) Credit score	0.6272	$6,886,724
	(B) Baseline variables	0.7190	$6,648,399
	(C) Baseline + total number of bids	0.7209	$6,619,877
	(D) Baseline + simple RWOC variables	0.7384	$6,335,270
	(E) Baseline + engineered absolute bid amount variables	0.7628	$5,698,974
	(F) Baseline + engineered relative bid amount variables	0.7491	$6,291,413
	(G) Baseline + engineered bid timing variables	0.7363	$6,498,680
	(H) Baseline + all engineered RWOC variables	0.7654	$5,688,476
	(I) Baseline + no relative amount variables	0.7633	$5,749,112
	(J) All engineered RWOC variables	0.6955	$6,121,821
LightGBM	(A) Credit score	0.6222	$6,886,724
	(B) Baseline variables	0.7581	$5,456,783
	(C) Baseline + total number of bids	0.7552	$5,510,822
	(D) Baseline + simple RWOC variables	0.7643	$4,378,800
	(E) Baseline + engineered absolute bid amount variables	0.7824	$4,690,052

Table 2-4. Continued

	(F) Baseline + engineered relative bid amount variables	0.7734	$4,778,969
	(G) Baseline + engineered bid timing variables	0.7635	$4,566,343
	(H) Baseline + all engineered RWOC variables	0.7831	$4,412,212
	(I) Baseline + no relative amount variables	0.7817	$4,248,388
	(J) All engineered RWOC variables	0.7318	$3,833,954
XGBoost	(A) Credit score	0.6251	$6,570,643
	(B) Baseline variables	0.7636	$5,159,066
	(C) Baseline + total number of bids	0.7624	$5,222,467
	(D) Baseline + simple RWOC variables	0.7672	$4,515,613
	(E) Baseline + engineered absolute bid amount variables	0.7832	$4,558,412
	(F) Baseline + engineered relative bid amount variables	0.7743	$4,440,922
	(G) Baseline + engineered bid timing variables	0.7687	$4,537,821
	(H) Baseline + all engineered RWOC variables	0.7840	$4,521,064
	(I) Baseline + no relative amount variables	0.7824	$4,754,126
	(J) All engineered RWOC variables	0.7314	$4,164,881
MLP	(A) Credit score	0.6296	$6,886,724
	(B) Baseline variables	0.7543	$5,998,029
	(C) Baseline + total number of bids	0.7497	$6,073,459
	(D) Baseline + simple RWOC variables	0.7662	$5,970,391
	(E) Baseline + engineered absolute bid amount variables	0.7887	$5,364,104
	(F) Baseline + engineered relative bid amount variables	0.7804	$5,928,951
	(G) Baseline + engineered bid timing variables	0.7649	$5,965,027
	(H) Baseline + all engineered RWOC variables	0.7932	$5,345,816
	(I) Baseline + no relative amount variables	0.7880	$5,414,947
	(J) All engineered RWOC variables	0.7188	$5,442,303

Notes. Each row displays the performance of an algorithm using the corresponding feature set as predictors. Performance is measured using the area under the Receiver Operating Characteristics Curve (ROC-AUC) and misclassification cost. The outcome variable is default indicator. Finance, finance variables about borrower credit and loan features; RWOC, all bid variables on Level 4 of Figure 2-1; Logistic, multinomial logistic regression; LightGBM, Light Gradient Boosting Machine; XGBoost, eXtreme Gradient Boosting; MLP, multiplayer perceptron.

Comparing the three baseline models in each algorithm, we first find that the credit score alone (Feature Set A) can achieve as much as 58.08% predictive power of all financial features (Feature Set B)[13]. By comparing predictions between Feature Sets B vs. C, we find that if we only add total bids as an additional predictor, it does not significantly increase, and sometimes slightly decrease, AUC. This result is consistent with our descriptive analyses and supports our argument that crowds, as a whole, are not always wise.

We next examine the predictive performance of models with RWOC variables and find that incorporating RWOC variables consistently improve predictive performance. The feature sets with RWOC variables (Feature Sets D – H) consistently outperform the corresponding baseline feature sets (Features Sets A – C), regardless of which algorithm is used (including the best performer in baseline feature sets, MLP). Within every algorithm, Feature Set H with all engineered RWOC variables always performs the best. To calibrate the AUC improvement, we follow Iyer et al. (2016), who also published a series of models using Prosper.com data. Applying their procedure (Iyer et al. 2016, p1565, footnote 17) to our context, we find that adding only simple RWOC variables (Feature Set D) can increase AUC by as much as 8.86% ((0.7384-0.5)/(0.7190-0.5)-1 based on Logistic) from Feature Set B. The inclusion of engineered RWOC variables improves predictive performance by as much as 21.19% ((0.7654-0.5)/(0.7190-0.5)-1 based on Logistic). Even using the algorithm that performs the best using Feature Set B (XGBoost) the inclusion of engineered RWOC variables improves predictive

[13] This is achieved by Logistic algorithm. We followed Iyer et al. (2016) and calculate it as (0.6272-0.5)/(0.7190-0.5) = 58.08%.

performance by 7.74% ((0.7840-0.5)/(0.7636-0.5) – 1). All results together lend strong support to the value of RWOC variables in predicting loan defaults. If we compare predictions against the more demanding baseline, Feature Set C, including RWOC variables still improves performance across all these algorithms. This result is particularly impressive given the tremendous effort and expenditure involved in collecting the financial information of borrowers.

Moreover, to test whether the performance of the feature sets that incorporate RWOC variables statistically improves from baseline features, we again follow the literature (Ben-Assuli and Padman 2020, Berg et al. 2020, Iyer et al. 2016) and examine the significance of the AUC increases. This approach was first presented in DeLong et al. (1988), and we implement it using the roccomp command in the STATA, as implemented in Iyer et al. (2016). We find that all algorithms' ROC-AUC improvements of Feature Set H from Feature Set B are significant at the 1% level, providing further support for the predictive power of RWOC variables.

Table 2-4 Column 2 shows that including RWOC variables results in a significant reduction in investment losses. For our sample of 29,900 loans, there are additional savings of as much as $1,044,571 (0.47% of the total funded amount) of Feature Set H. Even for the algorithm that generates the smallest misclassification costs for Feature Set B (XGBoost), the savings are still $638,002 (0.28% of the total funded amount). Given the magnitude of debt-based crowdfunding markets (over $25 billion funded globally as of 2020), such improvement is substantial and economically meaningful.

To further gauge the informativeness of RWOC variables, we construct additional models with different predictor sets and compare their performance. We first construct

Feature Set I, which has no private lender information. It adds the RWOC variables of absolute bid amount and bid timing, but not relative bid amount. Compared with Feature Set B, Feature Set I, which is superior from a privacy point of view, also achieves a decent improvement (20.23% higher AUC).

We next consider Feature Set J with only engineered RWOC variables but no finance variables. Although it is unrealistic to build practical prediction models with solely RWOC variables, we report its results for technical demonstration and completeness. A comparison of Feature Set J and Feature Set B shows that RWOC variables alone provide as much as 89.81% predictive power compared with what all financial information does. This confirms the importance of lender heterogeneous behaviors when borrower information is completely unavailable.

2.5.2 Comparisons with Existing Models

We next compare our models with the ones in the literature to ensure the RWOC variables remain valuable in them. Specifically, we replicate our baseline models using the datasets from two prior papers, Fu et al. (2021) and Iyer et al. (2016). Both studies employ the same data source (Prosper.com) and performance metric (ROC-AUC). We first reconstruct their datasets, which cover different time periods from ours. We then retrain the algorithms using Feature Set B on each dataset separately (Table 2-5).

Across all algorithms, our baseline models generate higher AUCs than the published predictive models. Thus, the results demonstrate that our baseline models not only match but indeed outperform those from the aforementioned studies, further underscoring the value of incorporating the RWOC variables.

Table 2-5. Applying Our Models to Datasets in Literature

	Fu et al. (2021)	Our algorithms with Feature Set A	Iyer et al. (2016)	Our algorithms with Feature Set A
Sample		Loans originated Mar. 2007 – Oct. 2008		Loans posted Feb. 12, 2007 – Oct. 16, 2008
Regression	/	0.8247	0.7103	0.8242
LightGBM	/	0.8299	/	0.8303
XGBoost	0.741	0.8335	/	0.8333
MLP	/	0.8346	/	0.8317

Notes. This table compares the predictive performance (ROC-AUC) of our algorithms using Feature Set A and two published predictive models. The published models were trained on the same data source (Prosper) as ours but in different time windows. When trained on the same time windows, our baseline models produce improved results. The outcome variable is default indicator. Regression in Iyer et al. (2016), linear regression; Regression in our algorithms, multinomial logistic regression; LightGBM, Light Gradient Boosting Machine; XGBoost, eXtreme Gradient Boosting; MLP, multiplayer perceptron.

2.5.3 Performance Improvements Do Not Come from Experts

Similar to our robustness checks in the empirical analysis, we examine whether predictive improvements provided by the RWOC variables are fully contributed by the bids from expert investors. Expert investors are suggested to perform better than normal investors (Jiang et al. 2020, Kim and Viswanathan 2019, Lin et al. 2022). If expert bids have better predictive power than others, the bidding behaviors of expert lenders should be separately considered in our models.

We first construct a baseline with the financial variables and all the bid types on Level 2 of Figure 2-1 (Feature Set K). Unlike our primary predictive models that use Level 4 bids as RWOC variables, here we use Level 2 bids. This is because, as we move down through the hierarchy, some types of bids in Level 3 or 4 do not contain any bids from experts. To ensure sufficient data to train the models, we use bid types on Level 2. Next, we train three models that replace RWOC variables with three bid sets: Level 2 bids from only experts (Feature Set L), Level 2 bids from only non-experts (Feature Set M), and Level 2 bids from both experts and non-experts (Feature Set N). Table 2-6 presents AUC from different algorithms (columns) using different feature sets (rows).

Table 2-6. Predictive Performance of Models Using Bids from Experts vs. Non-Experts

Feature Set	Logistic	LightGBM	XGBoost	MLP
(G) Finance + Level 2 bids	0.7610	0.7745	0.7781	0.7931
(H) Finance + Level 2 bids from experts	0.7559	0.7720	0.7757	0.7889
(I) Finance + Level 2 bids from nonexperts	0.7601	0.7775	0.7793	0.7900
(J) Finance + Level 2 bids from experts + Level 2 bids from nonexperts	0.7596	0.7745	0.7775	0.7878

Notes. Each row displays ROC-AUC produced by an algorithm using the corresponding feature set as predictors. The outcome variable is default indicator. Finance, finance variables about borrower credit and loan features; Logistic, multinomial logistic regression; LightGBM, Light Gradient Boosting Machine; XGBoost, eXtreme Gradient Boosting; MLP, multiplayer perceptron.

Comparing bids from experts with those from non-experts, we find that the latter (Feature Set M) has higher predictive power than the former (Feature Set L). In other words, the increase of predictive power provided by adding RWOC variables is primarily contributed by normal investors rather than special investors. Interestingly, across all algorithms, Feature Set N does not improve further, and even performs slightly worse, than Feature Set K, indicating that further dividing *action* variables by *identities* does not generate extra value. This result again confirms the value of RWOC variables.

2.5.4 Platform Auction Format and Predictive Model Performance

The predictive model results reported above are based on data from Prosper after it implemented the fixed-price format, where the platform pre-determines the interest rate of a loan and lenders decide whether to participate under this interest rate. To verify the general applicability of the predictive model, we replicate the predictive model using Prosper.com data before this regime change, i.e., when loans were funded through auctions (Wei and Lin 2017). We find the predictive model performs even better under auctions. Even when after we match the loans from these two periods formats based on interest rates, borrower characteristics, and other loan characteristics, the predictive model still performs better under auctions. This is consistent with Wei and Lin (2017) in that under the fixed-price format, the platform tends to price the loans' interest rate higher than the crowd would do to attract investors, thereby leading to efficiency loss.

2.6 RWOC Variables from Early Bids

While the above analyses demonstrate the value of adding the RWOC variables, one may argue that these are only achievable after observing the full sequence of lender investments after the funding process has ended. Though such a situation would be useful for secondary market pricing, it would be even better if RWOC variables can help investors avoid investing in a bad loan in the first place. We therefore test the value of RWOC variables *during* the funding process, by only using early bids to predict quality, funding likelihood, and funding speed.

2.6.1 Predicting Loan Quality using Early Bids

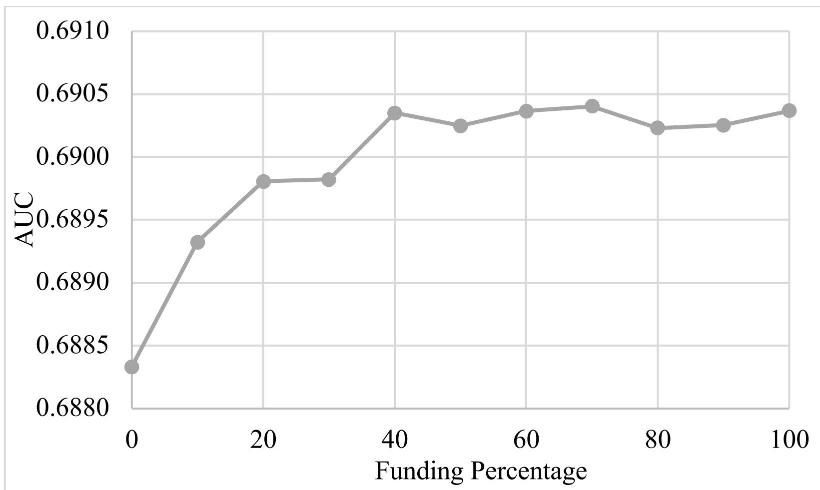
We start our analyses by investigating whether early bids alone predict loan quality using the same tests described in §5.1. Similar to the previous models, we build three revised models, in which the predictors include early bids that are separately defined as bids placed in the first half of the total funding time, the same definition used in the empirical analyses (Feature Set O); bids placed on the first funding day (Feature Set P); and bids placed on the first two funding days (Feature Set Q) separately. Table 2-7 Column 1 presents the performance. Comparing Feature Set O with previous feature sets, the default was predicted with as much as 18.22% greater accuracy than Feature Set B and achieves as much as 97.99% of the increase achieved by Feature Set H. Feature Sets P and Q also achieve decent improvements from the baseline models. Thus, early bids alone, though not as powerful as the entire set of RWOC variables, improve predictive performance significantly. Considering the fact that early bids compose only 37.25% of total bids in our dataset, such an improvement further attests to the value of the RWOC approach.

Table 2-7. Predictions using Early Bids

Algorithm	Feature Set	(1) Default Indicator	(2) Funding Success
Logistic	(B) Baseline variables	0.7190	0.6958
	(O) Baseline + early bids	0.7589	0.7875
	(P) Baseline + first day bids	0.7581	0.8046
	(Q) Baseline + first two-day bids	0.7588	0.8183
LightGBM	(B) Baseline variables	0.7581	0.7326
	(O) Baseline + early bids	0.7747	0.8445
	(P) Baseline + first day bids	0.7762	0.8323
	(Q) Baseline + first two-day bids	0.7756	0.8452
XGBoost	(B) Baseline variables	0.7636	0.7354
	(O) Baseline + early bids	0.7779	0.8448
	(P) Baseline + first day bids	0.7780	0.8342
	(Q) Baseline + first two-day bids	0.7787	0.8457
MLP	(B) Baseline variables	0.7543	0.7270
	(O) Baseline + early bids	0.7873	0.8257
	(P) Baseline + first day bids	0.7925	0.8398
	(Q) Baseline + first two-day bids	0.7902	0.8466

Notes. Each row displays the ROC-AUC from an algorithm using the corresponding feature set as predictors. The outcome variable is funding indicator. Finance, finance variables about borrower credit and loan features; Logistic, multinomial logistic regression; LightGBM, Light Gradient Boosting Machine; XGBoost, eXtreme Gradient Boosting; MLP, multiplayer perceptron.

Since bids are timestamped, we further examine how predictive power changes as bidding progresses. We create a separate feature set for every additional decile of cumulative funding (i.e., 0%, 10%, …, 90%, 100%; 11 in total). Each feature set is composed of all finance variables and all the bids that have been placed through each decile. Figure 2-2 plots AUC as a function of funding percentage. For brevity, we present only the Logistic algorithm, though the other algorithms are qualitatively consistent.



Notes. This analysis is performed using the Logistic algorithm. AUC increases as a function of funding percentage early but reaches a plateau at approximately 40%.

Figure 2-2. Predictive Performance Increases with Funding Percentage

Figure 2-2 shows that, during early bidding, AUC increases with funding percentage. That is, the predictive power of the RWOC variables increases rapidly when more early bids are placed. However, AUC reaches a plateau at a funding percentage of approximately 40%, close to the maximum. In other words, RWOC variables significantly improve predictions even if only bids from the first half of the funding period are used. This is consistent with what we find in the descriptive model–compared with late bids, early bids contain more useful information and are more strongly associated with loan quality.

2.6.2 Predicting Full Funding Using Early Bids

In addition to the prediction of loan quality, another important application of early bids, as prior studies have addressed (Burtch et al. 2016, Zhang and Liu 2012), is to predict the funding success of listings. Compared with borrower information available before funding starts, early RWOC bids partially reveal market sentiments, helping to predict funding success. Since we are now examining full funding likelihood, we expand our sample to include all listings that are not funded in our study period (between January 2011 and December 2012). Before building a predictive model, we perform a series of survival analyses using listing-day level panel data and verify that there is indeed a positive relationship between early large bids and completing funding more rapidly.

We examine the power of early bids in predicting funding success under the prediction framework. We build revised models using three definitions of early bids (Feature Sets O, P and Q). All models predict a binary outcome variable for funding success–the funding indicator, which is one if a listing is fully funded and zero otherwise. Table 2-7 Column 2 displays the results for each algorithm using different feature sets.

Across all the algorithms, feature sets with early bids (Feature Set O, P, and Q) consistently outperform the corresponding baselines lacking early bids (Feature Set B). After adding early bids to finance variables, AUC increases as much as 76.10% for Feature Set O, 73.54% for Feature Set P, and 77.02% for Feature Set Q. This result is consistent with our results from the survival analyses in that early bids are informative of funding success.

In addition to funding success, we use early bids to predict speed in hours to total funding. Across all the algorithms, using Feature Set P (bids from the first funding day) significantly improves the prediction of funding time relative to Feature Set B (no RWOC bids) (Table 2-8). Overall, our study of early bids in this section demonstrates that even a subset of RWOC variables is a powerful predictor of both loan quality and funding success.

Table 2-8. Funding Speed Prediction Using Early Bids

Algorithm	Model	ROC-AUC
Logistic	(B) Baseline variables	0.6272
	(P) Baseline + first day bids	0.8100
LightGBM	(B) Baseline variables	0.6569
	(P) Baseline + first day bids	0.8601
XGBoost	(B) Baseline variables	0.6650
	(P) Baseline + first day bids	0.8631
MLP	(B) Baseline variables	0.7314
	(P) Baseline + first day bids	0.8767

Notes. Each row displays ROC-AUC from an algorithm using the corresponding feature set as predictors. The outcome variable is funding time in hours. Finance, finance variables about borrower credit and loan features; Logistic, multinomial logistic regression; LightGBM, Light Gradient Boosting Machine; XGBoost, eXtreme Gradient Boosting; MLP, multiplayer perceptron.

2.7 RWOC Variables and Financial Inclusiveness

An original value proposition of the broader crowdfunding phenomenon is to better match the supply and demand of funds and to improve financial inclusiveness (G20 Global Partnership for Financial Inclusion white paper[14]). In this spirit, we examine the implications of RWOC variables for this important issue. Specifically, we test whether including RWOC variables would improve relative loan quality prediction for borrowers

[14] https://www.gpfi.org/sites/gpfi/files/documents/GPFI_WhitePaper_Mar2016.pdf

who can more easily secure funding, relative to those who have more challenges in doing so. We focus on borrower differentiation by credit grade, as low credit borrowers tend to have less financial access (Sufi 2009), and gender, as female borrowers tend to have more difficulty securing funds (Kanze et al. 2018).

For credit grades, we follow the literature (Netzer et al. 2019) and create three loan bins: high (AA and A), medium (B, C, and D), and low (E and HR). We apply the trained algorithms using Feature Set B and Feature Set H from §5.1 to each bin (Table 2-9, Panel A). We find that the *increase* of AUC is the largest for low-grade borrowers who generally have less access to traditional loans. While low-credit borrowers tend to be riskier, RWOC variables are useful for predicting loan outcomes and therefore can help investors find good candidates among them.

Table 2-9. Value of RWOC Variables for Financial Inclusiveness

Panel A: Credit Grade							
		(1)		(2)		(3)	
Subgroups		High		Medium		Low	
Number of Observations		5,810		15,513		8,577	
	(B) Baseline variables	0.7171		0.6816		0.6278	
Logistic	(H) Baseline + engineered RWOC variables	0.7128	-2.0pp	0.6887	3.9pp	0.6347	5.4pp
	(B) Baseline variables	0.7499		0.7001		0.6519	
LightGBM	(H) Baseline + engineered RWOC variables	0.8064	22.6pp	0.7897	44.8pp	0.7888	90.1pp
XGBoost	(B) Baseline variables	0.7520	39.6pp	0.6865	52.6pp	0.6399	100.6pp
	(H) Baseline + engineered RWOC variables	0.8519		0.7846		0.7807	

Table 2-9. Continued

MLP	(B) Baseline variables	0.7126		0.6885		0.6377	
	(H) Baseline + engineered RWOC variables	0.7205	3.7pp	0.7020	7.2pp	0.6514	9.9pp
Panel B: Gender							
		(4)		(5)			
Subgroups		Male		Female			
Number of Observations		7,291		9,444			
Logistic	(B) Baseline variables	0.8328		0.8220			
	(H) Baseline + engineered RWOC variables	0.8357	0.9pp	0.8257	1.1pp		
LightGBM	(B) Baseline variables	0.8467		0.8403			
	(H) Baseline + engineered RWOC variables	0.8794	9.4pp	0.8755	10.3pp		
XGBoost	(B) Baseline variables	0.8421		0.8337			
	(H) Baseline + engineered RWOC variables	0.8792	10.8pp	0.8712	11.2pp		
MLP	(B) Baseline variables	0.8436		0.8337			
	(H) Baseline + engineered RWOC variables	0.8480	1.3pp	0.8374	1.1pp		

Notes. This table reports the performance (ROC-AUC) of loan default prediction within different subgroups and the increase of AUC between each pair of feature sets. The outcome variable is default indicator. pp stands for percentage point. Finance, finance variables about borrower credit and loan features; RWOC, all bid variables on Level 4 of Figure 2-1; Logistic, multinomial logistic regression; LightGBM, Light Gradient Boosting Machine; XGBoost, eXtreme Gradient Boosting; MLP, multiplayer perceptron.

