Crowdsourced reviews and FinTech Lending Industry

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Abstract

This paper examines the extent to which crowdsourced reviews predict FinTech platform performance and survival probability. We conduct textual analysis of 152,676 reviews published on one of the most popular FinTech information providers between 2015 and 2019. We find that negative sentiment predicts lower trading volume, fewer investors, and fewer loans in a FinTech platform. This result is robust to a series of sensitivity tests and is more prominent that we apply the difference-in-differences approach to establish causality. Moreover, we observe that informative negative reviews are related to worse platform performance while informative positive reviews do not seem to matter. The further analysis uncovers that FinTech platforms experiencing increases in negative reviews are significantly less likely to survive. Our study suggests that crowdsourced review is a critical component that could be considered in regulating the FinTech marketplace.

1. Introduction

FinTech lending, directly matching lenders and borrowers through online services, was first introduced in China in 2007. Over the past ten years, the Chinese FinTech market has enjoyed phenomenal growth and has become a vital financial industry component. By early 2018, more than 5,000 FinTech platforms were established in China, facilitating loans of around $800 billion. However, a phenomenally high failure rate has accompanied this tremendous growth. By early 2018, over 60% of 5,000 FinTech platforms that ever operated were closed. The fails left a big question to regulators - how to effectively regulate the industry to avoid investors' massive loss?

A traditional way to address this challenge is that the regulator oversees the industry relying on experts' reports at the whole level and unable to obtain any expert views for any individual platform. The information asymmetry among platforms, customers (especially for investors), and the regulator are more pronounced than other financial institutions. If investors look for an investment platform, they could follow experts' advice through TV channels, which may be not independent, resulting in massive losses.[1] Instead of relying on expert advice, investors increasingly turn to fellow investors when choosing among platforms. This strategy could help investors identify the platforms that best match their idiosyncratic investment preferences.

Customer authored platform reviews offer a potentially fertile setting for uncovering platform-specific information. Investors/borrowers have unique information about the platform they invest/borrow. They are generally incentivised to provide honest evaluations due to the benefits associated with contributing to the public good (Lerner and Tirole, 2002). Marketing research shows that consumers are increasingly relying on online product peer reviews to make purchase decisions (e.g., Chen and Xie, 2008). Recent studies in the accounting and finance area have started to find that that peer opinions also play a more significant role in financial

[1] According to *21jingji*.com, 23 Chinese platforms collapsed with endorsed by over 30 famous economists in 2017.

markets and corporate prospects. For example, Chen et al. (2014) find that investor options transmitted through social media predict future stock returns and earnings surprises. Huang (2018) shows that information from product reviews (Amazon.com) has predicted power for stock pricing and the firm's fundamentals. It should be noted that the review setting is not typical wisdom of the crowded environment since the customer primarily evaluates their own opinion rather than influencing the platform's trading volume. Thus, our underlying premise is that the platform's function and environment may affect the overall peer review sentiment and the averaging across investors/borrowers, which in turn reveals information about the platform's performance.

We study the development and dynamics of the overall Chinese FinTech marketplace by investigating whether peer reviews are related to the platform performance and survival dynamics in the Chinese FinTech marketplace. Particularly, we investigate whether the anecdotal evidence holds more systematically across platforms by analyzing over 152,676 customer-level platform reviews for 428 unique platforms between 2015 and 2019. These customer reviews are collected from the FinTech platform review website *Wdzj.com*, one of the largest and the most popular online information provider for FinTech platforms in China. Each review contains narratives about particular platform investment experience, and ratings range from one to five for several customer satisfaction dimensions: *Pending Investment*, *Customer Service*, *Web/App Experience*, and *Funding Withdraw*. We use the machine learning method to abstract information from peer opinions across all platforms, then merge the information with the FinTech platform characteristics and performance data to conduct the analyses.

We begin our analysis by exploring the determinants of the sentiment for FinTech platforms. The average review sentiment is significantly positively related to the number of investors, total outstanding balance, and negative related to average maturity, total outstanding balance. Then we focus on the negative sentiment, the percentage of negative reviews in each month, and find that negative sentiment is negatively associated with the number of reviews and average interest rates and a positive relationship with average maturity, however, it is not significantly related to other platform characteristics. It indicates that none of the time-varying platform trading activities (i.e. platform performance measures) can predict sentiment reliably.

Then, we conjecture that the information in a review is incorporated into the FinTech platform's performance with a lag. Our analysis uncovers a negative relationship between negative sentiment and the trading volume for the FinTech platform, a one-standard deviation increase in the fraction of negative reviews is associated with a decrease of 5.57% of the future trading volume for the FinTech platform. The estimations with other performance measures, *Number of Investors* and *Number of Loans*, also illustrate the consistent results and predictability.

These results are robust in many aspects. First, we use customer ratings as alternative measures to test the consistency of the commentator's review sentiment. Second, we consider the impact of the positive reviews and the average sentiment score on FinTech platform performance. Third, we use the sample for only survival FinTech platforms to avoid the effect from defunct platforms; we change the sample period from 2015 to 2018 to exclude the potential impact of the new regulation in some provinces implemented at the end of 2018 may discourage platform trading activities; we use the quarterly sample. Lastly, we test the predicting power of review sentiment over a longer period. Overall, our results are consistent with the baseline regression.

We also employ a difference-in-differences (DID) design to address the endogeneity concern. As omitted time-varying factors could determine both FinTech platform performance and negative reviews. We identify a series of new regulation adoption as exogenous shocks on FinTech lending businesses during the November 2017 - November 2018 period. We use the staggered DID method to examine the variation in treatment timing and dynamic treatment effects. This empirical framework alleviates time-invariant unobservable factors on both sentiment and FinTech platform performance and helps address the endogeneity concern. The DID test further suggests that our baseline results are robust when we consider the endogeneity issue.

We expand the analysis by exploring whether the review informativeness adds value to the predicting power. Because the variation in the review quality raises concerns on the effective use of the reviews (Liu et al., 2008), the helpfulness reviews can provide more accurate reputation information, more trust in product market settings (Bolton et al., 2013). Our results suggest that more informative negative reviews have a strong predicting power on future trading volume and informative positive reviews do not matter. It is consistent with previous findings that negative word of mouth can more accurately predict decreases in firm performance than positive word of mouth predicts firm growth (Kirby and Marsden, 2006; Ferguson, 2008).

We further investigate whether review sentiment can predict platform survival. Using the Cox model, we document that excess negative sentiment is associated with a lower probability of the FinTech platform's survival. In contrast, the excess positive sentiment will not indicate a higher survival rate for the platforms, suggesting that negative reviews are more potent than other corpora (positive and neutral).

Our study contributes to serval strands of the growing FinTech lending literature. First, we contribute to the literature that examines the importance of soft information on FinTech lending (e.g., Pope and Sydnor, 2011; Duarte et al., 2012; Lin et al., 2013; and Freedman and Jin, 2017). Second, we contribute to the literature that evaluates market mechanism in FinTech marketplace (e.g., Iyer et al., 2015; Wei and Lin, 2017; and Hertzberg et al., 2018). Finally, we contribute to the literature that analyzes the relationship between FinTech marketplace and traditional firm structures (e.g., Tang, 2019; Vallee and Zeng, 2019; and Jiang et al., 2019). Despite that, most of the studies focus on a single platform. To our best knowledge, we are the first study to examine the FinTech performance and crowdsourced reviews at the platform level. It provides novel insights to both practitioners and regulators.

Our study contributes to the literature on the usefulness of crowdsourced reviews (e.g., Liu et al., 2008; Zhu and Zhang, 2010; and Bolton et al., 2013;). Our study is related to the literature that analyzes the effect of crowdsourced reviews on the financial market (e.g., Tetlock et al., 2008; Chen et al., 2014; and Green et al., 2019). In particular, we provide initial evidence that the peer-based reviews play a valuable role in the FinTech marketplace.

The rest of the chapter proceeds as follows. Section 2 provides literature review, hypothesis development and institutional background. Section 3 provides the measurement of sentiment. Section 4 describes sample construction summary statistics. Section 5 presents the empirical results. Section 6 concludes.

2 Literature Review, Hypothesis Development and Institutional Background

2.1 Literature Review

i. The Harnessing the Wisdom of Crowds in Revealing Firm Information

This chapter is mainly related to two strands of literature. The first is the finance literature on harnessing the wisdom of crowds to reveal firm information. For example, focusing on investor's reviews, empirical studies show that investors' social media posts (Chen et al., 2014), crowdsourced earnings forecasts (Jame et al. 2016), internet co-searchers (Lee et al. 2015), and aggregating retail investor trades (Kelly and Tetlock, 2013) help predict various firms financial information such as stock returns, cash flows and firm news. In terms of employee opinions, Green et al. (2019) and Huang et al. (2020) find that employee predictions of companies' outlook in Glassdoor.com are incrementally informative in predicting stock returns, future operating performance, bad news. On the other hand, other studies demonstrate that some other types of crowd activities expose little information about firm fundamentals (Antweiler and

Franck 2004; Da et al. 2011). The mixed findings indicate that the sources of crowds' information influence the predict power of "wisdom of crowds".