We similarly examine the benefits of RWOC variables for female versus male borrowers.[15] Table 2-9 Panel B shows that the increase of female AUCs are always larger than male AUCs. This result is consistent with recent findings that crowdfunding can help bridge gender gaps documented in traditional financing (Bapna and Ganco 2021).

Taken together, our results suggest that RWOC variables are particularly useful in "thin file" situations, where the financial information about borrowers is sparse. These two analyses highlight the benefits of RWOC variables for further improving crowdfunding access for traditionally underserved groups of borrowers.

2.8 Discussion and Conclusions

This chapter studies the informational value of heterogeneous investment behavior in online debt crowdfunding. Using a combination of both descriptive and predictive models (Hofman et al. 2021, Shmueli and Koppius 2011), we identify simple variables based on the amount (both absolute and relative) and timing of bids received from investors that improve the performance of loan quality predictive models. Under a descriptive framework based on an incremental classification of bids, we show that a simple count of the number of bids (Level 0) is not significantly associated with loan quality. By distinguishing minimum bids from the others, we find that only the number of bids that exceed the platform-mandated minimum is positively associated with loan

[15] Prosper does not directly collect or reveal a borrower's gender. Hence, we encode the variable gender in two steps. We first analyze all the photos posted by borrowers through Microsoft Azure Face API, which is an AI service that analyzes faces in images. One of the analysis results returned from the API is the gender of the figure shown in an image. Second, we analyze borrower's narrative listing descriptions by keyword extraction. As Prosper suspended the display of personal photos in 2010 and the display of listing descriptions in 2013, we limit the listings in the sample of this test to 2005-2010. After these two steps, we identify 7,291 male borrowers and 9,444 female borrowers. We retrain Models A and B on the new sample and then apply the trained models on the male group and the female group separately.

quality. Further down the hierarchy, we show that among bids that exceed the platform minimum, those that are large in absolute terms (defined as three standard deviations higher than the mean of all bids in the same week of the bid), those that are large in relative terms (compared to the focal investors' historical mode of bid amount), and large bids that are placed earlier in the funding period have increasingly stronger correlations with loan quality.

We then use a predictive modeling framework to demonstrate that incorporating RWOC variables improve loan quality predictions. We show that under a variety of predictive models, including those published in top journals based on data from the same context as well as different prediction algorithms, adding RWOC variables as additional predictors consistently improves predictive performance. Furthermore, we show that even if RWOC variables are derived from bids placed in the first half of the funding period, they still predict loan quality well. They also predict the likelihood of full funding before they became loans. We also show that early bids contribute much more to predictive efficacy than later bids. Finally, we show the potential benefit of RWOC variables in promoting the inclusion of traditionally marginalized borrower groups.

The RWOC approach has several unique advantages. Regardless of what information investors can access, all that our approach requires is available on the platform. RWOC variables represent detailed but still aggregated information about bid heterogeneity; moreover, calculations are easily implemented and scalable. It provides an efficient and effective manner of extracting crowd wisdom, superior to a simple aggregate of the crowd.

Our study makes several contributions to the theoretical and empirical research literature. First, even though the term "wisdom of the crowd" is used broadly in online communities and markets, the crowd is often viewed as a monolithic entity. Yet, no two individuals are truly identical, and actions by the same individual at different times may be driven by very different information. By recognizing that different actions have different values, we can better identify signals (informative actions) from noise (imitations or trivial actions). This mixture of useful and less-useful crowd actions is broadly applicable to other online communities and markets (e.g., crowdsourcing and open innovation), in which the crowd wisdom concept is applied.

Our study also contributes to the growing finance literature, especially in fintech, by proposing a new method of quality evaluation. While existing studies focus on borrower characteristics, our study highlights the possibilities of extracting information from investors' reactions. Whether the same logic applies to product markets remains an open question.

Our study also highlights a potential synergy between machine learning (predictive) and crowd wisdom. For example, rather than simply predicting loan quality based on borrower information, it allows learning from the reactions of the crowd. Future studies can and should examine how crowds react to such updated predictions.

This study has multiple practical implications. First and foremost, this chapter provides an approach to distill several pieces of succinct information from the complicated list of bidding history in an easily scalable manner. Platforms can implement our method to help investors make decisions without potentially compromising privacy, especially when investors cannot directly access such data. For example, instead of showing the full bidding history, the platform can simply show one or more of the following metrics: (1) number of large bids based on typical bidding behaviors in the market; (2) number of bids in amounts that significantly exceed the typical bidding amount of their originating investors; and (3) number of bids in the first two categories that had been placed in the first day of the bidding process. Furthermore, our approach can be immediately applied to evaluating P2P loan quality in secondary markets, in which individual or institutional investors sell shares of previously funded loans (Holden et al. 2020). Investor bidding behavior revealed during the previous funding process can be exploited to improve the pricing of secondary-market loans. Moreover, if a borrower requests an additional loan while their previous loan has not yet matured (e.g., Prosper.com allows two concurrent loans subject to a combined limit), the platform can leverage the bidding information from the previous loan to help evaluate the second loan.

Our study also contributes to the ongoing discussion about tradeoffs between market efficiency and privacy. While more information typically improves efficiency, privacy is an increasingly significant concern. Further, each investor may or may not have the mental or computational capacity to process detailed bidding data. These reasons lead some platforms to stop providing detailed bidding histories. Our approach, especially analyzing only early bids, strikes a balance between these opposing needs by focusing on investor actions over investor identities. In lieu of providing detailed bidding histories, platforms could generate RWOC-based metrics behind a privacy wall and present them to investors.

By implementing our approach, platforms can not only improve predictive performance, but more so for those who tend to be financially marginalized. While loan requests from low-credit borrowers typically offer higher returns, our approach should help investors identify better candidates among them, thereby benefiting both sides of these markets and improving financial inclusiveness.

Our study suggests fruitful avenues for future research. While we conducted our analyses using only publicly available information from debt-based crowdfunding, future studies may evaluate the benefit of this approach (i.e., its generalizability) in other types of crowdfunding. Equity crowdfunding will likely generate similar results if bids are not frequently withdrawn. Reward crowdfunding, however, may be less applicable due to the lack of flexibility in contribution amounts (i.e., limited number of rewards). Beyond crowdfunding, given the significance of secondary markets in our economic system (such as mortgage-backed securities), there will likely be value in assessing investor reactions to the underlying original loans in those markets as well.

Another interesting direction for future research is the threshold for participation in online financial markets. What is the smallest amount that investors should pay to participate in a loan, or a future in equity crowdfunding? Many markets establish low participation thresholds and lower them over time to increase the number of participants, which is an important metric for investors who evaluate these platforms as investment opportunities. Prosper.com initially required a $50 minimum but later reduced that to $25 before our study period. There are interesting variations among fintech startups. Among UK equity crowdfunding platforms, Crowdcube and Seedrs require as little as £10, whereas SyndicateRoom requires a minimum of £1000. These lower thresholds enable broader access but may also reduce bid informational value: minimum bids, in our study, were poor predictors of loan quality, regardless of how many there were. It remains an open question whether such changes would make a crowd more prone to irrationality.

CHAPTER 3. BEWILDERED OR EMPOWERED? THE AMBIGUOUS EFFECTS OF INFORMATION PROVISION ON SEQUENTIAL INVESTORS

3.1 Introduction

Online trading markets for retail investors face a perpetual predicament when providing financial information. While comprehensive financial details can empower investors to make informed decisions, the complexity of such information may also overwhelm them. This dilemma becomes even more pronounced in crowdfunding, where nonexpert individual investors are responsible for evaluating investment opportunities and peer actions are highly visible. On one hand, displaying peer behaviors, such as investment history, can offer extra informational signals to potential investors, helping them navigate complex financial decisions and reduce information asymmetry. Extensive research has shown that seemingly unsophisticated investors in crowdfunding platforms can derive meaningful insights from investment history and engage in active observational learning (Iyer et al. 2016; Zhang and Liu 2012). These investors demonstrate the ability to discern subtle differences in peer behavior and leverage the credible signals provided by more experienced ones (Kim and Viswanathan 2019). Further, the sharing of investors' actions can foster transparency in the funding process, thereby enhancing investors' trust in the platform (Burtch et al. 2016). On the other hand, excessive display of peer information can cause negative consequences to individual investors, particularly considering their limited cognitive capacity. An overwhelming amount of information may impose a significant cognitive cost on investors, leading to suboptimal decision-making such as defaulting to predetermined options or focusing on a limited set of information (Agnew and Szykman 2005; Liao et al. 2021). Excessive exposure to others' behavior can even contribute to irrational herding behavior, undermining the collective wisdom of crowds (Da and Huang 2019). Moreover, the mandatory disclosure of detailed peer information raises concerns regarding investor privacy and the confidentiality of their investment decisions (Burtch et al. 2015). Overall, the impact of peer information display on investor behavior is theoretically ambiguous.

The challenge of providing peer information to investors has led crowdfunding platforms to adopt various market designs in addressing this issue. For example, some equity crowdfunding platforms such as Crowdcube and Seedrs choose to present only aggregated peer information, including the total funded amount and the overall number of investors, on loan request pages. In contrast, rewards-based crowdfunding platforms such as Kickstarter and Indiegogo provide more detailed information, specifying the number of investors for each reward tier. Previously, some P2P lending platforms like Prosper presented transactional-level investment history for each loan request. However, there is a recent trend among platforms to remove features and display less comprehensive information on webpages. Although these changes could be possibly driven by privacy concerns, completely eliminating peer information may not be the optimal design. Instead, alternative approaches such as presenting a moderate amount of aggregated information could be more advantageous (Yao et al. 2022).

Given the various displays of peer behavior information, it remains unclear what trade-offs exist between the benefits investors gain and the cognitive costs they incur when utilizing information at different levels of detail. Further, while we qualitatively recognize that too much information can be overwhelming, determining the threshold for "too much" information in platform designs is challenging. Thus, our research aims to address the following question: *How does the display of peer investment information influence financial decision-making behavior in crowdfunding?* Specifically, we investigate the influence of two prevalent elements of displaying peer investment history in crowdfunding: number of participating lenders and detailed investment history. Accordingly, we examine three displays: displaying only the total funded amount and no other peer information, displaying the number of participating lenders together with the total funded amount, and displaying detailed transactional-level peer investment history. We examine how these display formats influence investor behavior in terms of platform abandonment, decision time, investment willingness, and risk preference.

We focus our investigation of investment history display in the context of peer-to-peer (P2P) lending, motivated by the measurable and objective features of loan requests as well as the clear financial motivations of P2P lenders. In contrast to projects on equity or rewards-based crowdfunding, P2P loans are often more comparable due to their quantitative financial characteristics. Moreover, P2P lenders have stronger economic incentives to evaluate the quality of loans and the investment actions of their peers, unlike backers in donation or rewards-based crowdfunding who are at least partially driven by altruism (Dai and Zhang 2019).

To answer our research question, we first conducted two experimental studies, in which subjects engaged in hypothetical peer-to-peer (P2P) lending scenarios and were tasked with making investment decisions. We then performed a field study that leveraged a peer information design change happened on Prosper.com, one of the largest P2P lending platforms in the US. While observational data from P2P lending platforms provides rich information, this study mainly draws on controlled experiments as the core methodology, supplemented by the field study to demonstrate the generalizability of our findings. This is because, first, no platform has implemented more than two types of displays, making a comparison of all displays challenging. Moreover, a platform change often involves simultaneous modifications of other loan features, which will introduce confounding factors to empirical tests. Furthermore, the dual-sided nature of crowdfunding platforms poses a challenge in examining the behavioral change of one side (lenders) while assuming consistency on the other side (borrowers). In contrast, controlled experiments can better address these challenges. By controlling the supply (borrower) side and all irrelevant environmental factors, we are able to observe and analyze investment behaviors under all display formats at an individual level.

Our three studies yield consistent results. Investors show a higher acceptance of simpler displays of peer investment history, while they are more likely to quit when presented with a detailed display. In terms of decision-making efficiency, investors take a longer time to make decisions when presented with detailed history, but the inclusion of aggregated history does not prolong decision time compared to not displaying any history. Such differences in decision time are more significant for medium-risk loans (vs. high- or low-risk). Conditional on accepting a display format, investors' total investment amount remains similar across different displays. However, their investment allocation (over different risk levels) is influenced more when prior investments are displayed in an aggregated format, suggesting the saliency of aggregation manner. This effect is more pronounced for risk-seeking investors.

Our findings provide several notable contributions. First, our work contributes directly to the theory and practice of platform design. The importance of information provision and presentation in online financial platforms has been long recognized in shaping investor decision-making and market outcome (Burtch et al., 2016; Glazer et al., 2021; Liao et al., 2021; Gao et al. 2023). Our research adds to this stream of literature by shedding light on the level of detail in peer investment history display. Our findings indicate that overly detailed information may overwhelm nonexpert investors due to their cognitive limitations. Instead, more digestible data could be more salient and effective. Secondly, our work contributes to the studies on peer effects, especially those in the context of crowdfunding (Burtch et al. 2013, Herzenstein et al. 2011, Kim and Viswanathan 2019, Zhang and Liu 2012). While prior work has demonstrated the prevalence of peer effects in financial decision-making, this study provides a deeper understanding of how peer effects are influenced by different displays of peer behavior information. Lastly, this study enriches the emerging Fintech literature. By recognizing the potential information overload of retailer investors and its negative consequences, we highlight the significance of interface design in facilitating more effective decision-making in crowdfunding environments.

3.2 Theoretical Foundations

Our study is built on multiple streams of management and economic literature. Specifically, this study is first grounded in the literature concerning information provision and presentation in online platforms. Further, this study draws on studies on cognitive cost and information overload. Finally, this study is closely related to the crowdfunding literature that focuses on peer influence.

3.2.1 Information Provision and Presentation

The provision and presentation of information in online platforms have been shown to produce significant impacts on investor decision-making in financial markets. For example, there is a substantial body of auction research that studies how the disclosure of bidder identity influences bidders' participation and bidding strategies (e.g., Lu et al. 2019). For retail investors, Barber et al. (2022) find that platform or app design can significantly affect their attention toward specific stocks. In the realm of crowdfunding, platform design is also a significant determinant of investor decision-making and market outcomes. For instance, Gao et al. (2023) demonstrate that platform choices–such as the level of prescreening, the creation of separate markets for experts and nonexperts, and the supply of listings–considerably affect market efficiency and the benefits accrued by different groups of investors. Jiang et al. (2020) also find that both on-platform and off-platform information can influence lenders' investment speed and investment amount.

One prominent factor in information display design is the amount of information provided to users. More detailed information is typically considered to improve environmental transparency and help investors make informed decisions. For instance, Liberman et al. (2018) study the effects of restricting information provision on consumer credit markets using a large-scale policy change in Chile. They find that after credit bureaus stopped reporting defaults for 21% of the adult population, both borrowers' and lenders' surpluses were reduced. Xu and Zhang (2013) show that information aggregation on Wikipedia improves the information environment for the financial market. Chen et al. (2022) also find that a reduction in information-acquisition costs enhanced analysts' information production and improved their forecast accuracy. The linkage principle in auction theory even suggests that sellers should disclose all relevant information to buyers (Milgrom and Weber 1982). Similar effects have also been observed in crowdfunding markets. Vallee and Zeng (2019) leverage a natural event on LendingClub in which half of the 100 variables on borrower characteristics that used to be provided to investors were removed unexpectedly. They find that reducing information provision to investors decreased the outperformance of sophisticated investors, highlighting the advantage of rich loan characteristics.

On the other hand, research has also highlighted the detrimental impact of excessive information exposure. For example, Lu et al. (2019) find that revealing winners' identities in auctions significantly decrease the average winning price, leading to reduced revenue for sellers. Madsen and McMullin (2020) examine the introduction of a voluntary and unverified "risks and challenges" section on a rewards-based crowdfunding platform, Kickstarter.com, and find that the support for high-risk projects decreased after the implementation of this section. Kim et al. (2022) utilize the same policy change on Kickstarter and report consistent results. For nonexpert and inexperienced retail investors in online financial markets, one important factor that contributes to the negative effect of information disclosure is cognitive overload caused by excessive information, which will be discussed in detail in the next section. Considering the inconsistent results found in existing literature, further empirical research is necessary to enhance our understanding of the impacts of information display.

In addition to the quantity of information, the presentation and communication of information are also important in shaping financial decisions. Various design factors, such as presentation formats (Kaufmann et al. 2013), available options (Agnew and Szykman 2005), default options (Madrian and Shea 2001), and gamification (Barber et al. 2022), have been found to influence investment behaviors. Among all, one key factor is the salience of characteristics. Salience, a concept in cognitive psychology, causes investors to focus on the most noticeable or essential aspects when immersed in an information-rich environment (Bordalo et al. 2012). When a dimension's salience increases, decision-makers place significantly more weight on that dimension (Choi et al. 2017; Frydman and Wang 2020). Crowdfunding research indicates that, under time pressure, P2P investors tend to use the most salient loan features, such as credit grade and interest rate, to make better decisions (Liao et al. 2021). This behavior can be attributed to cognitive load reduction, where investors prioritize the most effortless features when faced with information overload, as discussed in the next section.

3.2.2 Cognitive Cost and Information Overload

Despite the crucial role of information richness and transparency in decision-making, an excessive amount of information may not always be beneficial. This is because humans have a limited capacity to process and store information in their memory (Miller 1956). When presented with a large amount of information that is not easily processable, people may incur high cognitive costs, leading to a "poverty of attention" (Simon 1982). One recent example is social media: the explosion of social media content leads to information overload for consumers during product searches, which negatively affects their decision-making abilities (Ghose et al. 2019). Similarly, research on financial markets has also realized that humans' bounded rationality can cause markets to depart from informational efficiency (Pernagallo and Torrisi 2022).

Information overload lowers the likelihood that information is channeled to the proper decision-makers, resulting in delays, information distortions, and ineffective decisions (Huber 1991). Overwhelmed information also discourages decision-makers from evaluating opportunities, which could ultimately result in a situation where no decision is made at all (Agnew and Szykman 2005; Kuksov and Villas-Boas 2010). For platforms, this would lower the participation rate and transaction rate (Ghose et al. 2014).

Researchers have long been investigating effective ways to communicate information to alleviate the adverse impact of information overload. Some work focuses primarily on the amount of information such as the number of attributes and alternatives, while some other research has expanded to include other dimensions such as information quality and context factors (Agnew and Szykman 2005). Additionally, insufficient organization of information can also lead to information overload. Specifically, research finds that decision-makers tend to use information more extensively when it is easier and less costly to acquire and digest (Stigler 1961). Decision-makers who are given summarized data, such as simple descriptive statistics, are reported to make higher-quality decisions, compared to those receiving the same data in standard formats (Chervany and Dickson 1974). In a more recent paper, Guo et al. (2017) propose a system framework to extract representative information from intra-organizational blogging platforms, so that organizers can look beyond the overloaded information and utilize accumulated data for managerial effectiveness. In the same spirit, Hvalshagen et al. (2022) propose a data narrative to support naive employees in understanding organizational data and information technologies, which has shown significant alleviation of cognitive overload.

3.2.3 Crowdfunding and Peer Effects

Crowdfunding, a highly successful financial innovation, has experienced significant growth over the past two decades. This innovative funding model has revolutionized the way individuals and businesses raise capital by connecting borrowers directly with individual lenders. The funding process of P2P lending is as follows: A borrower initiates the funding process by posting a loan request, also known as a "listing," containing essential details such as the requested loan amount, interest rate, loan purpose, campaign duration, and various credit information. Lenders, on the other side, browse through the available listings on the crowdfunding platform and place bids on the ones that capture their interest. If a listing successfully accumulates sufficient funds from lenders, it becomes a loan, and the borrower receives full loan amount. Subsequently, the borrower begins making monthly repayments, including both principal and interest. The loan is considered completed once the borrower fully repays the loan as originally planned, or classified as defaulted if a monthly payment is delayed by two or more months or the borrower stops payment.

As crowdfunding relies on a large number of lenders to raise funds, it is highly susceptible to peer influence like other crowd-based platforms. Peer influence refers to the phenomenon where individuals are influenced by their peers' behavior, attitudes, and beliefs, and it has been observed across a variety of domains such as movie rating, energy conservation, food ordering, charitable giving, and online community contributions (e.g., Cai et al. 2009; Lee et al. 2015). Prior research extensively documented the irrational herding phenomenon caused by peer influenced, in which individuals predominantly follow the popularity and passively mimic others. For example, Simonsohn and Ariely

(2008) find that bidders tend to herd into online auctions with more bids, despite it not being a signal of higher quality. Individuals exposed to peer effects tend to be less independent, reflected giving less weight to their own private information when they are exposed to more public information (Da and Huang 2020). As a result, such herding increases the unpredictability and inequality of the whole market (Salganik et al. 2006). Because of the various channels of peer effects such as social learning and social utility, greater information provision may only partially alleviate herding behavior, but not eliminate it (Bursztyn et al. 2014).

Studies on crowdfunding consistently demonstrate the widespread presence of peer influence among funders. In donation-based and reward-based crowdfunding, social influence significantly impacts campaign success, but the direction of peer effects varies depending on the perspective. While early investors' participation can attract more subsequent investors (Zhang and Liu 2012), a project's cumulated support and backers' perception of campaign success can also negatively affect subsequent backers' willingness to contribute (Burtch et al. 2013; Kuppuswamy and Bayus 2018). Interestingly, a majority of literature finds that peer influence in lending-based crowdfunding tends to have positive effects. Herzenstein et al. (2011) provide evidence of strategic herding among lenders in P2P loan auctions, where lenders bid on auctions with more prior bids up to the point of full funding, and this herding behavior is positively associated with loan repayment performance. Zhang and Liu (2012) also find that P2P lenders engage in active observational learning, exhibiting rational herding instead of blindly following their peers. Kim and Viswanathan (2019) show that the majority of investors in the crowdfunding market–those with less experience–are surprisingly sophisticated in identifying and herding after their experienced peers. Kai et al. (2022) also demonstrate that uninformed investors are able to learn from informed investors, supporting the low-credit yet high-quality borrowers. Peer influence can even extend beyond contribution decisions and affect other behaviors in crowdfunding. For example, Burtch et al. (2016) find that when campaign contributors choose to conceal their username or contribution amount from public display, subsequent contributors are also more likely to conform to social norms and conceal their information as well.

Despite the extensive research on peer influence in crowd-based platforms, the majority of studies focus on its influence on financial decision-making. While some literature examines factors influencing herding behavior, such as the expertise of funders (Kim and Viswanathan 2019) and username authenticity (Jiang et al. 2022), to the best of our knowledge, no study has investigated how various display formats of peer behavior information impact subsequent lenders' investment decisions. The provision and presentation of peer information on crowdfunding platforms can shape both the direction and the strength of peer effects, as well as the types of signals that peers follow. This design question becomes particularly crucial as crowdfunding platforms primarily target inexperienced individual investors who have been shown to be more vulnerable to changes in platform design (Liao et al. 2021). Moreover, the specific objective of debt-based crowdfunding adds further significance to this design question. In reward-based crowdfunding, the emphasis is on attracting as many backers as possible (only quantity matters), allowing the design to align with basic marketing principles. However, lenders in debt-based crowdfunding are responsible for screening investment opportunities, making the quality of investment decisions matter as much as the quantity of investments.

Therefore, a better understanding on the role of peer behavior information display in investment decision-making would enhance the investment quality and improve the overall effectiveness of crowdfunding markets.

3.3 Hypothesis Development

3.3.1 Platform Abandonment

Investor abandonment is crucial to the active engagement and cash flow of P2P lending platforms. In peer-to-peer (P2P) lending, each loan is typically funded by a substantial number of individual investors, often ranging from tens to even hundreds of lenders per loan (Yao et al., 2022). Each investment record includes key information such as the investment amount, investment time, and the names of the lenders involved. Additionally, investors have the option to explore more background information about each lender if desired. However, when making a single investment decision, investors often need to process information from multiple loans, often under significant time pressure. Our data indicates that some highly desirable loan requests can be fully funded in just a few minutes. The combination of a high volume of information and limited decision time can lead to information overload for non-expert retail investors, causing investors to focus only on one or a few key features (Liao et al. 2021). As a result, retail investors may be deterred from actively engaging in investment activities when feeling information overload (Jones et al. 2004). Further, the disclosure of bidders' identities within each investment can create a screening effect, which can deter participation and drive down prices (Snir and Hitt 2003, Hong et al. 2016). This screening effect has led popular online auction markets, such as eBay, to transition to less transparent settings where bidder identities are kept private. Thus, a detailed display of peer behavior information in P2P lending could discourage active investor engagement, subsequently leading to higher platform abandonment.

Aggregated information, in contrast to detailed information, typically presents a more straightforward and digestible format. By pre-processing information, platforms can significantly reduce the cognitive load on investors, making them easier to interpret and utilize the data at hand. The use of aggregated information also allows investors to grasp an overall picture without getting lost in the minutiae. This high-level view often makes it easier for investors to identify patterns and trends, thereby improving their decision-making efficiency. Aggregated information is particularly beneficial for retail investors who may not have the time, expertise, or resources to analyze detailed information. These investors often rely on cues and heuristics to make their decisions, and aggregated information provides a clear, concise cue for decision-making. For instance, presenting the number of previous investors allows subsequent investors to quickly gauge a loan's popularity, which can then influence their own investing behaviors (Zhang and Liu, 2012). Additionally, presenting information in an aggregated format helps to mitigate the potential privacy concerns associated with the disclosure of individual investor behavior, further encouraging participation. Thus, displaying aggregated peer investment history should remain or even decrease investor abandonment of P2P lending platforms. We propose the following.

Hypothesis 1 (H1): Investors' abandonment is higher when presented with detailed peer investment history.

3.3.2 Decision Time

Decision time is another essential factor that shapes financial behaviors. Decision time reflects the duration of mental processes involved in decision-making and is widely used as a proxy of subjects' cognitive effort and labor input (Spiliopoulos and Ortmann 2018). Prior research suggests that suggests that response time can reflect the strength of preference–beyond what has been reflected in the final choice (Konovalov and Krajbich 2019). Longer decision time is usually associated with more challenging tasks, smaller differences among choices, and greater uncertainty (Bazley et al. 2021; Frydman and Krajbich 2022; Speier and Morris 2003). In the general context of crowdfunding, although investors are not strictly constrained by any time limits, delaying decision-making can result in significant opportunity costs, such as missing out on a high-quality loan (Krajbich et al. 2014). Thus, decision time is intimately related to investors' sense of ease in decision-making, their confidence in their choices, and the efficiency of their investment decisions. Considering the potential information overload brought about by an excessively detailed display of investment history and the cognitive relief offered by an aggregated display, it's logical to hypothesize that decision time will be impacted. The granularity of the detailed peer investment history requires a more substantial cognitive load to analyze, potentially slowing down the decision-making process. On the other hand, the simplicity and digestibility of aggregated history or the absence of prior investment history should allow for quicker decision-making, as they place less cognitive demand on investors. Thus, we hypothesize that:

Hypothesis 2 (H2): Investors' decision speed is slower when presented with detailed peer investment history.

3.3.3 Investment Willingness

Our third area of focus concerns investment willingness, which is the extent to which investors are prepared to commit their resources to the loans given their willingness to engage with the platform. Investment willingness directly impacts the success of funding campaigns and the revenue generated by the platforms. Much like our first two hypotheses, we anticipate the overall investment willingness of investors to be lower when they are presented with detailed peer investment history. The intricate and exhaustive nature of detailed investment histories can often be daunting, especially for retail investors who might not have the expertise to decipher such intricate information swiftly. Investors might find themselves less eager to invest a substantial amount when they feel mentally burdened and uncertain about potential loan outcomes due to the sheer volume of details. This uncertainty can intensify the perceived risks and insecurities tied to an investment, thus lowering investment willingness. On the other hand, aggregated information provides a more straightforward and accessible alternative. The clear-cut, concise information conveyed by the number of participating lenders serves as a more intuitive cue. It provides investors with an easy-to-process metric that can enhance their confidence in the investment and, consequently, foster a greater willingness to invest. Given these insights, we propose that

Hypothesis 3 (H3): Investors' investment willingness is lower when presented with detailed peer investment history.

3.3.4 Risk Preference

Determining the level of risk to undertake is a fundamental decision in any financial venture (Kaufmann et al. 2013; Tasoff and Zhang 2022). In our study, we specifically focus on lenders' credit risk preference, which represents the most prevalent type of financial risk in P2P lending (Liao et al. 2021). Existing research has shown that risk preference is susceptible to various external factors, such as group membership (Sitkin and Pablo 1992), emotional shocks (Wang and Young 2020), and even seasonal changes (Kamstra et al. 2017). Among these factors, peer behavior has been found to significantly sway investors' decisions on risk allocation. Thus, the manner in which peer investment history is displayed can influence the prominence of peer actions and consequently vary this influence. Compared to a full list of investment history, aggregated information can help subsequent investors more effectively summarize crowd reactions, thereby amplifying the influence of their peers. When investors are presented with aggregated peer investment information, they are tasked with processing information that is less complex. As a result, they may find it easier to adjust their risk preferences based on this more digestible input. For instance, literature on crowdfunding demonstrates that the number of prior lenders of a loan can serve as a potent indicator of the investment amount of subsequent lenders (e.g., Kim and Viswanathan 2019; Yao et al. 2022; Zhang and Liu 2012). On the other hand, when faced with detailed or no investment history, investors are thrust into a more uncertain decision-making environment. This uncertainty may cause less sensitivity to risks, as investors may fall back on their inherent risk tolerance and usual strategies when confronted with ambiguity. Therefore, we propose that

Hypothesis 4 (H4): Investors' risk preference varies more when presented with aggregated peer investment history.

3.4 Study 1: Experiment

In this study, we conducted an online controlled experiment to directly manipulate the display of peer investment history into three distinct formats, while controlling for potential differences in substantive investment history or loan features. In a simulated P2P lending scenario, each subject was required to allocate a fixed budget to three loan requests, which were similar in all loan characteristics except the level of risk. By comparing the abandonment rate, decision time, investment willingness, and investment allocation among the three groups, we were able to identify the impact of different displays of peer investment history on investor decision-making.

3.4.1 Procedure

We recruited the experiment subjects from Prolific and conducted the experiment on Qualtrics. To ensure that subjects possessed sufficient financial knowledge and could fully comprehend the experiment, we administered a financial knowledge check to Prolific workers who expressed interest in participating. Only by answering all three questions correctly could they participate in the experiment. Those who did not pass the financial knowledge check were not compensated, and individuals who did not pass the check or had previously quit the experiment were not eligible to re-participate.

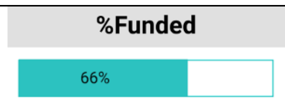
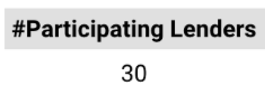
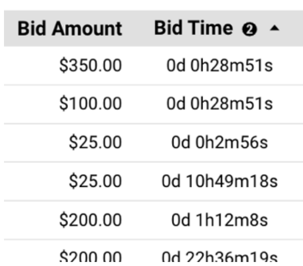
In the cover story, subjects were asked to imagine they were P2P lenders and need to select loan requests for investment. All subjects underwent a training session, which provided them with background information on P2P lending and loan features, an explanation of the experiment procedure, details about compensation, and an overview of the experiment interface. To be consistent with the currently prevalent model of P2P lending, we set the experiment as a fixed interest model rather than an auction model; that is, once a bid is placed, it cannot be withdrawn. Importantly, subjects were informed that they could earn bonus rewards based on the returns of their investments, serving as a motivation for them to make informed decisions.

Following the training session, we assessed subjects' understanding and acceptance of the experiment interface design. They were required to pass a knowledge check that examined their comprehension of the experiment interface and loan features. This check not only ensured subjects fully understood the experiment setup but also evaluated their speed and degree of acceptance of the interface. Subjects had unlimited attempts to pass the knowledge check: if they answered all questions correctly, they proceeded with the formal experiment; if they answered any question incorrectly, the system reminded them that there was at least one incorrect answer and prompted them to retake the knowledge check. Subjects could revisit the training section any time during the knowledge check, and they could also quit the experiment if they were unable to pass the knowledge check. They were informed that they would not receive compensation if they chose to quit at this stage.

Subjects who successfully passed the knowledge check entered the formal experiment phase. They were instructed to allocate 1000 virtual experiment currency (EC) among three loan requests: one from each credit risk (i.e., low, medium, and high risk). The three loans were carefully designed to have identical expected returns but varying levels of risk, which allowed us to examine subjects' risk allocation behavior.

The loans were also highly comparable in other loan features (loan category, requested amount, percentage funded, and remaining campaign time), differing only in credit risk, interest rate, and risks and returns (see Table 3-1 for the experiment group design and Figure 3-1 for the experiment interface).

Table 3-1. Study 1: Experiment Group Setup

Peer Investment History Element	Condition A (Current Prosper.com Design)	Condition B (Rewards Crowdfunding Design)	Condition C (Previous Prosper.com Design)
	✓	✓	✓
		✓	✓̸ (inferred)
			

✓*Note.* ✓ means the condition contains the corresponding peer investment history element. ✓̸ means that the element is not explicitly displayed but can be inferred from other information.

Condition A: Only Funding Percentage

Loan ID ▲	Rating	Loan Category	Amount	Yield	%Funded	Time Left
1	A	Debt Consolidation	$6,000.00	10.34%	66%	08d 12h
2	C	Debt Consolidation	$6,000.00	20.99%	65%	08d 18h
3	E	Debt Consolidation	$6,000.00	30.99%	67%	08d 08h

Condition B: Funding Percentage and Number of Participating Lenders

Loan ID...	Rating	Loan Category	Amount	Yield	%Funded	#Participating Lenders	Time Left
1	A	Debt Consolidation	$6,000.00	10.34%	66%	30	08d 12h
2	C	Debt Consolidation	$6,000.00	20.99%	65%	31	08d 18h
3	E	Debt Consolidation	$6,000.00	30.99%	67%	29	08d 08h

Condition C: Detailed Investment History

Loan ID...	Rating	Loan Category	Amount	Yield	%Funded	Time Left
1	A	Debt Consolidation	$6,000.00	10.34%	66%	08d 12h
2	C	Debt Consolidation	$6,000.00	20.99%	65%	08d 18h
3	E	Debt Consolidation	$6,000.00	30.99%	67%	08d 08h

Click to select a loan to view its bid history
1
2
3

Loan ID ❶...	Bid Amount	Bid Time ❷ ▲
1	$350.00	0d 0h28m51s
1	$100.00	0d 0h28m51s
1	$25.00	0d 0h2m56s
1	$25.00	0d 10h49m18s
1	$200.00	0d 1h12m8s
1	$200.00	0d 22h36m19s
1	$500.00	0d 2h38m43s
1	$25.00	0d 2h53m8s
1	$25.00	0d 2h9m51s
1	$25.00	0d 7h27m17s

Expected Returns of Three Loans

Loan ID	Probability and Returns
1	95% chance of earning EC 7 ; 5% chance of losing EC5.4
2	87% chance of earning EC16; 13% chance of losing EC58
3	77% chance of earning EC30; 23% chance of losing EC72.7

Figure 3-1. Study 1: Experiment Interface

Subjects who entered the formal experiment were randomly assigned to one of three groups, each displaying peer investment history differently: Condition A: displaying only the total funded amount and no other peer information; Condition B: displaying the number of participating lenders together with the total funded amount; and Condition C: displaying detailed transactional-level peer investment history. In Condition B, we presented subjects with a specific type of aggregated peer investment information: the number of lenders who have already placed investments into this loan (*#Participating Lenders*). This feature provided valuable insights of other investors' investment decisions as it reflects the average funding amount per lender and the overall crowd reactions towards the loan. Existing literature has highlighted the importance of this feature in influencing crowd herding behavior (Zhang and Liu 2012). *#Participating Lenders* was also set to be consistent across the three loans, as were the other loan features. For Condition C, we constructed bid transactions that exhibited similar bid amount and timing distributions for the three loans. After submitting their investment allocations, subjects need to complete a survey about their demographics, risk tolerance, and what features they relied on making decisions.

We took three steps to ensure participation quality. Firstly, all subjects were required to correctly answer three basic finance questions before entering the experiment. This initial financial knowledge check resulted in 746 respondents from Prolific who met the criteria and were eligible to participate in our experiment. Secondly, we administered a knowledge check to assess subjects' understanding of the experiment setup following the training session. Subjects had to answer all questions correctly, with no limit on the number of attempts. Failure to pass this check prevented subjects from proceeding to the formal experiment and receiving compensation. Out of the initial pool, 608 respondents (82%) successfully passed the knowledge check and were compensated for their participation. Lastly, during data processing, we filtered out subjects who exhibited either an excessively short duration (lowest 5%; 398 seconds) or long duration (highest 5%; 1736 seconds) within the experiment. This step aimed to exclude subjects who may have rushed through the tasks or spent an unusually long time, which could potentially affect the validity of the data. Ultimately, our final sample comprised 547 respondents.

3.4.2 Results

The final sample consisted of 187 subjects in Condition A, 192 subjects in Condition B, and 168 subjects in Condition C. To ensure no systematic bias was introduced, we surveyed subjects regarding their P2P investment experience, general investment experience, age, gender, income, and education level. No significant differences were found across any of these aspects among the three groups, indicating a balanced representation of subjects.

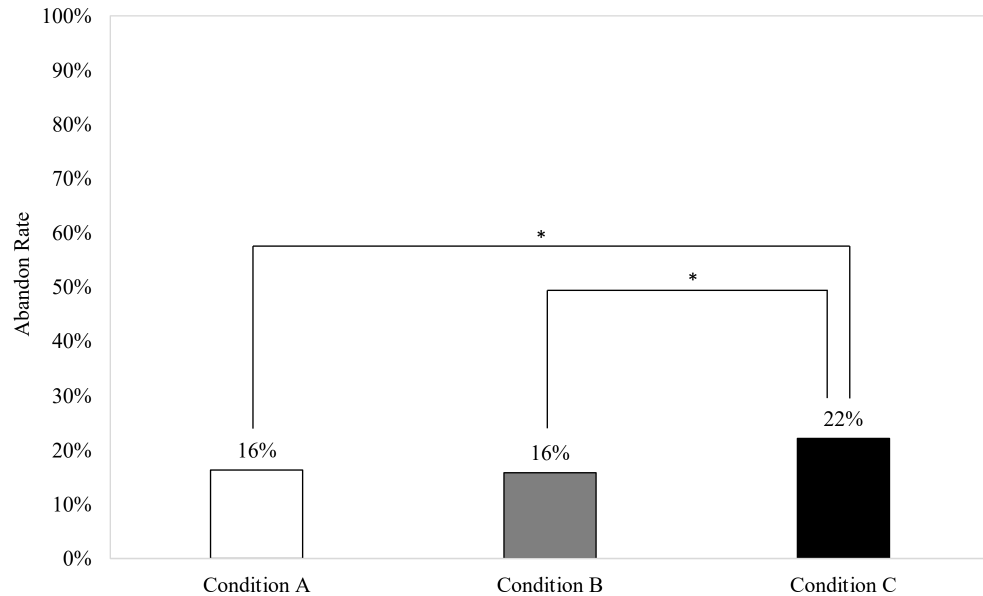
Before further analysis, we first conducted a pretest to confirm the successful design of the experiment. A separate group of 30 subjects underwent a similar procedure to the main study, but instead of allocating a budget, they were asked to evaluate the similarity among the three loans in all aspects. The results revealed that the three loans were indeed perceived to be identical in all aspects except their risks.

We next conducted a manipulation check to ensure that subjects accurately identified the display formats in the stimulus materials. The results indicated that subjects correctly recalled the display format of investment history in their respective groups, confirming the successful implementation of our display format manipulations.

3.4.2.1 Platform Abandonment

We first explored how displaying peer investment history influences investors' abandonment of a platform. As introduced in the experiment design, subjects underwent a knowledge check immediately after the training session and had to answer all three questions correctly to proceed to the formal experiment. While subjects were not limited in the number of attempts, some individuals chose to quit the experiment and forgo compensation after a few unsuccessful attempts at this stage. Thus, we used the abandonment rate of this knowledge check as an approximation of platform abandonment of different display designs. The abandonment rate was calculated by dividing the number of subjects who failed the knowledge check by the total number of subjects. A higher abandonment rate indicated that subjects found the website layout harder to learn and were more likely to leave the platform, while a lower abandonment rate suggested lower learning friction and higher platform usage. To mitigate the potential influence of unserious subjects, we filtered out those who spent either too short or too long time in the training process within each group. Figure 3-2 shows the passing rate for each group.

To assess the significance of the observed differences, we conducted an ANCOVA with the passing dummy as the dependent variable, groups as a between-subject factor, and subjects' learning time as a covariate. The results suggested a significant difference among the three groups ($F(2, 724) = 4.03$, $p = 0.0181$). Pairwise comparisons showed that the abandonment rate of Condition C ($M_C = 22.22\%$) was significantly lower than Condition A ($M_A = 16.39\%$, $t(476) = 1.62$, $p = 0.1066$) and Condition B ($M_B = 15.94\%$, $t(483) = 1.77$, $p = 0.0780$). Meanwhile, there was no significant difference between Condition A and B ($t(493) = 0.14$, $p = 0.8904$). Hence, more investors were inclined to abandon the platform when the detailed investment history was present and the interface was more complex. Our hypothesis H1 is supported.

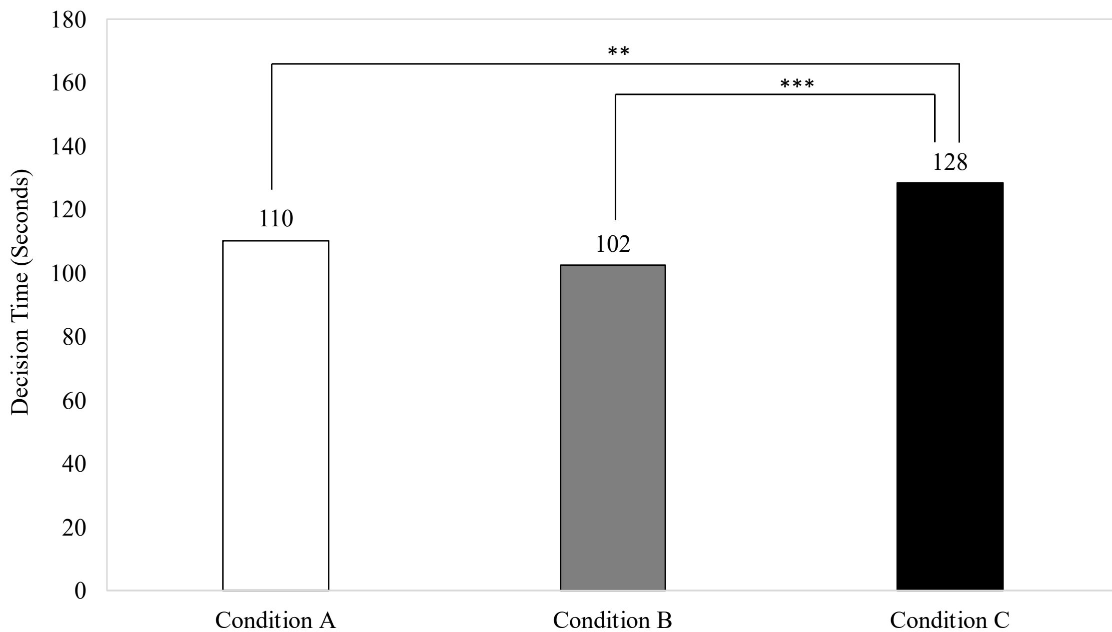


Notes. Pairwise comparisons show that the passing rate of the knowledge check in Condition C is significantly lower than that of Condition A and B. Condition A displays only total funding percentage; Condition B displays the number of participating lenders together with total funding percentage; Condition C displays detailed investment history together with total funding percentage. Significance levels are denoted by * at p <.10, ** at p < .05, and *** at p < .001.

Figure 3-2. Study 1: Investors More Likely to Abandon Platforms When Full Investment History is Presented

3.4.2.2 Decision Time

We continued to examine the decision speed of subjects, which was measured by the total time they spent on allocating their 1000 EC to the three loans. Figure 3-3 showed the total decision time in seconds across the three experimental groups. To explore the effect of peer investment history design on decision time, we conducted an ANCOVA with design groups as a between-subject factor and subjects' learning time as a covariate. The results indicated a significant difference in decision time across the three groups ($F(2, 543) = 5.76$, $p = 0.0034$). In line with H2, Condition C spent significantly more time on average (M_C = 128.44 seconds) than Condition A (M_A = 110.29 seconds, $t(353) = 1.96$, $p = 0.0509$) and Condition B (M_B = 102.47 seconds, $t(358) = 2.82$, $p = 0.050$). Condition B, surprisingly, spent the shortest time on average among the three groups, though it was not significantly shorter than Condition A ($t(377) = -0.97$, $p = 0.3330$). Hence, the inclusion of the *#Participating Lenders* feature did not prolong subjects' decision time compared to not displaying any peer investment history. Our hypothesis H2 was supported.