ii. Consumer Satisfaction and Firm Economic Outcomes

The chapter is also related to literature that examines the relation between consumer satisfaction and economic performance. In general, extant empirical research shows that the customer satisfactions could be an indicator of accounting performance (Ittner and Larcker, 1998), high returns and low risk in stock prices (e.g., Fornell et al., 2006; Fornell et al 2016), shareholder value (e.g., Anderson et al., 2004; Luo et al. 2013), and lower cost of equity capital (Truong et al., 2020). The marketing literature (e.g., Luo et al. 2013) adopts data from social media that often contains a small set of firms and does not distinguish whether the relationship between social media buss and economic performance is driven by information or investor attention. Recent financial studies start to use 'big data' technique to reveal the information in the consumer reviews covering a larger sample size (e.g., Huang et al., 2018; Zhu, 2019). They find that the information from consumer reviews or consumer transactions have a significant relationship with firm outcomes, for instants, stock returns, cash surprises, institutional investor behaviour and managers' investment decisions. These results suggest that online consumers reviews and transactions could generate real-time indicators of firm fundamentals after controlling firm characteristics. Note that the samples in these studies are comprised of US public manufactory companies that sell consumer products on the e-commerce platform. These firms are under multiple disclosure mechanisms to protect the interests of stakeholders, comparing with small and medium size firms.

Focusing on FinTech startups, we tend to explore whether customer reviews could be used as a real-time governance mechanism for investors, regulators and public to monitor the start-ups in FinTech industry. Start-up firms with new technology are racing to fill the holes in the customer experience left by traditional firms on FinTech activities. The transparency of the products and services in FinTech is the key issue for its success to obtain regularity and public acceptance (Treleaven, 2015). However, the regulatory framework has always lagged behind financial innovations, so the governance and disclosure are still weak in the FinTech industry. The literature on start-up governance suggests different stakeholders such as investors (venture capital), founders, executives, directors and employees could play key roles in the growth and survival of start-ups (see the review by Pollman, 2019).

2.2 Hypothesis Development

Crowdsourced reviews, a conspicuous outlet based on social media, have raised many debates in marketing studies. Dellarocas (2003) indicates that online consumer feedback helps establish sellers' reputations in online marketplaces (e.g., eBay.com). Deloitte (2008) finds that 82% of online consumers are directly influenced by peer reviews on purchasing goods. Datamonitor (2010) points out that the influence of traditional sources (e.g., Consumer Reports) is falling, while online-based peer advice is rising. Chen and Xie (2008) argue that consumer reviews can help consumers screen the products and match idiosyncratic conditions with product attributes.

Crowdsourced reviews have also begun to play a more vital role in the finance area. A growing literature highlights the value of crowd wisdom uncovers fundamental firm information. From the financial market perspective, Chen et al. (2014) show evidence that investors' opinions from social media can predict stock returns and earnings surprises. Jame et al. (2016) reveal that crowdsourced earnings forecasts are incrementally helpful, and Kelley and Tetlock (2013) suggest that aggregating retail investor trades help predict stock returns and corporate news. Da and Huang (2020) uncover the herding behavior in harnessing crowds' wisdom and find that herding results in poorer consensus, i.e., independent voice provides more accurate financial forecasts. At the firm level, Green et al. (2019) find that crowdsourced employee reviews can predict firm performance and earnings surprises.

Regarding firm growth, some marketing and decision studies document that online reviews help forecast firm revenues (e.g., Duan et al., 2008; Zhu and Zhang, 2010). As a new business model, FinTech platforms do not have a longstanding history compared with traditional banks. Investors have more incentive to explore the platforms before making investment decisions through online reviews.

Big data analysis techniques make it feasible to aggregate FinTech customers opinions, so academics and practitioners (e.g., Treleaven, 2015; Zhu, 2019; fstech2020 by PwC, 2020) suggest that customer intelligence would be the most crucial predictor of revenue growth and profitability in FinTech. Yet little evidence exists on this relation. We propose that the consumer reviews in the FinTech industry have value to monitor individual institutions' activities and overall systemic activity more effectively and predict potential problems instead of regulating after the fact. Thus, we conjecture the importance of peer reviews on the growth of FinTech platforms.

Hypothesis 1. *The negative review is negatively associated with the performance of the FinTech platform.*

Investors can take advantage of a large number of online reviews to make a decision. Many marketing studies indicate that online reviews positively affect the volume of sales (Archak et al., 2011; Chen and Xie, 2008). However, the issue of the trustworthiness of online has been discussed by many studies (Pavlou and Dimoka, 2006). For instance, consensus reviews are more helpful by potential users than those showing the polarity of sentiments (Jiang et al., 2010).

As such, the textual reviews then act as a filter between one consumer's expectations and the actual review posted by another (Korfiatis et al., 2012). Online platforms also allow readers of a review to post whether they think that review is helpful by voting for or against it, then the quality of reviews can be determined by sorting by the number of voting for helpfulness (Liu et al., 2008). From the finance perspective, Chen et al. (2014) point out the importance of value-relevant information about the online reviews on the stock return. Green et al. (2019) examine the effects of review informativeness and find that reviews' length and timeline are more indicative of firm information. Thus, we posit that the helpfulness of the reviews has an impact on platform performance.

Hypothesis 2a: *Informativeness with positive reviews is positively associated with the FinTech platform performance.*

Hypothesis 2b: *Informativeness with negative reviews is negatively associated with the FinTech platform performance.*

Unlike established firms, FinTech platforms are more likely referred to as entrepreneurial firms with limited operational experience. There is a high degree of information asymmetry between the platforms and its customers (investors and borrowers) due to the lack of disclosure and a performance track record, and a high degree of uncertainty about future performance. Reducing information asymmetry is the key to the survival of startup firms (Jensen and Meckling, 1976).

The consumers are among the most critical stakeholders of firms, as they largely decide firms' cash flows. The internet development provides ordinary consumers with a channel to create and share products' information about consuming experience. Thus, the online consumer reviews contain useful information about a firm's products and influence the consumers' purchasing on a large scale (e.g., Archak et al., 2011; Floyd et al., 2014), which may directly influence firm's sales and profitability. Only a few empirical studies investigate whether the aggregating consumer opinions help predict the firm's future stock return, cash flows and performance, and find mixed results. Based on online customer reviews from Amazon, eBay and Yahoo, Tirunillai and Tellis (2012) show that numerical ratings in reviews do not have predictability for subsequent stock returns and that positive sentiment based on textual analysis of reviews does not have predictability. In contrast, Huang (2018) finds the abnormal consumer product reviews on Amazon predict firm stock returns and cash flows. This chapter complements these studies by highlight the information role of consumers in FinTech innovations that could be useful for predicting the FinTech start-ups growth and survival. Thus, we propose the following hypotheses:

Hypothesis 3a: *Excess positive sentiment is associated with a higher probability of the FinTech platform's survival.*

Hypothesis 3b: *Excess negative sentiment is associated with a lower probability of the FinTech platform's survival.*

2.3 Institutional Background

i. Chinese FinTech Lending Industry

Since the first FinTech lending platform (Ppdai.com) in China was launched in 2007, the marketplace has experienced dramatic growth. Given the substantial demand for this alternative capital channel and ample funding supply, the total transaction volume in the Chinese FinTech lending market in 2018 reached about \$178.89 billion comparing \$8.21 billion in the U.S. marketplace (according to wdzj.com). Why the extraordinary growth in FinTech lending has been taking place in China? A possible explanation is that the current bank system could not efficiently allocate the financial resources for the private sector- the main driver of economic growth (Allen et al., 2005).

Due to the incomplete information sharing, Chinese FinTech lending platforms play a crucial role in society, which provides a channel for those who are challenging to access traditional financial institutions (e.g., small- and medium-sized enterprises (SMEs) and individuals without credit records).[2] From the investors' perspective, FinTech lending creates a new

[2] According to the 2014 wave of China Household Finance Studies, only 21.8% of financially constrained individuals and 46.2% of SMEs are issued by the traditional financial institutions.

investment channel for Chinese households, which can provide an average 10% annualized return that is significantly higher than other typical channels, such as bonds, stocks, and the housing rent. Despite that, the risk for a capital loss occurs in both loan defaults and platform collapses (such as a platform shut down without notice and investors lose all the investments).

According to wdzj.com, 3,701 FinTech platforms had closed out of a total of 5,890 platforms by early 2018 (about 63%), while only three U.S. FinTech lending platforms are reported to have failed. Jiang et al. (2019) report that 40% of defunct platforms were closed due to fraud, 18% were liquidated due to poor performance, and others for unknown reasons. As such, investors suffer a profound loss in those defunct platforms. Trustworthiness is a crucial factor between investors and platforms. Unlike the U.S. marketplace, the Chinese FinTech platform has an immense presence in matching loans and funding operations. The FinTech platform typically provides loans with less information to its investors, which enhances the intermediate role. The investment risk is amplified as investors should also consider the platform's risk (e.g., operational risk). Thus, peer review could be a useful information channel for investors to mitigate the information asymmetry between platforms and investors.

ii. Regulation Stage

In July 2015, the regulators issued "The Guidelines on Promoting the Healthy Development of Internet Finance." [3] The Guidelines first introduced the regulatory framework and fundamental principles in governing the FinTech lending industry. It emphasized that the FinTech lending platform should be an information intermediary and provide information services rather than provide credit enhancement services or engage in illegal fundraising to create a funding pool.