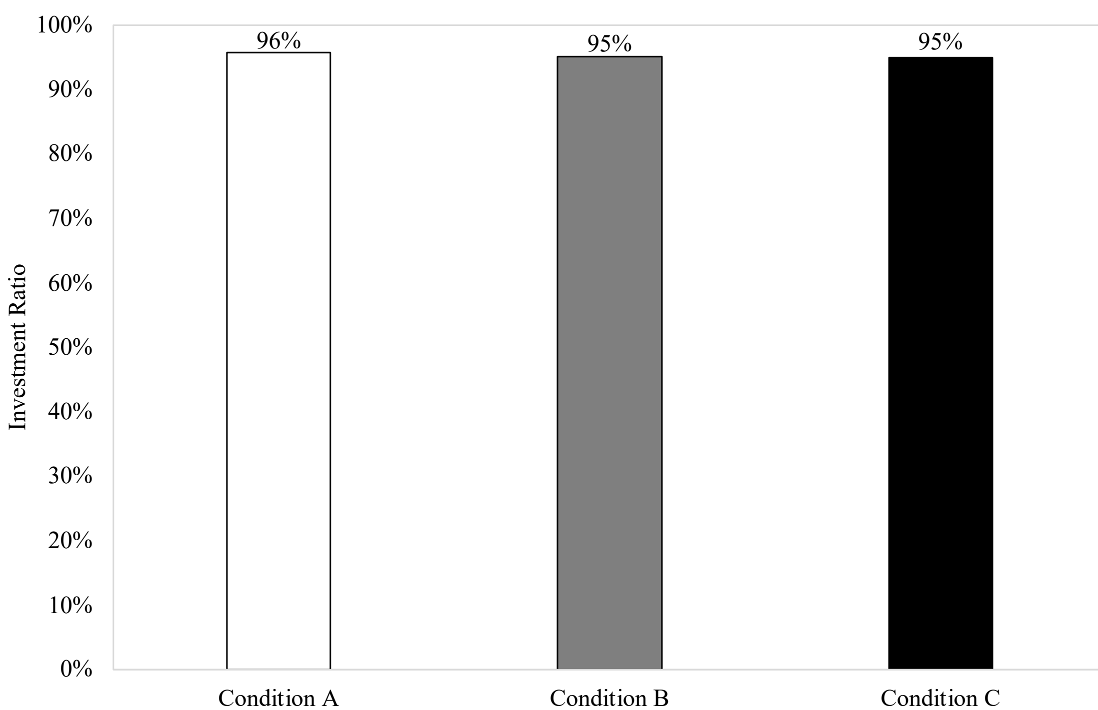


Notes. Pairwise comparisons show that subjects in Condition C spent significantly longer time than the those in Condition A and B. Subjects are based on those who did not abandon the platform. Condition A displays only total funding percentage; Condition B displays the number of participating lenders together with total funding percentage; Condition C displays detailed investment history together with total funding percentage. Significance levels are denoted by * at p <.10, ** at p < .05, and *** at p < .001.

Figure 3-3. Study 1: Subjects Require More Time to Make Decisions When Full Investment History is Presented

3.4.2.3 Investment Willingness

The third crucial aspect of investment behavior pertained to subjects' willingness to invest. We measured each subject's investment willingness by the ratio of the total invested amount to the total 1000 EC they were provided. Figure 3-4 displayed the results of *Investment Ratio* of the three groups, which were very close (M_A = 95.67%, M_B = 95.49%, and M_C = 94.75%). We conducted an Analysis of Covariance (ANCOVA) with investment ratio as the dependent variable, groups as a between-subject factor, and subjects' risk tolerance and learning time as covariates. Results suggested that the three groups did not differ in investment ratio ($F(2, 521) = 0.23$, $p = 0.7944$). Pairwise comparisons also confirmed that the investment ratio did not differ significantly between any group pairs. Hence, individual-level investment willingness was similar across different displays, and the hypothesis H3 was partially supported.

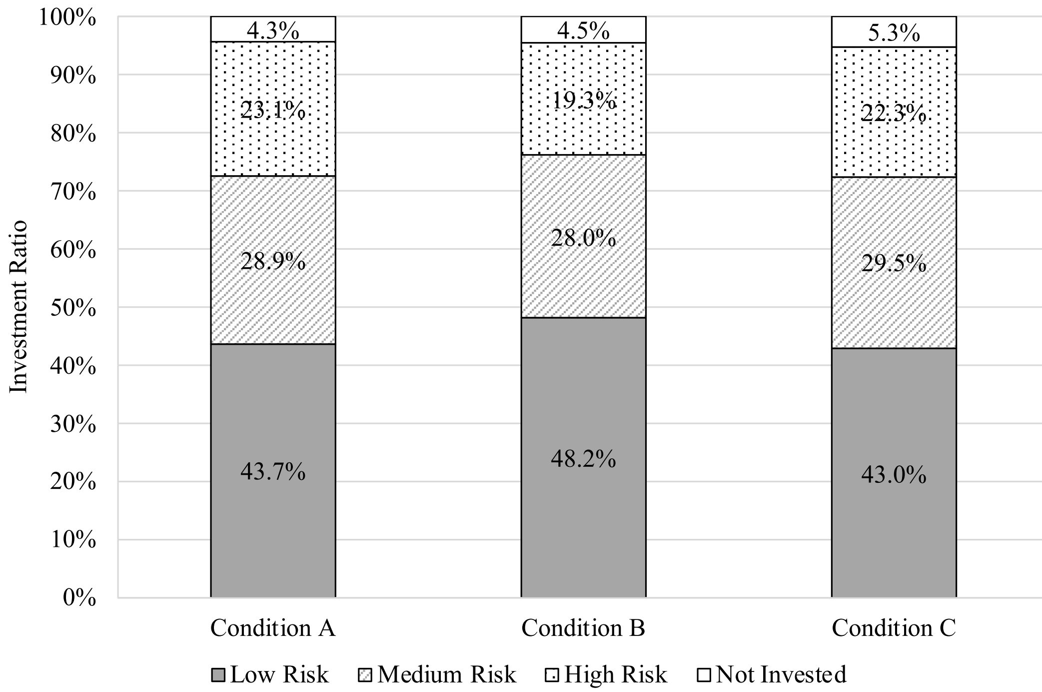


Notes. Pairwise comparisons show that the three groups do not differ significantly in individual-level total investment ratio. Condition A displays only total funding percentage; Condition B displays the number of participating lenders together with total funding percentage; Condition C displays detailed investment history together with total funding percentage.

Figure 3-4. Study 1: Investment Willingness Not Significantly Different across Displays

3.4.2.4 Risk Preference

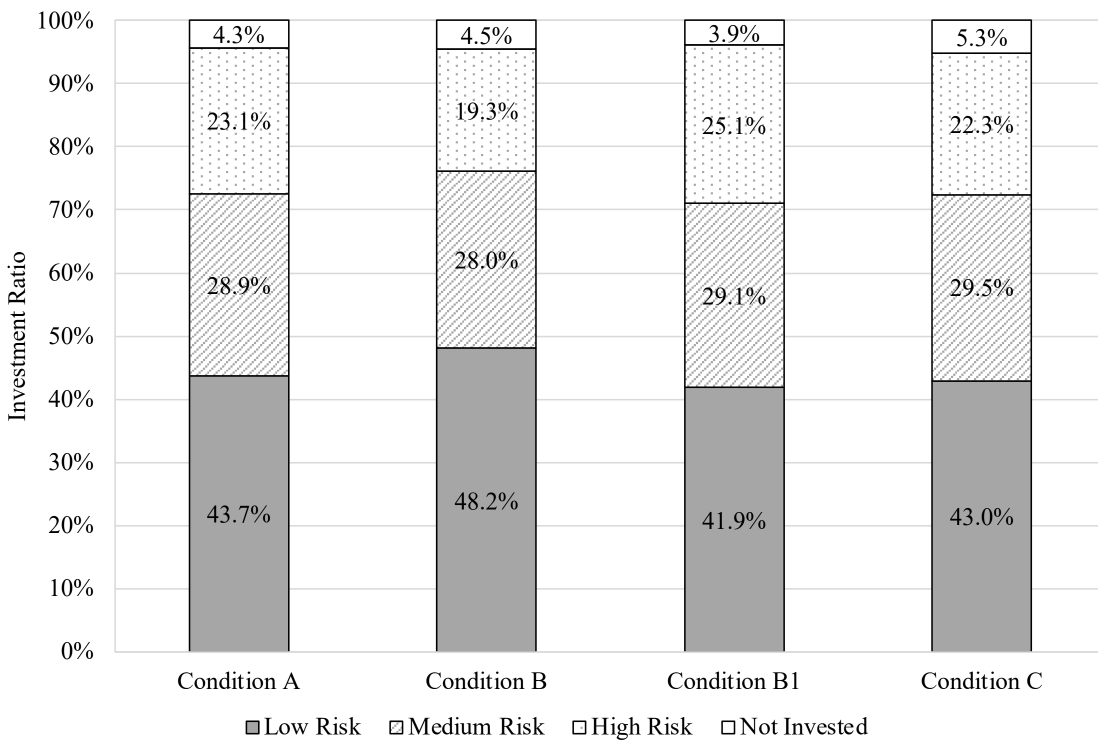
Next, we explored the impact of peer investment history display on risk preference, measured by investors' fund allocation across loans of differing risk levels. For each risk level, we calculated its corresponding investment ratio by the invested amount of the loan out of the total 1000 EC a subject owned. Figure 3-5 displayed the risk preference of the three groups. We first find that the investment allocations of Condition A and Condition C demonstrated strong similarity (43.7% vs. 43.0% in low-risk, 28.9% vs. 29.5% in medium-risk, and 23.1% vs. 22.3% in high-risk), and pairwise tests revealed no significant difference between any pairs of loans. In contrast, subjects in Condition B invested more in low-risk loans and less in high-risk loans, while remaining a similar level of medium-risk loan investment. In other words, subjects in Condition B were more risk averse than the other two conditions.



Notes. Condition A displays only total funding percentage; Condition B displays the number of participating lenders together with total funding percentage; Condition C displays detailed investment history together with total funding percentage.

Figure 3-5. Study 1: Subjects More Risk Averse in Condition B

To further test H4 and investigate the *variation* of risk preference, we collected data from another experiment group on the same day as the original experiment. This new group was identical to the original Condition B, with the exception that we manipulated the *#Participating Lenders* to reflect lower numbers (8, 9, and 7 for Loans 1, 2, and 3, respectively). With the total funded amount of a loan constant, a smaller number of prior lenders implies a larger average funding amount per lender. The new group served as a representation of varying actions from the prior lenders. We designated the new Condition B group as Condition B1. Figure 3-6 shows the comparison of the four groups. We find that the two Condition B showed noticeable variation in high- and low-risk loans when compared to Condition A and C. The risk preference depends on the number of prior lenders: when the number of prior lenders was large (indicating a lower average funding amount), lenders were more conservative and invested more in low-risk loans; conversely, when the number of prior lenders was small (signifying a higher average funding amount), investors showed a preference for higher risk. This divergence between the two Condition B groups suggested that the risk preference of subjects exposed to an aggregated peer information display, relative to no or detailed peer information display, was more sensitive to other peers' behavior. H4 was supported.



Notes. Both Condition B and B1 display the number of participating lenders together with total funding percentage. The only difference between the two groups is the numbers shown in the number of participating lenders feature: Condition B displays larger numbers, while Condition B1 displays smaller numbers.

Figure 3-6. Study 1: Investor Risk Preference Varies More When Aggregated Investment History is Presented

We also conducted a separate test to examine the heterogenous effects of aggregated investment history display on risk preference across lenders with different inherent risk tolerance. We categorized subjects into three groups–risk-averse, risk-neutral, and risk-seeking–based on their responses to a lottery task.[16] Not surprisingly, risk-averse subjects, when compared to their risk-seeking counterparts, allocated more of their investments towards low-risk loans and less towards high-risk loans on average. However, the disparities between the two Condition B groups were noticeably larger among risk-seeking subjects than among risk-averse subjects. Further multivariate regressions revealed that the interaction between inherent risk tolerance and the number of prior lenders displayed (large vs. small) was significant for both low-risk and high-risk loans. Thus, these results highlighted the heterogeneous effect of the aggregated display on investors' risk preference: risk-seeking lenders were more sensitive to peer behavior information than their risk-averse counterparts.

Additionally, we conducted a supplementary analysis on subjects' usage of loan features. The results indicated that the group exposed to detailed investment history rarely utilized the provided features, while the group exposed to aggregated investment history made more use of the *#Participating Lenders* feature.

[16] To measure subjects' risk tolerance, we adopted the lottery tasks that were initially proposed by Holt and Laury (2002) and have been used as a standard technique in the experimental economics literature (Carson et al. 2022). Subjects were asked to make hypothetical choices between guaranteed payments and gambles in the post-experiment survey (see Appendix A5-3 for the interface). According to their choices, we classified subjects as risk averse, risk neutral, and risk seeking. The distribution of risk tolerance did not differ significantly between the two Condition B groups.

3.4.3 Discussion

By directly manipulating the display of peer investment history and measuring multiple outcome variables, Study 1 provided supporting evidence for the hypotheses about abandonment rate (H1), decision speed (H2), and investment amount (H3), and challenged the hypothesis about risk allocation (H4). When detailed investment history was available, a higher number of subjects quit the experiment after learning the basic setup, and those who stayed also took significantly longer time to make decisions. In contrast, displaying certain highly representative information of investment history *(#Participating Lenders*) did not affect participation or decision time compared to not displaying any investment history. Taken together, our findings about detailed investment history (higher abandonment rate and longer decision time) suggested that it was highly likely to lead to information overload for retailer investors.

Conditional on subjects accepted the experimental setup and entered the formal experiment, subjects' total investment amount did not vary across different display designs. However, when the number of prior lenders was available, subjects exhibited more active reactions in terms of risk preference compared to the other two conditions. Subjects were more risk-seeking when the number of prior lenders was low and more risk-aversion when the number of prior lenders was high. In other words, the display of aggregated investment history amplified subjects' reactions to peer bidding behavior. This amplification effect was particularly pronounced among risk-seeking subjects.

Our experiment in this study was conducted at the portfolio level, where subjects were presented with multiple loans and had to distribute their investment amount among them. We believe this approach accurately emulates the investment process on P2P lending platforms and replicates real-world scenarios. However, there may be instances where investors have limited investment opportunities and need to decide whether to invest in one individual listing. Additionally, the experiment in this study simplified the loan selection process by displaying limited loan features, while investors may need to consider a broader range of loan and borrower characteristics in reality. To address concerns regarding the observation level and decision complexity, we incorporated an alternative design at the individual loan level in Study 2.

3.5 Study 2: Experiment

The primary objective of Study 2 was to examine the robustness of our previous findings in a binary decision setting, in which subjects were also required to process more loan features. Building upon the similarities observed between Condition A and Condition B in Study 1, the focus of this study was to compare Condition A with Condition C.

3.5.1 Procedure

Similar to the experiment conducted in Study 1, subjects were instructed to imagine themselves as P2P lenders and make investment decisions regarding loan requests. However, instead of allocating a fixed budget across multiple loans, subjects were sequentially presented with three separate loan listings at different risk levels (low, medium, and high separately). They were required to make binary decisions for each listing by selecting either “Bid” or “Not bid.” The three loans were constructed as the most typical loans from the actual Prosper dataset (see Study 3 for more details about the dataset). We also randomized the order in which the three loans were displayed to mitigate potential ordering effects.

Subjects who successfully passed the financial knowledge check and interface training were randomly assigned to one of two groups: Condition A, which did not include any peer information; or Condition C, which provided transactional-level investment history. An illustration of the experiment interface can be found in Figure 3-7. The remaining procedures mirrored those of the experiment conducted in Study 1. We also ensured that our sample consisted of subjects who demonstrated an adequate understanding of finance, familiarity with the experiment setup, and a reasonable duration of engagement with the tasks.

Condition A Condition C

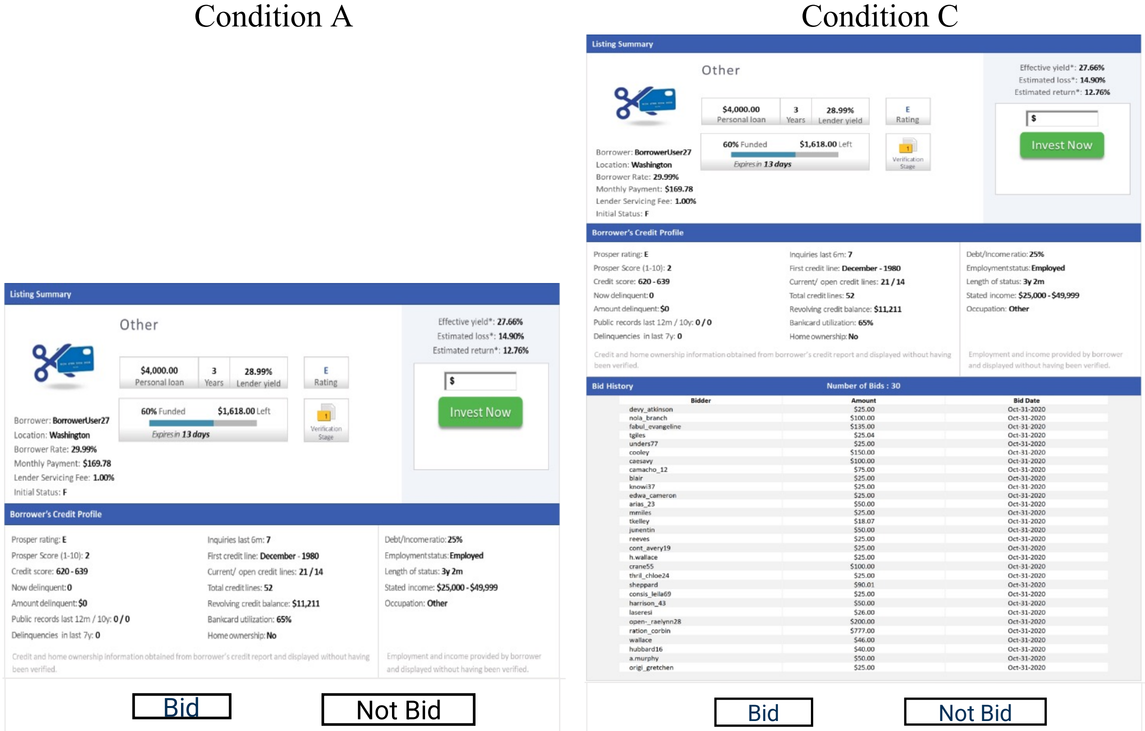


Figure 3-7. Study 2: Experiment Interface

3.5.2 Results

The final sample consisted of 238 subjects in the Condition A group and 227 subjects in the Condition C group. To ensure no systematic bias is introduced, we checked subject similarity between the two groups and found no significant difference in their demographics and P2P investment experience. Table 3-2 displays the results of Study 2.

Table 3-2. Study 2: Results

	#Observations		Mean		Difference
	Cond A	Cond C	Cond A	Cond C	= Cond C - Cond A
Panel A: Platform Abandonment					
Abandonment rate	303	409	0.221	0.379	0.158*** (0.035)
Panel B: Decision Time					
Total time for 3 loans	236	254	45.846	53.899	8.053** (3.607)
Time for 1 loan	708	762	15.282	17.966	2.684** (0.845)
Time for low risk loan	236	254	14.271	17.045	2.775** (1.276)
Time for medium risk loan	236	254	17.050	19.919	2 .869* (1.728)
Time for high risk loan	236	254	14.526	16.934	2 .409* (1.335)
Panel C: Investment Willingness					
#loans invested by one lender	236	254	2.085	2.098	0.014 (0.061)
Bidding probability of all loans	708	762	0.695	0.699	0.005 (0.024)
Bidding probability of low risk loans	236	254	0.877	0.909	0.033 (0.028)
Bidding probability of medium risk loans	236	254	0.835	0.843	0.008 (0.034)
Bidding probability of high risk loans	236	254	0.373	0.346	-0.026 (0.043)

Notes. Condition A displays only total funding percentage; Condition B displays the number of participating lenders together with total funding percentage; Condition C displays detailed investment history.

3.5.2.1 Platform Abandonment

We first examined the subjects' platform abandonment rate, as shown in Table 3-2 Panel A. Similar to our previous finding, the *t*-test showed that the abandonment rate of Condition C (62%) was much high than that of Condition A (78%), probably due to the significantly more complicated design of Condition C. The result supported H1. Given the large difference in the abandonment rate, we intentionally assigned more subjects to Condition C in this experiment to ensure a relatively balanced dataset for the subsequent tests on decision time, investment willingness, and risk preference.

3.5.2.2 Decision Time

Next, we compared the time that the subjects spent in making investment decisions. Table 3-2 Panel B displayed the results of decision time in seconds. A *t*-test showed that the total time spent by the subjects in Condition A (45.85 seconds) was significantly shorter than that spent by those in Condition C (53.90 seconds), and the average time spent investing in one loan showed a consistent result. These results evidenced the faster response time when detailed investment history was unavailable. The hypothesis H2 is supported.

We further conducted a separate test for the heterogeneous effects across different risk levels. The subjects spent the most time in medium-risk loans, irrespective of the displays. The time difference between the two groups was also larger in the medium-risk loan (2.87 seconds) than the difference in the low- or high-risk loans (2.78 and 2.41 seconds). This result is probably due to the uncertainty of medium-risk loans: while lenders seek secure returns in low-risk loans and seek high returns in high-risk loans, the decisions for medium-risk loans are not easy, given the tradeoff between risk and returns.

Hence, lenders are more likely to refer to their peers' decisions for more cues when investing in medium-credit loans, which results in a longer decision time. When peer information is unavailable, decision time also decreases the most in medium-risk loans.

3.5.2.3 Investment Willingness and Risk Preference

While our primary purpose of this experiment was not to examine subjects' investment willingness and risk preference,[17] we performed a series of comparisons on subjects' funding decisions and presented the results in Table 3-2 Panel C. We measured investment willingness by (A) the total number of loans a subject bids on (first row in Panel C) and (B) the likelihood that a subject selects "Bid" for a loan (second to fifth rows in Panel C). From the first two rows in Panel C, we could see that the overall investment willingness of Condition A and C was insignificant between the two groups. The results confirmed our results from Experiment 1 and refused our hypothesis H3.

To examine subjects' risk preference, we measured the bidding probability of the three loans at different risk levels separately. The *t*-tests showed that the bidding probabilities were insignificant between the two groups within any subsamples. In other words, the risk preference was similar in Condition A and C, consistent with our hypothesis H4 and our findings in Study 1.