In August 2016, the regulators decided to introduce detailed measures due to the growing chaos in the FinTech marketplace.[4] The new guidelines are named "The Interim Measures on

[3] The regulators include People's Bank of China (PBOC), together with nine other regulatory agencies.
[4] As from 2015, some influential platforms collapsed due to fraud (e.g., Ezubao collapsed in December 2015).

Administration of Business Activities of Online Lending Information Intermediaries," providing more detailed information regarding funding requirements and investor protection.[5] Furthermore, "Guidelines on the Filing-based Administration of the Online Lending Information Intermediaries" had been published in October 2016, emphasizing that the FinTech platforms should apply for a license certified by the local financial regulatory authority. Also, supplementary filings were introduced in August 2017, requiring the FinTech lending platforms to provide more information on their websites to improve transparency. However, at least until February 2019, the financial regulatory authorities are still in the process of the filing procedures, and none of the online lending information intermediaries have been permitted to apply for such filing.

[5] The interim guidelines contains: (i) fundraising for the platforms themselves, (ii) holding investors' fund, including accepting, collecting or gathering funds of lenders directly or indirectly, (iii) providing guarantee to investors as to the principals and returns of the investment, (iv) raising funds by issuing financial products as wealth management products, (v) mismatch between investor's expected timing of exit and the loan's maturity date, (vi) securitization, (vii) promoting its financing products on physical premises other than through the permitted electronic channels, such as telephones, mobile phones and Internet,14 (viii) providing loans with its own capital, except as otherwise permitted by laws and regulations, (ix) equity crowd-funding, (x) deducting interest from loan principal, (xi) outsourcing key services such as customer information collection, screening, credit evaluation, (xii) facilitating loans without a designated purpose15, and (xiii) fraud.

3 Measuring Sentiment

Sentiment analysis is the computational research regarding the tone or opinions of textual information using natural language processing, which has been widely employed in analyzing customers' reviews and social media users' behaviours. There are two standard methods for the sentiment analysis: dictionary-based approach and machine learning. The dictionary-based approach uses a predefined dictionary of positive and negative words to match the words, phrases or sentences into groups (Also called 'bag-of-words' model). In the accounting and finance literature, four different word lists have been extensively used by researchers: Henry (2008), Harvard's GI, Diction, and Loughran and McDonald (2011). However, the method does not consider the unexpected effect or inaccurate result due to the same word having a different tone in various industries or topics. For example, consider a sentence from a customer review translating into English "The product I invested has had generated good return, one of my friends told me that the platform may face a thunder." Based on National Taiwan University Semantic Dictionary (NTUSD), the sentence has a lot of positive words (such as "good return"). However, we can see that the overall tone tends to be negative, because the word "thunder" in Chinese FinTech industry actually means that a platform was not functioning.

We adopt the machine learning method, the Naïve Bayes methods, that apply algorithms as a classification problem to mitigate the disadvantage of the dictionary-based approach. We use a partition of the complete corpus of textual data to train a classifier based on linguistic features, then use the classifier to score the remaining corpus. The words in the training set are tokenized as "positive", "negative", or some other sentiment, for instance, "calm", "tense", "excited" and "upset" depend on the circumstance. The statistical inference picks up sentiment classification rules from the trained set and applies these rules to the entire textual data. The machine learning approach has the advantage of processing the particular textual data by constructing customised classifiers, which can be trained efficiently under supervised learning. The Naïve Bayes machine learning approach has been widely used to analyze disclosures in the U.S. market such as annual report fillings (Li, 2010; Purda and Skillicorn, 2015), analyst reports (Huang et al., 2014), and newspaper articles concerning U.S. merger announcements (Buehlmaier and Zechner, 2017).

Using segmented words as terms,[6] we create a term-document matrix that describes the frequency of terms that occur in a given document, where in rows correspond to the occurrence of terms in the document and columns correspond to the terms. Then we can reduce the sentences to a list of words (d) by their frequency in the sentences. The aim is to classify the sentence into a specific category (c) from a set of all predefined categories (positive, negative, and neutral). Let $\{w_1, \dots, w_t\}$ be a predefined set of sentences with t features. Let $n_i(d)$ be the occurrence of w_i in document d; we have the document vector $d = (n_1(d), \dots, n_t(d)$. So the best category can be described as $c^* = argmax_c P(c|d)$. Using Bayes' theorem, the conditional probability is:

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)}$$

Where $P(c)$ is the prior probability of a category, and $P(d|c)$ is the prior probability that the given document set is classified by a category. $P(d)$ is the prior probability that a given document set occurs. When we assume that all documents are independent, the problem is equivalent to:

$$P(c|d) = \frac{P(c) * P(w_1|c) * \dots * P(w_t|c)}{P(d)}$$

Since we have three categories, $P(d)$ has no effect in c^*. It can be eliminated. The equation can be rewritten as follows:

[6] All Chinese words in the reports have been segmented before we apply the machine learning method. Unlike English corpus, different combinations of Chinese characters often have different meaning. The Character Based Generative model is used because it provides the highest accuracy rate (94%) for Chinese segmentation (Wang et al., 2012).

$$P(c|d) = P(c) * P(w_1|c) * \dots * P(w_t|c)$$

And the document categorization algorithm is described as:

$$c^* = argmax_c(c) * P(w_1|c) * \dots * P(w_t|c)$$

The assumption is independence for each document, in that the probability of each word appearing in a document is unaffected by the presence or absence of each other word in the document. Although the conditional independence assumption does not fully hold in reality, the Naïve Bayesian algorithm has little effect on the results and still deliver accurate categorization (Lewis, 1998).

We employ BaiduAI (a leading Chinese textual analytic) in Python to conduct the sentiment calculation for the platform review. The package includes a predefined corpus from various sources (e.g. financial newspapers and social media). We use Application Programming Interface (API) to access BaiduAI and calculate the sentiment for each review by applying the algorithm we defined above. Finally, we obtain a score with value ranged (0, 1 or 2). 0 means this textual information has a negative sentiment, 1 represents neutral and 2 reflects positive. To construct an aggregated monthly measure, we follow Tetlock et al. (2008) and Chen et al. (2014) to define average negative sentiment:

$$Negative\ Sentimentit_{\ i,t} = \frac{No.of\ Negative\ Reviews_{i,t}}{No.of\ Total\ Reviews_{i,t}},$$

where *Negative Sentiment*$_{i,t}$ is the average fraction of negative reviews across all the reviews published *Wdzj.com* about platform *i* in month *t*.

4 Sample and Summary Statistics

4.1 Sample Construction

This section describes the sample construction and introduces our main variables. Our study uses customer reviews for FinTech platforms collected from *Wdzj.com*, and the FinTech platform characteristics and daily performance data from the China Stock Market & Accounting Research (CSMAR) database. The sample period is from September 2015 to October 2019.

Wdzj.com is the largest and the most popular online information provider for FinTech lending platforms in China. It hosts a database in which customers voluntarily and anonymously review the platforms they have invested/borrowed. As they do when posting reviews to E-business websites (e.g., Amazon). Figure 1 shows the review process through Wdzj.com. A contributor should be registered as a user of *Wdzj.com* with an email verification from an active email address or a valid mobile number. The site administrator also moderates content through manual censorship or reported by other users for specific reviews to avoid potential fraud or self-promotion. The review process contains two parts. First, the contributor should enter the one-to-five star of platform ratings of *Pending Investment*, *Customer Service*, *Web/App Experience*, *Funding Withdraw* and overall *Recommended* (Variable definitions are provided in Appendix A.3.1). This part is not compulsory to complete. Second, the contributor is required to input the textual comments for their investing/borrowing experience in the FinTech platform at least 15 characters (compulsory). Finally, the contributor can submit the review that will be publicly shown on the platform column of *Wdzj.com*. The original review sample contains over 200 thousands individual FinTech platform reviews with ratings for part of reviews. We aggregate the reviews in platform and month level.

The "trading sample" is coming from CSMAR, and data items include *Trading Volume*, *Number of Investors*, *Number of Loans, Average Return*, *Average Maturity*, and *Outstanding Balance.* The platform time-invariant characteristic contains *Size*, *Age*, *Automatic Investment,* *Secondary Market, Risk Control*, *SOE, Association, Risk Control, and Risk Reserve*. Detailed definitions are reported in Appendix A.3.1. The original trading sample provides daily basis FinTech platform performance data, we aggregate those figures in monthly basis for all time-varying variables.

To ensure that our data contain the most important and liquid platforms, we apply the following filters, similar to those in Green et al. (2019) and Surowiecki (2005). First, in our review sample, each platform should have a minimum of 5 reviews in each month and 15 reviews in each quarter to help average out idiosyncratic views. Second, to exclude platforms with insignificant market sizes, we require each platform to have at least 5 million Chinese RMB in registered capital. Third, to eliminate reporting errors and outliers, we winsorize *Trading Volume*, *Number of Investors* and *Number of Loans*, and *Size* at the 1st and 99th percentiles. The filtered sample contains 428 unique platforms and 152,676 individual FinTech platform reviews.

4.2 Summary Statistics

We merge *Wdzj.com* reviews with the trading and FinTech platform characteristics from CSMAR database, we retrieve *Wdzj.com* identifiers together with platform names to hand-match to CSMAR identifiers. Panel A of Table 1 reports review-level summary statistics for the September 2015 through October 2019 sample period. The FinTech platform review sample is comprised of 152,676 reviews for 428 FinTech platforms[7].