It is worth noting that the bidding probabilities in low- and medium-risk loans were much higher than that in low-credit loans, regardless of the display designs. This result indicated a dominant position of the credit risk feature, consistent with the findings in the literature (Liao et al. 2021). Meanwhile, the bidding probability of Condition A

[17] The experiment design required subjects to make binary decisions for each loan and did not limit the number of loans they could select. When there is no budget limitation, the measure of investment willingness and risk preference may not be accurate.

was closer to the middle point (0.5) while Condition C was more extreme (closer to 0 or 1) within every risk. Since subjects could only choose to “bid” or “not bid” for each loan, the average bidding probability should gravitate towards 0 (where most subjects choose “not bid”) or 1 (where most subjects choose “bid”) if there was greater consensus within a group. Conversely, an average bidding probability closer to 0.5 would indicate a higher degree of divergence among subjects. Thus, subjects in Condition A were more diverse in opinions than those in Condition C, suggesting that investment history may strengthen the signals by the predominant credit risk feature.

3.5.3 Discussion

Study 2 provided more nuanced insights into our questions. It not only supported all the hypotheses but also revealed that the differences in decision time between Condition A and C were most prominent in medium-risk loans. In other words, investors were more likely to refer to peer information when confronted with challenging choices.

The primary benefit of the experimental methodology used in Studies 1 and 2 was to manipulate peer investment history displays that are not typically found together in a single real-world platform. Further, the simplification allowed us to bypass potential confounding factors and directly investigate the influence of information displays on investor behavior. However, this design necessitated a certain level of artificiality in both the experimental task and the investment histories. To address these concerns, we turn our attention to real-world dataset in Study 3.

3.6 Study 3: Investment History Removal on Prosper

The primary goal of Study 3 was to examine the impact of peer investment history in a real-world setting. To control for the potential confounding factors in observational data, we utilize a sudden policy change happened on Prosper.com, one of the largest P2P lending platforms in the US. Prosper used to display transaction history on each listing's webpage in addition to other loan and borrower features. The investment history presented all the bids that have been placed to the listing before the focal moment, including lender username, bid amount, and bid time.[18] On March 1, 2013, Prosper unexpectedly removed the investment history from listing webpages, leaving all the other characteristics the same (similar to our experiment design in Study 2). While we were only able to access Prosper's loan-level data (rather than bid level), which limited our analysis to coarser aggregates, this design change provided a unique opportunity to compare the impact of detailed investment history display with no investment history display in a real-world setting without being confounded by other time trends.

3.6.1 Dataset, Variables, and Methods

The dataset for this study was obtained directly from the Prosper API, where the smallest unit of analysis was listings. For each loan, we collected various loan and borrower characteristics. To control for potential time trends and market factors, we first constructed a sample that comprised listings starting their funding campaigns within a short time window: 5 weeks before and 5 weeks after the website change (i.e., January 25

[18] To be consistent with the literature, we refer to each investment as a "bid". However, Prosper implemented a fixed interest rate model rather than an auction model during the time throughout our dataset.

to April 4, 2013). We conducted a comprehensive search of news and announcements about Prosper and found no other significant changes that occurred during this time period, ensuring that our analysis was not confounded by other events. To further minimize the influence of confounding factors related to individual listings and borrowers, we employed the propensity score matching (PSM) method: Each listing that started after the website change was matched with a listing that began before the change. The matching was performed based on the four most critical loan characteristics: Credit Risk, Term, Amount Requested, and Yield. Credit Risk consisted of three levels: low risk (AA or A credit rating), medium risk (B, C, or D credit rating), and high risk (E or HR credit rating). Term represented the length of the loan maturity, with options of 1-Year, 3-Year, and 5-Year. Amount Requested denoted the dollar amount requested by the borrower Yield indicated the interest rate that lenders could earn.

We conducted the empirical analysis using the following model:

$$Y_i = \beta_0 + \beta_1\, Post_i + \tau X_i + \varepsilon_i \tag{3-1}$$

where Y_i represented the dependent variable of Listing i, which was funding likelihood or funding speed. $Post_i$ took a value of zero if Listing i started before the website change (i.e., Week -5 to Week -1) and a value of one if Listing i started after the website change (i.e., Week 1 to Week 5). X_i was a vector of control variables, including loan characteristics, borrower characteristics, and market-related controls. Loan characteristics included all the variables we used for matching and the following variables: *Category,* the category of the loan, business, debt consolidation, and others; *Day-of-Week*, the day of the week for the first funding day. Borrower characteristics included *Income*, a categorical variable representing five levels of income range; *Homeowner*, a dummy variable that equaled one if the borrower owns a home and zero otherwise. Market-related controls included *Stock Market Return*, the average of daily market returns over the five trading days prior to a loan's first funding day; *Stock Market Volatility*, the standard deviation of daily market returns over the five trading days prior to a loan's first funding day; *Credit Spread*, the spread between the 5-year High Quality Market (HQM) corporate bond yield and the 5-year treasury yield for high- and medium-risk loans, or the spread between the 5-year high-yield CCC or below bond yield and the 5-year treasury yield for high-risk loans. To further control for the time trend, we constructed a series of financial market and Prosper market control variables: *Google Trend of Prosper*, an index reflecting the popularity of the search query "Prosper" in Google; *Number of Listings*, the number of newly posted listings on the first funding day of the listing; *Number of New Lenders*, the number of newly registered lenders on the first funding day of the listing.

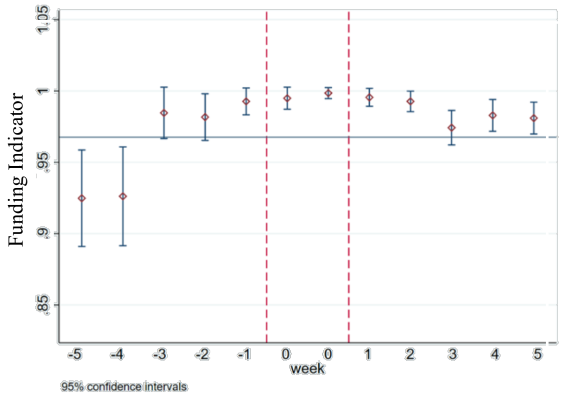
3.6.2 Data Analysis and Results

<u>3.6.2.1 Funding Likelihood</u>

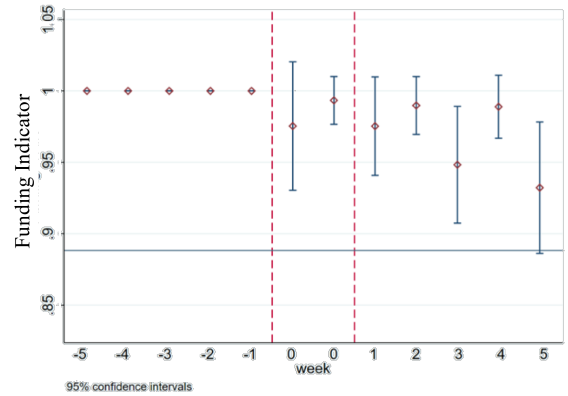
We began our analysis by examining the funding likelihood of listings. Two aspects of investor behavior could influence funding likelihood: the overall participation of all the lenders on the platform and each lender's investment willingness. Based on our hypotheses and results from the controlled experiments, we expected an increase in lender participation (H1: decrease in lender abandonment) and no change in each lender's investment willingness (results from Experiment 1 and 2) after the removal of detailed history. Therefore, assuming all else remained equal, the total funding likelihood, which is a product of these two factors, should only increase rather than decrease or remain unchanged.

We approximated the funding likelihood using *Funding Indicator*, which equaled one if a listing was successfully funded and zero otherwise. We first presented some model-free evidence of *Funding Indicator* in Figure 3-8. Panel A displayed the result of all the matched listings. Although the funding probability was already high before the investment history removal (almost 100%), it slightly increased after the removal. Next, we performed the multivariate estimates using Equation (1) with *Funding Indicator* as the dependent variable. Table 3-3 Panel A presented the results. Column (1) and (2) displayed the results using the full sample, while Column (3) and (4) used the matched sample described above. Columns (1) and (3) presented the findings without any control variables, whereas Columns (2) and (4) included all the controls. Across all four columns, the results consistently indicated a significant increase in the probability of funding after removing investment history, confirming our observation from Figure 3-8. Additional marginal analyses revealed that listings were 1.59% - 3.14% more likely to be fully funded after the investment history removal. Therefore, the results are in line with H1 and our previous results.

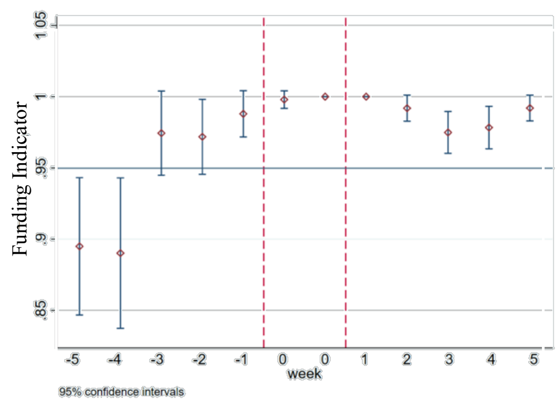
Panel A. All Matched Loans



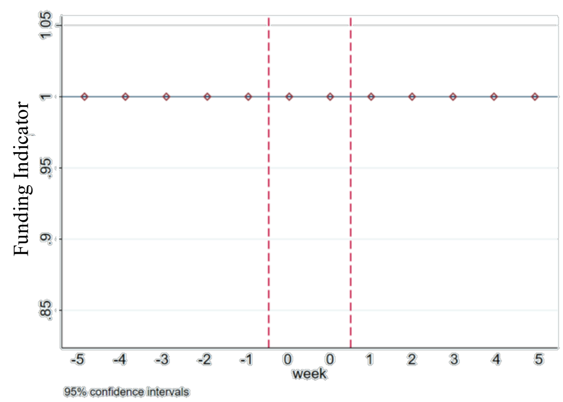
Panel B. Low-Risk Loans



Panel C. Medium-Risk Loans



Panel D. High-Risk Loans



Notes. The graphs plot the average funding likelihood of the matched listings by week with confidence intervals at 95% level. Since Prosper listed a loan request up to 14 days on their website and we aggregate listings to their funding start date, the website design change started to affect listings up to 14 days (i.e. 2 weeks) before the change. Hence, the time window was 12 weeks in total: 5 weeks before the event, 2 weeks during the event (since each listing had up to 14 days for lenders to fund), and 5 weeks after the event. The dashed red vertical line on the left represented the time that the event started to affect listings, and the right vertical line represented the exact time of the event. The horizontal solid blue line represented the mean of Week -5~-1 (5 weeks). The sample was winsorized at 1% and 99% to mitigate the influence of outliers.

Figure 3-8. Study 3: Funding Likelihood

Table 3-3. Study 3: Funding Likelihood and Funding Speed

	(1)	(2)	(3)	(4)
	Full Sample		Matched Sample	
Panel A: Funding Indicator				
Post	0.950***	1.206***	0.703**	1.085**
	(0.195)	(0.381)	(0.306)	(0.506)
Observations	4,575	3,813	4,066	3,341
Loan Characteristics	NO	YES	NO	YES
Borrower Characteristics	NO	YES	NO	YES
Market-Related Controls	NO	YES	NO	YES
Panel B: Funding Hours				
Post	-39.388***	-49.143***	-45.935***	-51.226***
	(2.805)	(3.314)	(4.624)	(4.686)
Observations	3,031	3,031	2,726	2,726
Loan Characteristics	NO	YES	NO	YES
Borrower Characteristics	NO	YES	NO	YES
Market-Related Controls	NO	YES	NO	YES

Notes. This table presents the estimates of Model (1). *Post* takes a value of zero for a loan started before the website change and one for a loan started after the website change. The dependent variable in *Panel A* is *Funding Indicator*, which equals one if a loan is successfully funded and zero otherwise. The dependent variable in *Panel B* is *Funding Hours*, which is measured by the number of hours of the loan campaign. Panel A estimates a Probit regression model, and Panel B estimates an OLS regression model. The data is winsorized at 1% and 99% level to mitigate the influence of outliers. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Robust standard errors in parentheses.

Furthermore, we investigated the heterogeneous effects across credit risks and plotted the results in Figure 3-8 Panels B, C, and D. Only medium-risk loans experienced a large increase in funding probability (Panel C), compared to the slight decrease in low-risk loans (Panel B) and no change in high-risk loans (Panel D). We also conducted multivariate analyses on credit risk subsamples, and the results showed a significant increase in the funding probability for medium-risk listings, while no significant changes were observed for low- or high-risk listings (results not reported here). However, it is worth noting that these results were primarily attributed to the extremely high funding likelihood of low- or high-risk listings (almost 100%), and thereby lenders had no more available options. Consequently, we were unable to examine the changes in investors' risk preferences (H4) as reflected in their investment allocation across credit risks.

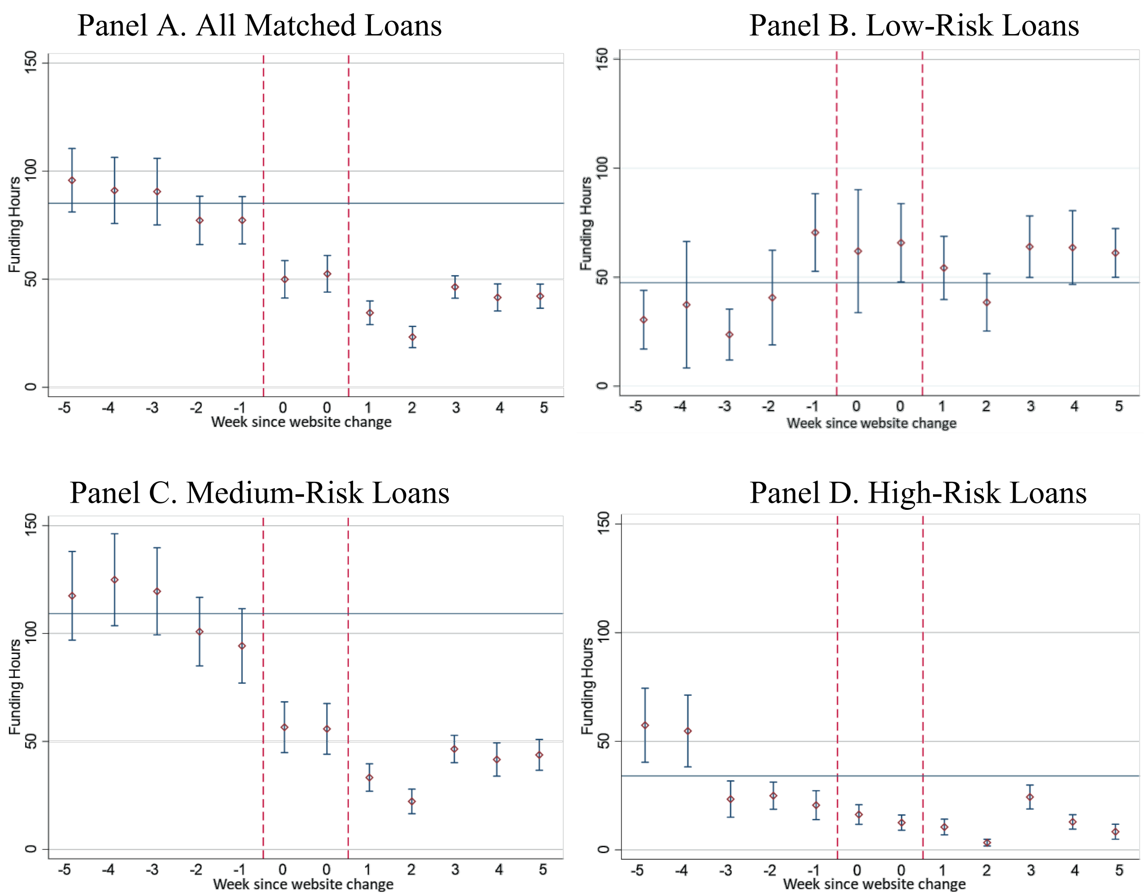
3.6.2.2 Funding Speed

Having estimated the change of funding likelihood, we turned our attention to funding speed. Similar to funding likelihood, funding speed of all listings on the platform is also influenced by two factors: the overall participation of all the lenders on the platform and each lender's decision time. Based on our hypotheses, we expected an increase in loan funding speed after the removal of detailed history due to a decrease of platform abandonment (H1) and an increase in decision speed (H2).

As our data from Prosper was on the loan level, we measured funding speed by the total funding time of each listing campaign in hours (*Funding Hours*). For this analysis, we restricted our sample to fully funded loans, as unfunded listings do not have an end time. Our robustness checks using the Heckman selection model and censored regression models with all the listings were qualitatively consistent with our findings.

Similar to the matching performed for the funding likelihood tests, we constructed a matched loan sample employing the same matching method and loan features. Our tests of *Funding Hours* started with some nonparametric comparisons, as depicted in Figure 3-9 Panel A. On average, the total funding time of a loan decreased from 85 hours to 38 hours after the investment history removal. A *t*-test showed that this time reduction was statistically significant at the 1% level. Our multivariate analysis verified the observations from the figures. Table 3-3 Panel B reported the estimates using Model (1) with *Funding*

Hours as the dependent variable. Across different columns, the coefficients associated with our variable of interest, *Post*, consistently indicated a decrease in funding hours (about 39-51 hours). In other words, listings on the market were collectively funded faster after the removal of investment history. Our results are in line with H1 and H2.



Notes. The graphs plot the average funding hours of the matched loans by week with confidence intervals at 95% level. Since Prosper listed loans up to 14 days and we aggregate the loans to their funding start date, the website change started to affect loans up to 14 days (i.e. 2 weeks) before the event. Hence, the time window is 12 weeks in total: 5 weeks before the event, 2 weeks during the event (since each loan has up to 14 days for lenders to fund), and 5 weeks after the event. The left dashed red vertical line represents the time that the event started to affect loans and the right dashed red vertical line represents the exact time of the event. The horizontal solid blue line represents the mean of Week -5~-1 (5 weeks). The sample is winsorized at 1% and 99% to mitigate the influence of outliers.

Figure 3-9. Study 3: Funding Speed

We also examined the change of funding speed for loans in different credit risks. Comparing the loans of low, medium, and high risks in Figure 3-9 Panel B, C, and D, we observed that prior to the website change, medium-risk loans exhibited significantly longer funding hours (109 hours) compared to low-risk loans (47 hours) or high-risk loans (34 hours). However, medium-risk loans experienced the most substantial decrease in funding hours after the website change (a decrease of 71 hours), while low-risk loans showed no significant change and high-risk loans decreased by 21 hours. Consistent with these observations, our multivariate analysis showed the funding hours for medium-risk and high-risk loans significantly decreased by 76 hours and 20 hours, respectively, while the coefficient for low-risk loans was positive and insignificant (results not reported here in the interest of space). Hence, the investment history removal resulted in the most substantial increase in funding speed for medium-risk loans, a finding that was consistent with our conclusion in Study 2.

3.6.3 Discussion

Utilizing the unexpected website design change from Prosper.com, Study 3 supplemented the first two studies by providing real-world evidence for our hypotheses. After the transactional-level investment history was removed, listings were more likely to be funded and got fully funded faster. The empirical findings supported our hypotheses H1, H2, and H3, and demonstrated the generalizability and robustness of our findings from the experiments.

Although our analysis was conducted at the loan level due to data constraints, we ensured that our sample was limited to a specific time window, during which no other confounding events happened. Moreover, the concerns of analysis level and confounding factors were not applicable to the experiments in Studies 1 and 2, which directly tested individual-level effects and held constant the market-level factors, and still obtained qualitatively consistent results.

3.7 Conclusions and Implications

Despite the wide recognition of peer influence in crowd-based platforms, the effects of peer information display on subsequent investors' decision-making are not yet well understood. This chapter addresses this gap by empirically examining how disclosure (disclose or hide) and presentation (aggregated or detailed) of peer investment history impact individual investors' decision-making. We conducted two online controlled experiments and analyzed a peer information design change that happened on a crowdfunding platform. Together, the three studies provided converging evidence (summarized in). Although each individual's investment willingness does not differ significantly under different investment history displays, more individuals are willing to engage with the platform when such information is simpler (no or aggregated investment history). Lenders presented with detailed investment history also spend significantly longer time in making decisions than those presented with the other two displays, especially when investing in medium-risk loans. Compared with no or detailed display, lenders presented with a moderate amount of aggregated peer investment history react the most in risk preference – they are more risk-seeking (averse) when the average funding amount of prior lenders is high (low). Such an effect is particularly strong for risk-seeking investors.

Table 3-4 Summary of Findings

Display	Number of participating lenders	Detailed investment history	Supported by
Platform abandonment	Same low level	Higher	Exp1, Exp2, Prosper
Decision speed	Same fast speed	Slower	Exp1, Exp2, Prosper
Investment willingness	Same	Same	Exp1, Exp2, Prosper
Risk Preference	Easier influenced by peers	Same	Exp1

3.7.1 Theoretical Implications

This study makes a number of theoretical contributions. To the best of our knowledge, this study is one of the first to provide both empirical and experimental evidence on the role of peer investment behavior display in financial decision-making. Our results highlight the importance of the level of detail in peer information presentation. Overly detailed information can overwhelm the cognitive capacity of retail investors, the typical users of online financial platforms, and thereby lead to reduced engagement and lower investment efficiency. In contrast, better information presentation can reduce retail investors' information overload, therefore reducing their platform abandonment and enhancing decision-making efficiency. Our study also depicts the factors influencing information saliency: physical prominence does not guarantee higher saliency for a feature; instead, increased cognitive accessibility can make features more compelling and draw more attention from decision-makers.

Our research also sheds light on the decision-making processes of investors when faced with varying levels of complexity and highlights the value of peer information in complicated decisions. Investors dealing with straightforward choices often make quick decisions based on obvious evidence. However, when facing ambiguous choices such as loans with medium-level risks, investors tend to engage in more evaluation and take into account more inconspicuous information, such as peer actions.

Additionally, this study enriches the understanding of social learning and herding. While the herding phenomenon is widely documented in various domains, our study sheds light on the signals that crowds are following. Our results suggest that when the number of individuals in a crowd and the confidence level of each individual are implicitly opposite (usually happens in cases where the total resource is fixed such as P2P lending loans), subsequent investors tend to follow more confident individuals rather than simply a larger crowd. In other words, investors are more influenced by the actions of their peers rather than the number of peers.