The mean *Sentiment Score* is 1.27, reflecting the average sentiment are around neural and shifting to positive. The mean for *Pending Investment*, *Customer Service*, *Web/App Experience* and *Funding Withdraw* vary from 3.33 to 3.80. *Settlement Dates* represents settlement dates of funding withdraw transactions that occur on a transaction date plus days. The mean *Settlement*

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[7] According to *Wdzj.com,* the total outstanding balance for loans in Chinese FinTech platforms was 811 in Billon RMB in 2018. Our sample includes the total outstanding balance of 691Billon RMB, which accounts for 86% of platforms active in the market.

Dates is 3.33 with standard deviation 1.38. 34% of reviews exhibit that the commentors would like to recommend the platform to peers. The Panel B of Table 1 reports Pearson correlations across *Sentiment Score* and rating categories. We observe that *Web/App Experience* is most correlated with *Sentiment Score* (0.58), other categories show the relatively similar correlations with *Sentiment Score* (0.49 with *Pending Investment, 0.57* with *Customer Service, 0.46* with *Funding Withdraw* and 0.56 with *Settlement Dates*). *Sentiment Score* is less correlated with all four scores (from 0.46 to 0.58), which generally helps mitigate concerns that reviewers present exactly the same opinion as score they entered. Also, the textual comments are compulsory to input while the ratings are not compulsorily required. Thus, we use *Sentiment Score* as our main variable to address the question of FinTech lending and customer review.

Panel C of Table 1 reports platform-level summary statistics. The average monthly *Trading Volume* is 46,814 million RMB, the first quartile is 3,260 million RMB, the median is 11,787 and the third quartile is 37,232, indicating that big platforms are usually generating larger amount of loans that results in the distribution skewed to the left. The average *Number of Investors* is 76,406, the median is 7,498, also suggesting a left skewed distribution. The average *Number of Loans* is 57,911, while the median is only 576. Thus, we use the natural log of these amounts in our regression analysis. We construct platform-level monthly sentiment variables from individual *Sentiment Score*. *Negative Sentiment* is the average fraction of negative reviews across all the platform reviews posted over the month, the mean *Negative Sentiment* is 0.33, indicating that 33% of reviews are negative across all FinTech platforms. *Positive Sentiment* is the average fraction of positive reviews across all the platform reviews posted over the month, the mean *Positive Sentiment* is 0.53, indicating that 53% of reviews expresses positive across all FinTech platforms. The mean *Number of Reviews* is 28. The average annualized return for platforms is 9.06% with Q1 3.48% and Q3 11.09%. *Average Sentiment* is the average value of *Sentiment Score* across all the platform reviews posted over the month. the mean *Average*

Sentiment is 1.28, which is the same as the pooled review sample. The mean of the average maturity for loans in each platform is 7 months and median is 4.76 months, suggesting that most of platforms prefer to provide short-term loans, unlike the US or UK, the FinTech investors in China demand their investment more quickly to return. The mean *Log(Outstanding Balance)* is 11.14. The mean *Log(Size)* is 8.78. The average platform *Age* is 4.16 years, indicating that the FinTech platforms are all start-up firms. 46% FinTech platforms explicit the risk control method. The FinTech platforms set up an average 444.96 million RMB as safeguard fund in order to cover those non-performing loans to investors. Also, 60% of FinTech platforms join memberships in industry associations, 26% of FinTech platforms have *Secondary Market,* 64% of FinTech platforms provide *Automatic Investment* tools and 16% of FinTech platforms are affiliated with State-Owned Enterprises (SOEs).

Table 1 Descriptive Statistics

Panel A: Review Sample

	# of Reviews	Mean	Std.dev.	Q1	Median	Q3
Sentiment Score	152,676	1.267	0.936	0.000	2.000	2.000
Pending Investment	54,507	3.804	1.532	3.000	4.000	5.000
Customer Service	56,147	3.697	1.496	3.000	4.000	5.000
Web/App Experience	78,818	3.634	0.57	3.000	4.000	5.000
Funding Withdraw	78,818	3.354	0.52	2.000	3.000	5.000
Settlement Dates	31,006	3.325	1.377	2.000	4.000	4.000
Recommended (1=Yes)	152,676	0.342	0.474	0.000	0.000	1.000

Panel B: Correlation Among Ratings and Sentiment

	Sentiment Score	*Pending Investment*	*Customer Service*	*Web/App Experience*	*Funding Withdraw*	*Settlement Dates*
Sentiment Score	1.000					
Pending Investment	0.489	1.000				
Customer Service	0.572	0.819	1.000			
Web/App Experience	0.580	0.821	0.907	1.000		
Funding Withdraw	0.456	0.715	0.734	0.731	1.000	
Settlement Dates	0.563	0.897	0.927	0.927	0.878	1.000