Lastly, this study contributes to the growing body of Fintech research. Due to the crowd nature of Fintech platforms, peer information has become another important information element alongside conventional borrower features (Zhang and Liu 2012; Vallee and Zeng 2019). Our findings provide a better understanding of how the prominence and presentation of such peer information affect investor attention, comprehension, and subsequent decision-making on crowd-based investment platforms.

3.7.2 Practical Implications

Practically, our study offers valuable insights for platform operators and practitioners. First, this chapter provides implications for the market design of crowdfunding platforms and broader Fintech platforms, which are envisioned for nonexpert retail investors. To incorporate the limited cognitive capacity of such investors, platforms need to carefully balance information transparency for decision effectiveness and information overload for decision efficiency. Our findings suggest that platforms may not necessarily benefit from disclosing all available information. Simplified or aggregated information with proper design can potentially attract investors and expedite funding process.

Our findings also highlight the tradeoff of three different designs of displaying investment history by investigating four critical aspects of investment decisions. For example, our investigation on risk preference underscores the potency of the aggregated peer information in steering investor attitudes toward risk. Such an understanding provides platform operators with more tools to align the platform's goals (e.g., promote less-risky loans) with the corresponding interface design.

Furthermore, our study sheds light on the presentation of salient features on platforms. Platform operators seeking to emphasize specific features may need to allocate larger space for them. Instead, designing these features to be more easily digestible and understandable can be more effective in capturing investors' attention and engagement.

Lastly, our research offers guidance to individual investors navigating the complex landscape of peer-informed investment decisions. Our study highlights the potential bias on risk preference caused by peer decisions, which call for more attention from investors to their own investment decisions. By understanding the impact of peer actions at different levels of detail and salience in information displays, investors can make more informed choices and improve their decision-making processes.

CHAPTER 4. BEYOND THE FINANCIAL VALUE OF CROWDFUNDING: EVIDENCE FROM AN INTERPRETABLE MACHINE LEARNING APPROACH

4.1 Introduction

Reward-based crowdfunding provides a channel for entrepreneurs to raise funds from a large group of backers and a pool of capital that were otherwise unavailable (Younkin and Kashkooli 2016). Despite its primary goal of financing, reward-based crowdfunding provides far more than monetary assistance. It bridges entrepreneurs directly to a testing market, helping them validate innovative ideas, estimate market demand, access early feedback, and examine mass production ability (Chemla and Tinn 2020). In the same vein as crowdsourcing, crowdfunding is also a distinct form of crowd-based knowledge sourcing for entrepreneurs (Cornelius and Gokpinar 2020). By interacting with early customers, crowdfunding project creators can elicit information from external problem solvers (Jeppesen and Lakhani 2010). While crowdfunding literature predominantly studies the exchange of financial resources between project creators and backers, they provide relatively scarce or indirect evidence on the *non-financial crowd* value of crowdfunding.

In the myriad of advantages brought forth by crowdfunding lies an overarching objective: a seamless transition to the mass market, ensuring the venture's sustainability and long-term profitability. However, existing literature predominantly centers around the immediate success metrics of crowdfunding campaigns. Such an emphasis often overshadows an even more crucial inquiry: does the initial success in crowdfunding genuinely translate to lasting achievements in the broader market landscape? While it is undeniable that crowdfunding platforms can spark initial interest and gather backing, the real test lies in its aftermath, and this pivotal aspect remains largely unexplored in the literature.

In order to fill such research gaps, this study delves into the non-financial advantages of crowdfunding, particularly its impact on entrepreneurial market success, transcending the commonly assessed financial gains. To this end, we predict entrepreneurs' market acceptance and performance using crowdfunding backers' comments and interactions between backers and entrepreneurs. Our research poses the following questions:

1. Can crowdfunding project features predict mass market potential?

2. Do non-financial crowd features contribute to the prediction of mass market potential, and how?

We use data from both reward-based crowdfunding and mass markets to answer the above research questions. Specifically, we use the tabletop game projects on Kickstarter, one of the largest reward-based crowdfunding platforms. The recent times have witnessed a remarkable surge in the tabletop gaming industry, particularly due to the burgeoning influence of crowdfunding platforms and the societal shifts brought about by the COVID-19 pandemic. Highlighting its growing significance, the global tabletop games market reached an impressive valuation of 13.75 billion USD in 2021, with projections estimating a further growth of 3.02 billion USD between 2022 and 2026.[19] Since the onset of the pandemic, tabletop gaming emerged as the most funded

[19] https://www.researchandmarkets.com/reports/4894386/global-board-games-market-2022-2026#rela0-5228437

subcategory on Kickstarter. Further, the tabletop game industry, marked by a relatively low entry barrier, offers a unique landscape where budding entrepreneurs can effectively challenge established corporations. Such dynamics not only make tabletop games an intriguing area of study but also ensure a data-rich environment for in-depth exploration into entrepreneurial strategies and their resulting outcomes. To examine the market performance of the Kickstarter tabletop game projects, we collect data from BoardGameGeek (BGG), a comprehensive tabletop game database and online forum. Differing from conventional marketplaces like Amazon, BGG is characterized by its vast array of user-generated content, providing a more holistic and objective assessment of market evaluation.

To examine the non-financial value of crowdfunding, we first construct a series of crowd features that are generated from market reaction and project features that are fully under the creators' control. For crowd features, we separate them by the crowd's financial and non-financial contributions. Financial crowd features reflect backers' monetary contributions and projects' financial outcome, while non-financial crowd features reflect the feedback from backers and interactions between project creators and backers in the comment section.

Next, we train a set of classification models to predict entrepreneurs' market performance in two stages, market launch and market rating. We compare the predictive performance of the models using only project features and those using both project and crowd features. We find that crowd features, especially the non-financial ones, significantly improve the prediction of both market performance metrics, verifying the value of early customers' involvement.

To investigate how crowd features contribute to the predictions, we employ SHAP (Shapley Additive exPlanations; Lundberg and Lee 2017), an interpretable machine learning technique, to explain feature importance in our prediction models. Our results show that both financial and non-financial crowd features are among the most important features, and these features reveal important implications to crowdfunding projects' future development. Our analysis shows that crowdfunding success does not always translate into mass market success. Successful crowdfunding projects, if primarily attract comments concerning shipping or excessively optimistic sentiments, should be cautious about mass market entry and future project trajectory. Meanwhile, a failed crowdfunding project is not automatically excluded from mass-market potential. If supported by ample backers and received sufficient positive comments, even failed crowdfunding projects can contain seeds indicating mass market success.

Our findings generate both theoretical and practical implications. We are among the first to provide evidence of the crowdsourcing aspect of crowdfunding. Research on the value of crowdfunding has primarily focused on the monetary impacts, and a few recent studies touching upon the non-financial value of crowdfunding focus solely on crowdfunding campaign performance (Babich et al. 2021; Chemla and Tinn 2020; Roma et al. 2018; Xu 2018; Xu and Ni 2022). Our study extends prior work in this stream of literature by highlighting the value of crowdfunding in perceiving the final mass market success and the critical role of early customers' involvement. The market reaction in the crowdfunding phase provides critical signals for entrepreneurs' future development.

This study also contributes to entrepreneurship literature. Entrepreneurs' market potential has always been the primary interests of investors. This study demonstrates that entrepreneurs' performance in reward-based crowdfunding can complement the existing potential signals and decrease the uncertainty about the market response forecast.

Practically, our study provides guidance for regulators and platform designers by highlighting the non-financial value of crowdfunding. Our explanatory models also offer detailed explanations of influencing factors for every individual project. This study also helps improve investors' screening ability of early entrepreneurial ideas.

4.2 Related Work

4.2.1 Reward-based Crowdfunding and Entrepreneurship

Crowdfunding received much attention from scholars in the past decade. Extensive research has been performed on factors contributing to crowdfunding success, such as category, timing, and location (Agrawal et al. 2015; Burtch et al. 2013), backers' contribution patterns (Mollick 2014; Burtch et al. 2015, Lin and Viswanathan 2016), and the rationality of crowd investments (Mollick and Nanda 2016; Iyer et al.), while rare research have focused on the post-crowdfunding performance. The few studies that examined the post-crowdfunding outcomes were predominately studied in the context of lending-based crowdfunding (e.g., Lin and Viswanathan 2016; Yao et al. 2022). The post-crowdfunding outcomes in other types of crowdfunding (i.e., donation-based, reward-based, and equity crowdfunding), however, was rarely studied, with a few exceptions in recent work. Chemla and Tinn (2020) develop a model and demonstrate that firms can learn about market demand from a limited consumer sample in reward-based crowdfunding. Xu and Ni (2022) model entrepreneurs' product launch decisions and find that the preselling information entrepreneurs collect from reward-based crowdfunding has a sizable impact on their product launch decisions. In another context, Gao et al. (2021) document a positive effect of online education crowdfunding on students' academic performance. To the best of our knowledge, this study is among the first to examine the value of reward-based crowdfunding, especially its non-financial value, in projects' mass-market success.

Reward-based crowdfunding can provide non-financial value from multiple aspects. First, crowdfunding campaigns serve as a direct conduit to potential markets, allowing entrepreneurs to vet their innovative ideas against real-world interests. This real-time validation can be invaluable in refining product designs, features, or even marketing strategies. Crowdfunding backers represent customers who show genuine interest in new products through their purchase of a product in an early stage (Chemla and Tinn 2020). As a crowd representative of actual customers, backers often know more about a project's potential than entrepreneurs. Such information can be conveyed to the entrepreneur through the crowd's collective funding decision and their feedback.

Besides validating ideas, the crowdfunding campaign can also help entrepreneurs better estimate market demand, practice price discrimination between consumers, enabling entrepreneurs to adjust inventory or scale their operations accordingly, mitigating potential losses from overproduction (Roma et al. 2018).

The third benefit of reward-based crowdfunding is that it provides a platform for entrepreneurs to involve early customers and get early feedback. Similar to crowdsourcing, crowdfunding offers entrepreneurs unique crowd-based insights (Cornelius and Gokpinar 2020). Early and honest feedback is a goldmine. It provides a preemptive insight into potential pitfalls or enhancements before a full-scale launch, thus saving their costs and resources. As Kickstarter claims on its website: “Kickstarter isn’t a store — it’s a new way for creators and audiences to work together to make things.”[20] In this sense, customers not only purchase innovative products but also collaborate with entrepreneurs to improve the product and develop entirely new products.

Furthermore, reward-based crowdfunding serves as an advertisement for new projects. Similar to the herding effect in other types of crowdfunding, a strong momentum can help entrepreneurs attract more customers. For example, Cornelius and Gokpinar (2020) find that crowdfunding projects that receive more customer comments raise a larger amount of money later in the campaign. The community-driven feedback loop with early customers can foster a loyal customer base even before the product hits the market. The early interaction with potential customers not only helps extract solutions from a wider external community but also serves as an organic marketing tool, building anticipation and word-of-mouth promotion (Jeppesen and Lakhani 2010).

Finally, reward-based crowdfunding can also be a litmus test for mass production ability (Chemla and Tinn 2020). With each pledged support, entrepreneurs can assess their production and supply chain capabilities, ensuring timely delivery and quality control. The preselling business model of reward-based crowdfunding not only helps VCs better explore if the idea “will have a product-market fit” but also helps them examine “whether the company can execute and scale manufacturing.”[21]

Despite the above-mentioned benefits of crowdfunding, some prior work also points out the potential risk of running a rewards crowdfunding campaign. Babich et al. (2020) show that venture capital investors may feel a reduced value of the project due to

[20] https://www.kickstarter.com/blog/kickstarter-is-not-a-store
[21] https://www.angon.co.id/tech/how-vcs-use-kickstarter-to-kick-the-tires-on-hardware-startups

crowdfunding investors and walk away from the deal directly. Roma et al. (2018) also suggest that a failed campaign may adversely affect the entrepreneur's access to subsequent funding from VCs.

Synthesizing the above facets, our study aims to empirically investigate the influence of reward-based crowdfunding, especially its non-financial value, on the final market performance of entrepreneurs.

4.2.2 Interpretable Machine Learning

Although the past decade has witnessed the significant rise of Artificial Intelligence (AI), the prevailing concerns over lack of transparency, undesired biases, and unethical use are still preventing AI adoption in many high-stake applications (Islam et al., 2021). Recent researchers have devoted an increased effort to the field of explainable artificial intelligence. The Explainable Artificial Intelligence (XAI), or Interpretable Machine Learning (IML), aims to design models in which humans can understand the predictions and decisions made by AI (Islam et al., 2021; Murdoch et al., 2019). Based on the scenarios and models, the explanations or interpretations may exhibit various forms, including mathematical structure, visualizations, natural language, and many others (Murdoch et al., 2019; Tjoa & Guan, 2021).

The literature of IML can be categorized in multiple ways. Based on the methods, the interpretability can be divided into model-based interpretability and post-hoc interpretability (Murdoch et al., 2019). Model-based interpretability techniques focus on designing intrinsically explainable models such as linear regression and decision trees (Islam et al., 2021). Although directly interpretable, such intrinsic property often comes with a cost of performance. Post-hoc interpretability techniques resort to a standalone explainable tool to interpret an already trained model (Islam et al., 2021). Popular techniques of such methods include LIME and SHAP (Lundberg and Lee 2017; Ribeiro et al. 2016).

4.3 Methodology

4.3.1 Task Formulation

There are N crowdfunding projects with N_s of them successfully launched in the mass market and the remaining N_f failed. Each project (denoted as n) is associated with financial features $\boldsymbol{x}_n^{(F)}$ and non-financial features $\boldsymbol{x}_n^{(N)}$. Successfully launched projects also receive evaluations (e.g., ratings, comments, etc.) from the mass market.

Task 1: For all crowdfunding projects, this task predicts whether a project (denoted as n) will be successfully launched on the market based on $\boldsymbol{x}_n^{(F)}$ and $\boldsymbol{x}_n^{(N)}$. In addition, what are the driving factors of the successful launch?

Task 2: For all successfully launched N_s crowdfunding projects, this task predicts the market rating of project n based on $\boldsymbol{x}_n^{(F)}$ and $\boldsymbol{x}_n^{(N)}$. In addition, what are the driving factors of market rating?

4.3.2 Datasets

We perform our study using data assets from two sources–Kickstarter and BoardGameGeek (BGG). Kickstarter provides crowdfunding-related data, and we selectively use only the Tabletop Games sub-category on Kickstarter. The game category in Kickstarter is the most funded category, with more than 32,000 successfully funded projects and 2 billion US dollars raised.[22] Within the game category, Tabletop Games is the largest sub-categories in terms of both the number of projects and the total dollars pledged. On Kickstarter, successful campaigns of tabletop games earned more than 234 million US dollars in 2020 alone.[23] Our data contains a total of 30,875 Kickstarter projects, which started their campaigns between May 2009 and April 2022. After a campaign ends, creators and backers can still post updates and comments on the campaign page.

Our data from BGG provides the market performance of Kickstarter projects. BGG is an online forum for tabletop gaming hobbyists and driven by user-generated content. It serves as a game database that holds reviews, images, and videos for over 259 thousand tabletop games. BGG was first launched in 2000, which is earlier than the launch of Kickstarter in 2009. Thus, BGG is comprehensive to contain all Kickstarter game projects as long as the crowdfunding projects have ever launched in mass markets. Moreover, this online forum holds extensive details about the tabletop game that are otherwise absent on Kickstarter. Our BGG data contains 257,883 games in total.

We match the games between Kickstarter and BGG in multiple steps. We first performed fuzzy matching of games based on their names and designers. To ensure accuracy, the machine-matched results then underwent thorough verification by Amazon Mechanical Turk (MTurk) workers and research assistants. Through this double-checking process, we successfully identified a total of 8,858 game pairs between the two platforms.

[22] https://mattiadistasi.com/the-most-funded-category-on-kickstarter/
[23] Data source: https://www.crowdcrux.com/kickstarter-tabletop-board-game-statistics-for-2021/#:~:text=The story gets more extreme, 33% more than in 2019

4.3.3 Feature Design

The features from Kickstarter are grouped into three categories–project features, crowd features, and market performance. Table 4-1 lists all the features.

Table 4-1. Feature Definition

Category	Sub-Category	Feature	Description
Project features	Campaign	Campaign Duration	Project campaign length set at project launch between 1 and 60 days
		Currency	Base currency used for the project, with top five frequent currencies used on Kickstarter and an Other category
		Number of FAQs	Total number of Frequently Asked Questions listed for a project
		Number of Updates	Total number of updates provided by the project creator
Project features	Project description	Project Profile Link	Binary flag indicating the presence/absence of project external profile link
		Title Word Count	Number of words in the project title
		Description Word Count	Number of words in the project short description
		Risk Word Count	Number of words in the project risk description
		Story Word Count	Number of words in the project story description
		Number of Images	Number of images presented on the project pages
	Rewards	Number of Rewards	Number of rewards listed for the project
		Estimated Delivery Time	Expected time to deliver a reward to the backer (days)

Table 4-1. Continued

Project features	Creator profile	Creator Description Word Count	Number of words in the creator profile description
		Creator Websites	Number of external websites listed on the creator's profile
		User Type	Binary flag indicating the user type as either individual or organization
		Number of Prior Created Projects	Number of projects started by the creator before current project
		Number of Prior Successful Projects	Number of projects successfully funded by the creator before current project
Crowd features	Financial features	Funded Amount	Total amount pledged by the backers in US Dollar
		Crowdfunding Success	Binary flag indicating the campaign status as Successful or not (Failed or Canceled)
	Non-financial features	Number of Backers	Total number unique users who have pledged/backed a project
		Backer Comments	Number of comments from the backer
		Creator Comments	Number of comments from the project creator
		Creator Comment Rate	Ratio of creator comments to the total number of comments
		Distinct Commenters	Number of distinct backers who commented
		Active Commenter Rate	Ratio of backers who commented five or more times to the Distinct Commenters
		Distinct Superbacker Commenters	Number of distinct superbackers who commented
		Comment Rate	Ratio of backer comments to the distinct commenters
		Superbacker Comment Rate	Ratio of distinct superbacker commenters to distinct commenters
		Shipping-related Comments	Number of comments that predominantly discuss the shipping of rewards

Table 4-1. Continued

Crowd features	Non-financial features	Comment Readability	Average readability score of all comments calculated by Lix, the rate of long words and average number of words per sentence
		Positive Comment	Total number of positive comments
		Negative Comment	Total number of negative comments
		Average of Comment Sentiment Score	Average sentiment of all comments
		Standard Deviation of Comment Sentiment Score	Standard deviation of sentiment of all comments
Market performance	Market acceptance	Market Launch	Binary variable indicating whether the project launches on the market or not
	Market evaluation	Market Rating	User ratings on a scale of 1 to 10 averaged

4.3.3.1 Project Features

Project features include all the Kickstarter crowdfunding project features that can be under the control of creators. We categorize the project features into four sub-categories. Campaign features includes both the features are set at the start of the project campaign and the features creators update during and even after the campaign. Project description refers to the set of features derived from the text and image in the project description. Reward features reflect the crowdfunding pledge returns promised to the backers by the project. Creator profile features are derived from the creators' description pages and other created projects.

4.3.2.2 Crowd Features

Crowd features are obtained from observable crowd engagement in a campaign, which are divided into financial features and non-financial features. Financial features quantify both the monetary contributions from backers and the financial results of projects. Conversely, non-financial features primarily emanate from the comments section where backers interact with project creators and their fellow backers. While Kickstarter provides backers with the access to privately interact with creators, we use the visible comments made available publicly in the projects' comment section. We summarize the meta features of comment, such as the number of comments from backers and creators separately. Additionally, we derive contextual data from the comment text in the form of a readability score and sentiment. We use Lix score to measure readability, which is a basic readability score calculated using the rate of long words and the average number of words per sentence. Lix scoring method is preferable due to the nature of crowdfunding comments, as they have unmet requirements of the minimum number of words or sentences for accurately using other scoring methods such as Dale-Chall, Gunning fog, SMOG, Coleman-Liau, and Automated Readability Index (ARI). To represent the overall sentiment of each project, we calculate the average and standard deviation of the comment sentiment score, which is measured using the 'distilbert-base-uncased-finetuned-sst-2-english' pre-trained model retrieved through the Hugging Face model repository. Similarly, to understand the comments related to shipping, we measure the shipping topic score taking a zero-shot classification approach using the 'facebook/bart-large-mnli' pre-trained model retrieved through the Hugging Face model repository.

4.3.2.3 Market Performance

We assess two distinct stages of a crowdfunding project's post-crowdfunding performance: market acceptance and market evaluation. Initially, the project faces the primary hurdle of transitioning into mass production. We introduce a binary dummy variable, Market Launch, which indicates whether the crowdfunding project successfully launches in the market or not. The second crucial challenge involves establishing a positive market reputation, which we quantify using the BGG's average rating of games. Customers can rate games on a scale of 1 to 10, with the minimum and maximum rating in our dataset as 2.37 to 9.47. To enhance data quality, we remove any outliers within the 1st percentile of the Market Rating.

We then perform several data preprocessing steps on the raw data. We first carefully select features, avoiding duplicate and correlated variables. Further, we apply one-hot encoding for categorical variables to convert them into a suitable format for analysis. To ensure consistent scales, we normalize the predictor variables using min-max normalization. Additionally, we create two distinct feature sets—one excluding non-financial features and the other including them—to explore the impact of non-financial features on the prediction outcomes.

We further perform feature engineering to all the features. Notably, we remove duplicate features with high correlation. Though our prediction model of choice, LightGBM, can handle collinearity, the explanatory machine learning method we adopt (SHapley Additive exPlanations; see the next section for details) assumes feature independence and calculates feature attribution for all input features. Thus, it is important to select and retain only single features among the correlated features and measure feature attribution of the selected feature. We calculate the Pearson correlation coefficient with significance level at 0.00001 and exclude duplicate correlated feature with an absolute coefficient value more than 0.40.

4.3.4 Model Building and Performance Evaluation

For the predictive modeling, we select LightGBM due to its outstanding accuracy and efficient processing capabilities (Ke et al. 2017). To evaluate the model's performance, we utilize different metrics based on the nature of the outcome variable: For the binary outcome variable, Market Launch, we measure the Area Under Curve (ROC-AUC), while for the continuous outcome variable, Market Rating, we assess the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

To ensure the reliability and robustness of our prediction models, we employ five-fold cross-validation and conduct hyper-parameter tuning across various parameters, such as boosting type, learning rate, number of leaves, max depth, and number of estimators. This thorough process helps us identify the optimal configuration for our models.

To analyze the contributions of individual features to the final predictions, we employed the SHapley Additive exPlanations (SHAP) approach, which is rooted in game theory and assigns importance values to each feature for specific predictions made by any machine learning algorithm (Lundberg and Lee 2017; Ma et al. 2022). SHAP unifies additive feature attributions methods using cooperative game theory properties, namely from the Shapley value estimation method, and serves as a model-agnostic prediction explainer. SHAP provides an explanatory framework to measure the contribution of each independent variable in predicting the dependent variable, with whose value we can explain the relationship between the features and the outcomes. We perform the SHAP feature explanation on the best-performing prediction model. SHAP offers distinct advantages compared to other explanatory algorithms and approaches:

First, SHAP is a model-agnostic approach, granting us the flexibility to select the machine learning model with the best predictive performance, thereby enhancing our ability to evaluate feature importance accurately. In essence, SHAP ensures a balance between high prediction accuracy and robust explanatory power.

Second, traditional feature importance techniques merely reveal which features are important without clarifying how they influence prediction outcomes. In contrast, SHAP values provide deeper insights by reflecting how each feature positively or negatively influences the prediction for each individual observation. This richer understanding of feature influence enhances the interpretability of the model's predictions and facilitates more informed decision-making.

4.4 Descriptive Analyses

We start our analysis with some descriptive analysis of the dataset regarding the performance of crowdfunding projects in mass markets. Our data shows that 28% of Kickstarter tabletop game projects finally launched in the market. If we separate the successful crowdfunding projects with the failed ones, not surprisingly, successful projects are more likely to launch in markets (Table 4-2). Moreover, we observe that a significant proportion of successful crowdfunding projects still failed to launch in the market, and failed projects still launched in the market. In other words, crowdfunding success does not always translate into mass market success.

Table 4-2. Market Launch Outcome of Crowdfunding Projects

Number of projects	Launched	Not Launch
Crowdfunding Failed	2,246	8,420
Crowdfunding Successful	6,551	13,913

We further examine the market rating of crowdfunding projects upon launching in the market. Overall, crowdfunding projects perform significantly better than the other projects in the market, with an average rating of 7.02 compared while other projects rated of 6.70 (BGG rating ranges from 1 to 10). More interestingly, failed crowdfunding projects (7.16) even rate higher than successful projects (6.99). To further investigate this surprising result, we plot the distribution of projects across discrete ratings (Figure 4-1). Compared with successful projects, failed ones are more polarized in their market rating; that is, they get notably more high and low ratings.

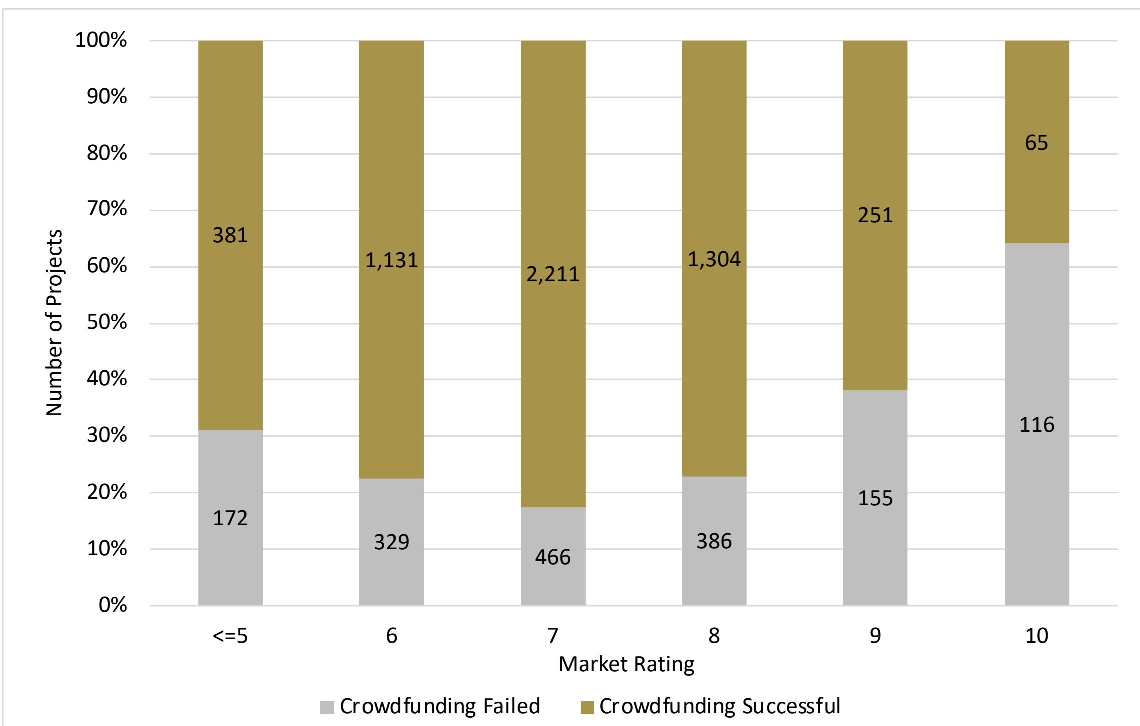


Figure 4-1. Market Rating of Successful and Failed Crowdfunding Projects

4.5 Prediction Results and Feature Importance

In this section, we perform the market performance prediction and explore the contribution of crowd features in the predictions.

4.5.1 Market Launch Prediction

We start with the prediction of market launch, which is measured by whether a crowdfunding project eventually launches on mass markets (i.e., shows in the BGG dataset). We train a series of classification machine learning models using the LightGBM algorithm (Ke et al. 2017), given its high accuracy and fast operation.

4.5.1.1 Prediction Performance

Our goal is to examine whether we can improve the performance of market launch prediction by incorporating crowd features as additional predictors. Table 4-3 presents the model performance of ROC-AUC for different feature set combinations. Using project features as the benchmark, we find that the ROC-AUC significantly increases after adding financial crowd features, non-financial crowd features, and both financial and non-financial crowd features. Among all, adding both financial and non-financial crowd features achieves the highest improvement (11.47%). This result confirms the value of crowd features derived from the market reaction in crowdfunding. Furthermore, we compare the predictive capacities of financial with non-financial features: Compared with the model using only project features, non-financial crowd features improve prediction (9.49%) much more than financial crowd features (3.66%). In other words, non-financial crowd elements possess a superior predictive potency compared to their financial counterparts.

Table 4-3. Performance of Market Launch Prediction

Feature Set	ROC-AUC	Improvement from using project features
Project features	0.7676	/
Financial and non-financial crowd features	0.7551	/
Project features + financial crowd features	0.7774	3.66%
Project features + non-financial crowd features	0.7930	9.49%
Project features + financial and non-financial crowd features	0.7983	11.47%

4.5.1.2 Feature Importance and Attribution

Next, we move onto the model explanation and discuss the correlation between the input features and the outcome variable, market launch, with an emphasis on understanding the financial and non-financial crowd features. Figure 4-2 shows the feature importance and attribution plotted from the SHAP values for the best performing prediction model, whose input features are project features, financial crowd features, and non-financial crowd features.

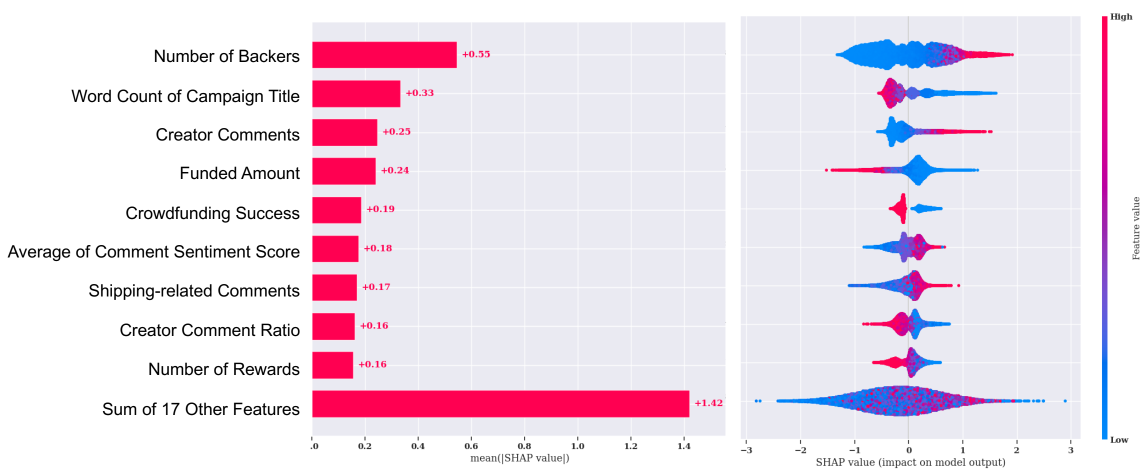


Figure 4-22. Feature Attribution of Market Launch Prediction

The graph on the left is a bar plot representing the global feature importance with the mean absolute SHAP value, sorted from the most important to less important. For financial crowd features, both Funded Amount and Crowdfunding Success show up in the top influencing features. This result validates the importance of financial support that crowdfunding provides to entrepreneurs. Furthermore, there are five non-financial features showing in top features, which are Number of Backers, Creator Comments, Average of Comment Sentiment Score, Shipping-related Comments, and Creator Comment Ratio. This result suggests that non-financial crowd features play important roles in predicting market launch.

The graph on the right is a beeswarm plot capturing the individual instances of each feature and their corresponding SHAP value, the density of the SHAP values, and ordered from smaller to larger actual feature values. We observe that most small values of Number of Backers (blue) are concentrated with negative SHAP values, while most large values of Number of Backers (red) are concentrated with positive SHAP values. This indicates a strong positive relationship between Number of Backers and Market Launch: a larger number of backers is associated with a larger Market Launch probability. Similarly, a larger number of Creator Comments, Average of Comment Sentiment Score, Shipping-related Comments, and Creator Comment Ratio are all associated with a larger Market Launch probability. We will discuss the relationship between such features and market performance in more details in §4.5. In summary, we see that crowd engagement in crowdfunding has strong predictive power in market launch prediction.

4.5.2 Market Rating Prediction

Next, we move on to the prediction of market rating, which we use consumer-generated ratings on the BGG platform as a proxy. As market rating is a continuous outcome variable, we train regression machine learning models using the LightGBM algorithm.

<u>4.5.2.1 Prediction Performance</u>

Similar to market launch prediction, our goal is to examine whether the addition of crowd features can improve the market rating prediction. Table 4-4 presents the model performance of the selected regression metrics for all feature sets.

Table 4-4. Performance of Market Rating Prediction

	RMSE	Improvement	MAE	Improvement	MAPE	Improvement
Baseline using mean as predicted value	0.8119	/	0.6318	/	9.47%	/
Project features	0.7466	8.05%	0.5713	9.58%	8.58%	9.44%
Financial and non-financial crowd features	0.7293	10.18%	0.5477	13.31%	8.25%	12.93%
Project features + financial crowd features	0.7240	10.83%	0.5500	12.95%	8.26%	12.82%
Project features + non-financial crowd features	0.7252	10.68%	0.5512	12.76%	8.29%	12.50%
Project + financial and non-financial crowd features	0.6957	14.32%	0.5237	17.11%	7.88%	16.83%

We use a simple, intuitive baseline–the mean of the Average Rating. We find that project features, financial crowd features, non-financial crowd features, and both financial and non-financial crowd features all significantly improve the baseline prediction across all the regression metrics. The feature set that includes all the features (i.e., project features, financial and non-financial crowd features) still performs the best of all. Comparing the predictive performance of only project features with only financial and non-financial crowd features, we can see that crowd features alone even have stronger prediction power than project features. This result confirms the value of crowd features in predicting market evaluation. Additionally, non-financial and financial crowd features achieve similar levels of improvement in predicting market ratings.

4.5.2.2 Feature Importance and Attribution

We then apply the SHAP interpretation to the best performing prediction model to further understand the correlation between market rating and crowd features. Figure 4-3 shows the feature importance and attribution plotted from the SHAP values with root mean squared error metric. From the figure, we observe that the SHAP interpretation of this prediction model lists four non-financial features (Number of Backers, Shipping-related Comments, Average Comment Sentiment Score, and Ratio of Superbackers), as well as one financial feature (Funded Amount) in top features. This result further validates the importance of crowd features, especially the non-financial features, in predicting market rating.

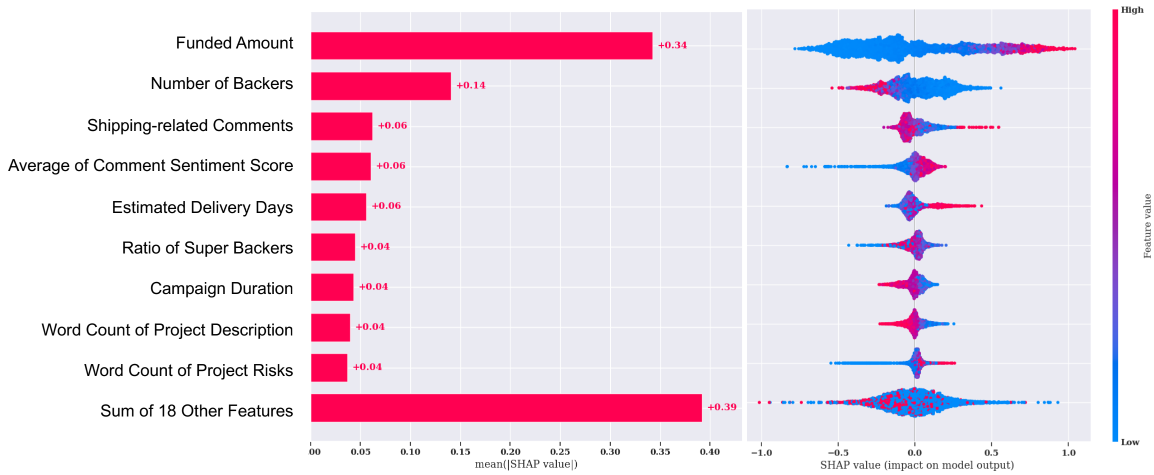


Figure 4-33. Feature Attribution of Market Rating Prediction

4.6 Post Prediction Analysis

In the two predictions of market launch and market rating, we identify three overlapping non-financial features that show up in the top 10 features, Number of Backers, Shipping-related Comments, and Average of Comment Sentiment Score. These features suggest important aspects of crowdfunding's non-financial value. Number of backers serves as a signal for the market demand and popularity of a product, beyond what can be reflected in the total funded amount. Shipping-related Comments reveals the product maturity during its preselling in crowdfunding campaigns and the entrepreneur's operational ability in transitioning a concept into mass production. Average of Comment Sentiment Score directly reveals the crowd's perception towards the product. In this section, we examine how these features are related to market success.

4.6.1 Number of Backers and Market Performance

We analyse the relationship between the number of backers and market performance in successful and failed crowdfunding projects and present the results in

Tables 4-5 and Table 4-6. The first key observation is that the crowdfunding projects that receive support from a larger number of backers have a higher likelihood of launching in markets. This finding is intuitive, as a higher number of backers indicates a broader base of interest and support in the project, and typically suggests that there is a higher demand for the product in the mass market. As a result, these projects' creators have higher interests to push the products to mass markets.

More importantly, we find that even failed crowdfunding projects, despite their failure to reach their monetary funding goals, can still launch in the market and perform well, upon the condition that they manage to attract enough backers. Such projects also receive market ratings as high as those of successful crowdfunding projects. This result suggests that sufficient backing received during the crowdfunding campaign can serve as a useful indictor of market demand.

In sum, the Number of Backers highlights the value of crowd non-financial features in determining market performance. Entrepreneurs and innovators can gauge the level of interest and demand for their offerings before investing significant resources in manufacturing, production, or development. If the product receives sufficient backers, it provides a green signal to proceed with the market launch, with the knowledge that there is already a base of potential customers waiting to purchase it and evaluate it highly.

Table 4-5.5 Successful Market Launch Rate by Number of Backers

	Number of Backers Smaller than Median	Number of Backers Larger than Median
Crowdfunding Failed	17.39%	45.95%
Crowdfunding Successful	13.87%	39.96%

Table 4-6. High Market Rating Rate by Number of Backers

	Number of Backers Smaller than Median	Number of Backers Larger than median
Crowdfunding Failed	67.72%	72.01%
Crowdfunding Successful	61.71%	72.96%

*4.6.*2 Shipping-related Comments and Market Performance

Next, we examine the relationship between the number of shipping-related comments and market performance, as shown in Tables 4-7 and 4-8. Projects with a higher number of shipping-related comments tend to launch in markets with higher probability than those with fewer shipping-related comments. This is probably because more comments about shipping indicate that these projects have reached a stage closer to production and delivery where shipping logistics become a priority.

Interestingly, there is a negative relationship between the number of shipping comments and the market evaluation for both successful and failed projects: Projects with more shipping-related comments tend to have lower market ratings. This result suggests that a more mature product, further along in its development process, leaves less room for backers to give feedback and creators to implement crowd suggestions.

The Number of Shipping-related Comments is another valuable non-financial crowd feature, and it is important for project creators to be aware of this dynamic. While managing crowd shipping expectations is necessary, it is equally important to maintain open channels to crowd feedback and act on the product improvement suggestions, if any, for mass market success.

Table 4-7. Successful Market Launch Rate by Shipping-related Comments

	Less Comments about Shipping	More Comments about Shipping
Crowdfunding Failed	19.88%	26.32%
Crowdfunding Successful	19.93%	38.09%

Table 4-8. High Market Rating Rate by Shipping-related Comments

	Less comments about shipping	More comments about shipping
Crowdfunding Failed	69.79%	67.17%
Crowdfunding Successful	77.38%	70.50%

4.6.3 Comment Sentiment and Market Performance

Last but not the least, we examine the relationship between crowdfunding comment sentiment and mass market performance. Tables 4-9 and 4-10 present the results. We first observe that a higher positive sentiment is related to a higher market launch rate. Interestingly, similar to the case of the number of backers, if failed projects receive overall more positive comments, they can even have a larger chance to launch in the market.

Regarding the market rating of crowdfunding projects, surprisingly, we find that crowd sentiment even has a negative relationship with market rating for successful projects, which calls for our attention to the potential over-optimism from the backer crowd. In other words, project creators may receive a false sense of security from the crowdfunding success and backers' comments, which may not always be the sentiment shared by the mass market.

Crowdfunding comment sentiment is another non-financial crowd feature that plays an important role in market performance. Projects with a sufficient positive crowd sentiment are likely to launch on the market successfully, including failed projects. However, successful crowdfunding projects need to be especially cautious about the potential over-optimism from backers, and they need to continue monitoring and maintaining mass market expectations.

Table 4-9. Successful Market Launch Rate by Comment Sentiment

	Sentiment More Negative	Sentiment More Positive
Crowdfunding Failed	15.55%	33.30%
Crowdfunding Successful	29.66%	30.29%

Table 4-10. High Market Rating Rate by Comment Sentiment

	Sentiment More Negative	Sentiment More Positive
Crowdfunding Failed	68.42%	69.57%
Crowdfunding Successful	73.72%	69.75%

4.7 Conclusions and Implications

Our study predicts the mass market potential of rewards crowdfunding projects. By proposing and defining the financial and non-financial crowd features, we find that market reactions from crowdfunding campaigns can significantly improve the prediction of the mass market performance for innovative projects. To the best of our knowledge, we are among the first to examine the post-crowdfunding performance of rewards crowdfunding projects. Beyond the commonly recognized financial significance of crowdfunding, our analyses underscore an equally pivotal dimension—its non-financial merit, achieved through the collective engagement of backers.

Our findings provide pivotal insights for crowdfunding stakeholders in this ecosystem. For reward-based crowdfunding platforms, our research highlights the integral non-financial contributions from the crowd. By integrating these crowd features, particularly the non-financial dimensions, we can more adeptly anticipate the market potential of crowdfunding ventures. This foresight is instrumental for the sustained growth of crowdfunding platforms.

For rewards crowdfunding creators, we provide improved prediction of their market performance. Besides showing the average impact of influencing factors, our method is able to provide detailed explanations of every factor for every individual project. Most importantly, our findings challenge the notion that a project's success in crowdfunding invariably translates to mass-market success. For instance, projects that, despite being successful in crowdfunding, primarily attract comments concerning shipping or excessively optimistic sentiments, should be cautious about the future development and may not wish to invest excessively on marketing to enter mass markets. Conversely, a project's failure in crowdfunding also does not automatically preclude it from mass-market potential. If supported by ample backers and received sufficient positive comments, even failed crowdfunding projects can contain seeds indicating mass market success. For crowdfunding backers, our insights equip them with a more refined lens, enabling more informed investment decisions in projects.

CHAPTER 5. SUMMARY

In this dissertation, I delve into the role of "crowd wisdom" within crowdfunding, using data from the two dominant types of crowdfunding—debt-based and rewards-based—which together represent 60% of the global market. My dissertation contributes to multiple research areas, including information systems, economics, marketing, finance, and entrepreneurship. First, even though the term “wisdom of the crowd” is used broadly in online communities and markets, I demonstrate the value of breaking down a crowd by their heterogeneous actions. My dissertation also contributes to the growing finance literature, especially in fintech, by proposing new methods of quality evaluation and highlighting the value of crowds in the ecosystem. Furthermore, the dissertation adds to the information systems literature by providing a better understanding of how the prominence and presentation of peer information affect investor attention, comprehension, and subsequent decision-making on crowd-based investment platforms. Additionally, my dissertation enriches the understanding of social learning and highlights a potential synergy between machine learning (predictive) and crowd wisdom.

The dissertation studies and proposes new platform design features for Fintech markets to enable a smarter crowd and a more efficient market. Chapter 2 shows that there is still untapped informational value in crowd actions that the platform can easily provide to users. Chapter 3 highlights the importance of the level of details in presenting crowd information on the platform. Chapters 2 and 3 together suggest that even in the name of privacy preservation, the platform need not completely eliminate crowd information from the platform, which may take away the benefit of a crowd-based market. Chapter 4 underscores the non-financial value that crowdfunding platforms can provide to entrepreneurs. By integrating these insights, the outcome and market potential of crowdfunding projects can be better predicted.

My dissertation also has important implications for fundraisers and creators. For fundraisers and project creators, my research offers enhanced post-crowdfunding performance predictions, aiding in future planning. Meanwhile, crowdfunding investors and backers gain vital insights to navigate the complex landscape of peer-contributed investment decisions.

REFERENCES

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Zheng, X. (2016). TensorFlow: a system for large-scale machine learning. *12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16)*, 265-283.

Agnew, J. R., & Szykman, L. R. (2005). Asset allocation and information overload: The influence of information display, asset choice, and investor experience. *The Journal of Behavioral Finance*, *6*(2), 57-70.

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy*, *14*(1), 63-97.

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, *24*(2), 253-274.

Atanasov, P., Rescober, P., Stone, E., Swift, S. A., Servan-Schreiber, E., Tetlock, P., & Mellers, B. (2017). Distilling the wisdom of crowds: Prediction markets vs. prediction polls. *Management Science*, *63*(3), 691-706.

Bansal, S., & Gutierrez, G. J. (2020). Estimating uncertainties using judgmental forecasts with expert heterogeneity. *Operations Research*, *68*(2), 363-380.

Bapna, R., Goes, P., & Gupta, A. (2003). Analysis and design of business-to-consumer online auctions. *Management Science*, *49*(1), 85-101.

Bapna, S., & Ganco, M. (2021). Gender gaps in equity crowdfunding: Evidence from a randomized field experiment. *Management Science*, *67*(5), 2679-2710.

Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-Induced Trading and Returns: Evidence from Robinhood Users. *The Journal of Finance*, *77*(6), 3141-3190.

Bayus, B. L. (2013). Crowdsourcing new product ideas over time: An analysis of the Dell IdeaStorm community. *Management Science*, *59*(1), 226-244.

Bazley, W. J., Cronqvist, H., & Mormann, M. (2021). Visual finance: the pervasive effects of red on investor behavior. *Management Science*, 67*(*9), 5616-5641.

Ben-Assuli, O., & Padman, R. (2020). Trajectories of repeated readmissions of chronic disease patients: Risk stratification, profiling, and prediction. *MIS Quarterly*, *44*(1), 201-227.

Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of Fintechs: Credit scoring using digital footprints. *The Review of Financial Studies*, *33*(7), 2845-2897.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 841-890.

Bikhchandani, S., Hirshleifer, D., Tamuz, O., & Welch, I. (2021). *Information cascades and social learning* (NBER Working Paper No. w28887). National Bureau of Economic Research. https://www.nber.org/papers/w28887

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, *127*(3), 1243-1285.

Boudreau, K. J., Lacetera, N., & Lakhani, K. R. (2011). Incentives and problem uncertainty in innovation contests: An empirical analysis. *Management Science*, *57*(5), 843-863.

Bowers, A. (2015). Relative comparison and category membership: The case of equity analysts. *Organization Science*, *26*(2), 571-583.

Budescu, D. V., & Chen, E. (2015). Identifying expertise to extract the wisdom of crowds. *Management Science*, *61*(2), 267-280.

Bursztyn, L., Ederer, F., Ferman, B., & Yuchtman, N. (2014). Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions. *Econometrica*, *82*(4), 1273-1301.

Burtch, G., Ghose, A., & Wattal, S. (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Information Systems Research*, *24*(3), 499-519.

Burtch, G., Ghose, A., & Wattal, S. (2014). Cultural differences and geography as determinants of online prosocial lending. *MIS Quarterly*, *38*(3), 773-794.

Burtch, G., Ghose, A., & Wattal, S. (2015). The hidden cost of accommodating crowdfunder privacy preferences: A randomized field experiment. *Management Science*, *61*(5), 949-962.

Burtch, G., Ghose, A., & Wattal, S. (2016). Secret admirers: An empirical examination of information hiding and contribution dynamics in online crowdfunding. *Information Systems Research*, *27*(3), 478-496.

Cai, H., Chen, Y., & Fang, H. (2009). Observational learning: Evidence from a randomized natural field experiment. *American Economic Review*, *99*(3), 864-882.

Carson, R. T., Graff Zivin, J., Louviere, J. J., Sadoff, S., & Shrader, J. G. (2022). The Risk of Caution: Evidence from an Experiment. *Management Science*. Articles in Advance.

Chemla, G., & Tinn, K. (2020). Learning through crowdfunding. *Management Science*, *66*(5), 1783-1801.

Chen, D., Ma, Y., Martin, X., & Michaely, R. (2022). On the fast track: Information acquisition costs and information production. *Journal of Financial Economics*, *143*(2), 794-823.

Chen, H., De, P., Hu, Y. J., & Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, *27*(5), 1367-1403.

Chen, J., & Stallaert, J. (2014). An economic analysis of online advertising using behavioral targeting. *MIS Quarterly*, *38*(2), 429-450.

Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. New York, USA.

Chervany, N. L., & Dickson, G. W. (1974). An experimental evaluation of information overload in a production environment. *Management Science*, *20*(10), 1335-1344.

Choi, H., Mela, C. F., Balseiro, S. R., & Leary, A. (2020). Online display advertising markets: A literature review and future directions. *Information Systems Research*, *31*(2), 556-575.

Choi, J. J., Haisley, E., Kurkoski, J., & Massey, C. (2017). Small cues change savings choices. *Journal of Economic Behavior & Organization*, *142*, 378-395.

Cornelius, P. B., & Gokpinar, B. (2020). The role of customer investor involvement in crowdfunding success. *Management Science*, *66*(1), 452-472.

Cox, D. R. (1958). The regression analysis of binary sequences. *Journal of the Royal Statistical Society: Series B (Methodological)*, *20*(2), 215-232.

Da, Z., & Huang, X. (2020). Harnessing the wisdom of crowds. *Management Science*, *66*(5), 1847-1867.

Dahlander, L., & Piezunka, H. (2014). Open to suggestions: How organizations elicit suggestions through proactive and reactive attention. *Research Policy*, *43*(5), 812-827.

Dai, H., & Zhang, D. J. (2019). Prosocial goal pursuit in crowdfunding: Evidence from Kickstarter. *Journal of Marketing Research*, *56*(3), 498-517.

DeLong, E. R., DeLong, D. M., & Clarke-Pearson, D. L. (1988). Comparing the areas under two or more correlated receiver operating characteristic curves: A nonparametric approach. *Biometrics, 44*(3): 837-845.

Donovan, J. (2021). Financial reporting and entrepreneurial finance: Evidence from equity crowdfunding. *Management Science*, *67*(11), 7214-7237.

Duarte, J., Siegel, S., & Young, L. (2012). Trust and credit: The role of appearance in peer-to-peer lending. *The Review of Financial Studies*, *25*(8), 2455-2484.

Ewens, M., & Townsend, R. R. (2020). Are early stage investors biased against women? *Journal of Financial Economics*, *135*(3), 653-677.

Fernández, A., García, S., Galar, M., Prati, R. C., Krawczyk, B., & Herrera, F. (2018). *Learning from Imbalanced Data Sets* (Vol. 11). Berlin: Springer.

Frydman, C., & Krajbich, I. (2022). Using response times to infer others' private information: an application to information cascades. *Management Science*, *68*(4), 2970-2986.

Frydman, C., & Wang, B. (2020). The impact of salience on investor behavior: Evidence from a natural experiment. *The Journal of Finance*, *75*(1), 229-276.

Fu, R., Huang, Y., & Singh, P. V. (2021). Crowds, lending, machine, and bias. *Information Systems Research*, *32*(1), 72-92.

Gao, Q., Lin, M., & Liu, Y. (2023). When "Signals" Boomerang: Employers' Reactions to a Novel Signaling Mechanism. *Working Paper*, City University of New York.

Gao, Q., Lin, M., & Sias, R. W. (2022). Words matter: The role of texts in online credit markets. *Journal of Financial and Quantitative Analysis*, forthcoming.

Gao, Q., Lin, M., & Wu, D. J. (2021). Education crowdfunding and student performance: An empirical study. *Information Systems Research*, *32*(1), 53-71.

Ghose, A., Ipeirotis, P. G., & Li, B. (2014). Examining the impact of ranking on consumer behavior and search engine revenue. *Management Science*, *60*(7), 1632-1654.

Ghose, A., Ipeirotis, P. G., & Li, B. (2019). Modeling consumer footprints on search engines: An interplay with social media. *Management Science*, *65*(3), 1363-1385.

Glazer, J., Kremer, I., & Perry, M. (2021). The wisdom of the crowd when acquiring information is costly. *Management Science, 67*(10), 6443-6456.

Greenstein, S., & Zhu, F. (2018). Do experts or crowd-based models produce more bias? Evidence from Encyclopedia Britannica and Wikipedia. *MIS Quarterly*, *42*(3), 945-959.

Grenadier, S. R., & Wang, N. (2005). Investment timing, agency, and information. *Journal of Financial Economics*, *75*(3), 493-533.

Guo, X., Wei, Q., Chen, G., Zhang, J., & Qiao, D. (2017). Extracting representative information on intra-organizational blogging platforms. *MIS Quarterly*, *41*(4), 1105-1128.

Hasan, I., He, Q., & Lu, H. (2022). Social capital, trusting, and trustworthiness: Evidence from peer-to-peer lending. *Journal of Financial and Quantitative Analysis*, *57*(4), 1409-1453.

Haykin, S. (1994). *Neural networks: a comprehensive foundation*. Prentice Hall PTR.

Herzenstein, M., Sonenshein, S., & Dholakia, U. M. (2011). Tell me a good story and I may lend you money: The role of narratives in peer-to-peer lending decisions. *Journal of Marketing Research*, *48*(SPL), S138-S149.

Hildebrand, T., Puri, M., & Rocholl, J. (2017). Adverse incentives in crowdfunding. *Management Science*, *63*(3), 587-608.

Hofman, J. M., Watts, D. J., Athey, S., Garip, F., Griffiths, T. L., Kleinberg, J., ... & Yarkoni, T. (2021). Integrating explanation and prediction in computational social science. *Nature*, *595*(7866), 181-188.

Holden, C., Lin, M., Lu, K., Wei, Z., & Yang, J. (2020). The effect of secondary market existence on primary market liquidity: Theory and evidence from a natural experiment in peer-to-peer lending. Working paper, Indiana University, Bloomington, Indiana.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644-1655.

Hong, Y., Hu, Y., & Burtch, G. (2018). Embeddedness, pro-sociality, and social influence: Evidence from online crowdfunding. *MIS Quarterly*, *42*(4), 1211-1224.

Hong, Y., Wang, C., & Pavlou, P. A. (2016). Comparing open and sealed bid auctions: Evidence from online labor markets. *Information Systems Research*, *27*(1), 49-69.

Huang, N., Burtch, G., Gu, B., Hong, Y., Liang, C., Wang, K., ... & Yang, B. (2019). Motivating user-generated content with performance feedback: Evidence from randomized field experiments. *Management Science*, *65*(1), 327-345.

Huber, G. P. (1991). Organizational learning: The contributing processes and the literatures. *Organization Science*, *2*(1), 88-115.

Hvalshagen, M., Lukyanenko, R., & Samuel, B. M. (2022). Empowering users with narratives: Examining the efficacy of narratives for understanding data-oriented conceptual models. *Information Systems Research*, Articles in Advance.

Islam, S. R., Eberle, W., Ghafoor, S. K., & Ahmed, M. (2021). Explainable Artificial Intelligence approaches: A Survey arXiv preprint arXiv:2101.09429.

Iyer, R., Khwaja, A. I., Luttmer, E. F., & Shue, K. (2016). Screening peers softly: Inferring the quality of small borrowers. *Management Science*, *62*(6), 1554-1577.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning*. New York: Springer.

Jeppesen, L. B., & Lakhani, K. R. (2010). Marginality and problem-solving effectiveness in broadcast search. *Organization Science*, *21*(5), 1016-1033.

Jiang, Y., Ho, Y. , Yan, X., & Tan, Y. (2020). When online lending meets real estate: Examining investment decisions in lending-based real estate crowdfunding. *Information Systems Research*, *31*(3), 715-730.

Jiang, Y., Ho, Y. C., Yan, X., & Tan, Y. (2022). What's in a "username"? The effect of perceived anonymity on herding in crowdfunding. *Information Systems Research*, *33*(1), 1-17.

Jones, Q., Ravid, G., & Rafaeli, S. (2004). Information overload and the message dynamics of online interaction spaces: A theoretical model and empirical exploration. *Information Systems Research*, *15*(2), 194-210.

Kamstra, M. J., Kramer, L. A., Levi, M. D., & Wermers, R. (2017). Seasonal asset allocation: Evidence from mutual fund flows. *Journal of Financial and Quantitative Analysis*, *52*(1), 71-109.

Kanze, D., Huang, L., Conley, M. A., & Higgins, E. T. (2018). We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal*, *61*(2), 586-614.

Kaufmann, C., Weber, M., & Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science*, *59*(2), 323-340.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., … Liu, T.-Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems*, *30*, 3146–3154.

Kim, K., & Viswanathan, S. (2019). The Experts in the crowd: The role of experienced investors in a crowdfunding market. *MIS Quarterly*, *43*(2), 347-372.

Kim, K., Park, J., Pan, Y., Zhang, K., & Zhang, X. (2022). Risk disclosure in crowdfunding. *Information Systems Research*, *33*(3), 1023-1041.

Konovalov, A., & Krajbich, I. (2017). Revealed indifference: Using response times to infer preferences.

Konovalov, A., & Krajbich, I. (2019). Revealed strength of preference: Inference from response times. *Judgment and Decision making*, *14*(4), 381-394.

Krajbich, I., Oud, B., & Fehr, E. (2014). Benefits of neuroeconomic modeling: New policy interventions and predictors of preference. *American Economic Review*, *104*(5), 501-06.

Krishnamurthi, L., & Raj, S. P. (1988). A model of brand choice and purchase quantity price sensitivities. *Marketing Science*, *7*(1), 1-20.

Kuksov, D., & Villas-Boas, J. M. (2010). When more alternatives lead to less choice. *Marketing Science*, *29*(3), 507-524.

Kuppuswamy, V., & Bayus, B. L. (2018). Crowdfunding creative ideas: The dynamics of project backers. *The economics of crowdfunding: Startups, portals and investor behavior*, 151-182.

Lee, H. C. B., Ba, S., Li, X., & Stallaert, J. (2018). Salience bias in crowdsourcing contests. *Information Systems Research*, *29*(2), 401-418.

Lee, Y. J., Hosanagar, K., & Tan, Y. (2015). Do I follow my friends or the crowd? Information cascades in online movie ratings. *Management Science*, 61(9), 2241-2258.

Liao, L., Wang, Z., Xiang, J., Yan, H., & Yang, J. (2021). User interface and firsthand experience in retail investing. *The Review of Financial Studies*, *34*(9), 4486-4523.

Liberman, A., Neilson, C., Opazo, L., & Zimmerman, S. (2018). *The equilibrium effects of information deletion: Evidence from consumer credit markets* (No. w25097). National Bureau of Economic Research. https://www.nber.org/papers/w25097

Lin, M., & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, *62*(5), 1393-1414.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, *59*(1), 17-35.

Lin, M., Sias, R. W., & Wei, Z. (2022). Experts vs. non-experts in online markets. *MIS Quarterly*. Forthcoming.

Liu, D., Brass, D. J., Lu, Y., & Chen, D. (2015). Friendships in online peer-to-peer lending: pipes, prisms, and relational herding. *MIS Quarterly*, *39*(3), 729-742.

Lu, K., Wei, Z., & Chan, T. Y. (2022). Information asymmetry among investors and strategic bidding in peer-to-peer lending. *Information Systems Research*, *33*(3), 824-845.

Lu, Y., Gupta, A., Ketter, W., & Van Heck, E. (2019). Information transparency in business-to-business auction markets: The role of winner identity disclosure. *Management Science*, *65*(9), 4261-4279.

Lukyanenko, R., Parsons, J., Wiersma, Y. F., & Maddah, M. (2019). Expecting the unexpected: Effects of data collection design choices on the quality of crowdsourced user-generated content. *MIS Quarterly*, *43*(2), 623-648.

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, *30*.

Ma, Y., Li, T., Mao, J., Ba, Z., & Li, G. (2022). Identifying widely disseminated scientific papers on social media. *Information Processing & Management*, *59*(3), 102945.

Madrian, B. C., & Shea, D. F. (2001). The power of suggestion: Inertia in 401 (k) participation and savings behavior. *The Quarterly Journal of Economics*, *116*(4), 1149-1187.

Madsen, J. M., & McMullin, J. L. (2020). Economic consequences of risk disclosures: Evidence from crowdfunding. *The Accounting Review*, *95*(4), 331-363.

Majchrzak, A., & Malhotra, A. (2016). Effect of knowledge-sharing trajectories on innovative outcomes in temporary online crowds. *Information Systems Research*, *27*(4), 685-703.

Mannes, A. E. (2009). Are we wise about the wisdom of crowds? The use of group judgments in belief revision. *Management Science*, *55*(8), 1267-1279.

Mata, R., Frey, R., Richter, D., Schupp, J., & Hertwig, R. (2018). Risk preference: A view from psychology. *Journal of Economic Perspectives*, *32*(2), 155-172.

Milgrom, P. R., & Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica: Journal of the Econometric Society*, 1089-1122.

Miller, G.A. (1956).The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychological Review*, 63(2).

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, *29*(1), 1-16.

Mollick, E., & Nanda, R. (2016). Wisdom or madness? Comparing crowds with expert evaluation in funding the arts. *Management Science*, *62*(6), 1533-1553.

Moritz, A., & Block, J. H. (2016). Crowdfunding: a literature review and research directions. *Crowdfunding in Europe*, 25-53.

Müller-Trede, J., Choshen-Hillel, S., Barneron, M., & Yaniv, I. (2018). The wisdom of crowds in matters of taste. *Management Science*, *64*(4), 1779-1803.

Murdoch, W. J., Singh, C., Kumbier, K., Abbasi-Asl, R., & Yu, B. (2019). Definitions, methods, and applications in interpretable machine learning. *Proceedings of the National Academy of Sciences*, *116*(44), 22071–22080.

Padmanabhan, B., Fang, X., Sahoo, N., & Burton-Jones, A. (2022). Machine learning in information systems research. *Management Information Systems Quarterly*, *46*(1), iii-xix.

Pang, M. S. (2017). Politics and information technology investments in the US Federal government in 2003-2016. *Information Systems Research*, *28*(1), 33-45.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics*, *11*(6), 619-632.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … others. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Pernagallo, G., & Torrisi, B. (2022). A theory of information overload applied to perfectly efficient financial markets. *Review of Behavioral Finance*, *14*(2), 223-236.

Piezunka, H., & Dahlander, L. (2015). Distant search, narrow attention: How crowding alters organizations' filtering of suggestions in crowdsourcing. *Academy of Management Journal*, *58*(3), 856-880.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should i trust you?" Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 1135-1144).

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*(5762), 854-856.

Samuelson, P. A. (1938). A note on the pure theory of consumer's behaviour. *Economica*, *5*(17), 61-71.

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly*, *35*(3), 553-572.

Simester, D., Timoshenko, A., & Zoumpoulis, S. I. (2020). Targeting prospective customers: Robustness of machine-learning methods to typical data challenges. *Management Science*, *66*(6), 2495-2522.

Simon, H. A. (1982). Models of Bounded Rationality, vols. 1 and 2. *Economic Analysis and Public Policy, MIT Press, Cambridge, Mass*.

Simonsohn, U., & Ariely, D. (2008). When rational sellers face nonrational buyers: evidence from herding on eBay. *Management Science*, *54*(9), 1624-1637.

Simpson, B., Schreier, M., Bitterl, S., & White, K. (2021). Making the world a better place: How crowdfunding increases consumer demand for social-good products. *Journal of Marketing Research*, *58*(2), 363-376.

Sitkin, S. B., & Pablo, A. L. (1992). Reconceptualizing the determinants of risk behavior. *Academy of Management Review*, *17*(1), 9-38.

Snir, E. M., & Hitt, L. M. (2003). Costly bidding in online markets for IT services. *Management Science*, *49*(11), 1504-1520.

Song, Y., Li, Z., & Sahoo, N. (2021). Matching Returning Donors to Projects on Philanthropic Crowdfunding Platforms. *Management Science, 68*(1), 355-375.

Song, Y., Li, Z., & Sahoo, N. (2022). Matching returning donors to projects on philanthropic crowdfunding platforms. *Management Science*, *68*(1), 355-375.

Spann, M., & Skiera, B. (2003). Internet-based virtual stock markets for business forecasting. *Management Science*, *49*(10), 1310-1326.

Speier, C., & Morris, M. G. (2003). The influence of query interface design on decision-making performance. *MIS Quarterly*, 397-423.

Spiliopoulos, L., & Ortmann, A. (2018). The BCD of response time analysis in experimental economics. *Experimental Economics*, *21*(2), 383-433.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy*, *69*(3), 213-225.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, *71*(3), 393-410.

Sufi, A. (2009). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *The Review of Financial Studies*, *22*(4), 1659-1691.

Surowiecki, J. (2005). *The Wisdom of Crowds*. Anchor.

Tasoff, J., & Zhang, W. (2022). The performance of time-preference and risk-preference measures in surveys. *Management Science*, *68*(2), 1149-1173.

Tjoa, E., & Guan, C. (2021). A survey on explainable artificial intelligence (XAI): Toward medical XAI. *IEEE Transactions on Neural Networks and Learning Systems*, *32*(11), 4793–4813.

Trusov, M., Ma, L., & Jamal, Z. (2016). Crumbs of the cookie: User profiling in customer-base analysis and behavioral targeting. *Marketing Science*, *35*(3), 405-426.

Vallee, B., & Zeng, Y. (2019). Marketplace lending: A new banking paradigm?. *The Review of Financial Studies*, *32*(5), 1939-1982.

Walters, D. J., Ülkümen, G., Tannenbaum, D., Erner, C., & Fox, C. R. (2023). Investor Behavior Under Epistemic vs. Aleatory Uncertainty. *Management Science*, *69*(5), 2761-2777.

Wang, A. Y., & Young, M. (2020). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics*, *137*(2), 491-514.

Wang, H., & Overby, E. (2020 January). How does algorithmic trading influence investor participation in peer-to-peer online lending markets? *Hawaii International Conference on System Sciences,* Maui, HI.

Wang, J., Ipeirotis, P. G., & Provost, F. (2017). Cost-effective quality assurance in crowd labeling. *Information Systems Research*, *28*(1), 137-158.

Wei, Z., & Lin, M. (2017). Market mechanisms in online peer-to-peer lending. *Management Science*, *63*(12), 4236-4257.

Xu, S. X., & Zhang, X. (2013). Impact of Wikipedia on market information environment: Evidence on management disclosure and investor reaction. *MIS Quarterly*, 1043-1068.

Xu, T. (2018). Learning from the crowd: The feedback value of crowdfunding. Working paper. University of Virginia, VA.

Yan Xu, Jian Ni (2022) Entrepreneurial Learning and Disincentives in Crowdfunding Markets. *Management Science*, *68*(9):6819-6864.

Yao, J., Lin, M., & Wu, D. J. (2022). Revealed Wisdom of the Crowd: Informational Value of Bids. Working Paper, Georgia Institute of Technology.

Younkin, P., & Kashkooli, K. (2016). What problems does crowdfunding solve?. *California Management Review*, *58(*2), 20-43.

Zhang, J., & Liu, P. (2012). Rational herding in microloan markets. *Management Science*, *58*(5), 892-912.