Table 1

Descriptive Statistics (*Continued*)

Panel C: Monthly Trading Sample

	Obs,	Mean	Std.dev.	Q1	Median	Q3
Main Dependent variables						
Trading Volume	4,793	46,813.651	107,332.439	3,259.800	11,787.170	37,231.699
Number of Investors	4,793	76,405.991	312,109.952	1,729.000	7,498.000	26,812.000
Number of Loans	4,793	57,911.521	345,262.818	118.000	576.000	5,349.000
Defunct Platform (1=Yes)	4,793	0.367	0.482	0.000	0.000	1.000
Main Independent variables						
Negative Sentiment	4,793	0.327	0.200	0.167	0.286	0.460
Positive Sentiment	4,793	0.533	0.223	0.375	0.562	0.706
Average Sentiment	4,793	1.282	0.577	0.951	1.343	1.750
Other variables						
Number of Reviews	4,793	28.208	56.061	7.000	11.000	27.000
Average Interest Rate (%)	4,793	9.056	3.479	7.659	9.494	11.089
Average Loan Maturity (Month)	4,793	6.997	7.131	2.566	4.757	8.376
Log(Outstanding Balance)	4,793	11.138	1.833	10.066	11.167	12.314
Log(Size)	4,793	8.775	0.872	8.517	8.700	9.210
Age(Year)	4,793	4.157	1.309	3.000	4.000	5.000
SOE (1=Yes)	4,793	0.159	0.366	0.000	0.000	0.000
Automatic Investment	4,557	0.635	0.481	0.000	1.000	1.000
Secondary Market (1=Yes)	4,793	0.257	0.437	0.000	0.000	1.000
Risk Control (1=Yes)	4,793	0.359	0.480	0.000	0.000	1.000
Risk Reserve	4,793	444.955	4,022.613	0.000	0.000	0.000
Association (1=Yes)	4,793	0.593	0.491	0.000	1.000	1.000

This table reports descriptive statistics of FinTech platform reviews from wdzj.com and platform trading activities from CSMAR from 2015 to 2019. The review sample covers 152,676 reviews for 428 unique platforms, and the merged trading sample includes 4,793 observations with platform-month level trading information and time-invariant characteristics. Panel A presents distribution and number of observations in sentiment, review ratings and other activities. Panel B reports Pearson correlation coefficients with significance at 1% level. Panel C presents the summary statistic of monthly trading variables, monthly aggregated sentiment variables and platform characteristics. All the variables are defined in Appendix Table A.1.

4.3 Determinants of sentiment for FinTech platforms

Table 2 explores determinants of sentiment by regressing *Average Sentiment*$_{t+1}$, *Negative Sentiment*$_{t+1}$ and *Positive Sentiment*$_{t+1}$ on platform characteristics such as *Log(Trading Volume), Log(Number of Investors)*, *Log(Number of Loans)*, *Average Loan Maturity*, *Average Interest Rate*, *Log(Number of Reviews)*, *Log(Outstanding Balance), Age*, *Log(Size)*, *Automatic Investment, Secondary Market, SOE, Association, Risk Control*, and *Risk Reserve*. We use the

OLS regression as first specification with time fixed effects to examine whether firm characteristics influence the sentiment measures and control both platform and time fixed effects in second specification.

In the cross-section of platforms, column (1), (3) and (5) of Table 2 report that *Average Sentiment*$_{t+1}$ is significantly positively related to trading volume, *Negative Sentiment*$_{t+1}$ is significantly negatively associated with trading volume, and *Positive Sentiment*$_{t+1}$ has a positive relation to trading volume. However, all the three sentiment measures are not statistically influenced by number of investors and number of loans, suggesting that number of investors and number of loans are unbale to predict future sentiments based on cross-section of platforms.

On the other hand, if we consider both time and platform fixed effects, column (2), (4) and (6) of Table 2 present that the coefficients of majority platform characteristics are insignificant for all sentiments measures, suggesting that none of the platform characteristics can reliably predict customer's sentiment. Particularly, the coefficients of the three platform performance measures (*Log(Trading Volume), Log(Number of Investors)* and *Log(Number of Loans)*) which implement in the later main analysis are statistically insignificant, suggesting that *Average Sentiment*, *Negative Sentiment* and *Positive Sentiment* are largely independent of the information included in platform characteristics (the results are more convinced by controlling platform fixed effects because the review sentiment on an individual platform is rarely associated with other platforms' performance). This finding provides the strong evidence that the reverse relationship between sentiment measures and platform performance is less concerned.

Table 2 Determinants of Average Sentiment and Negative and Positive Sentiment Ratio

Dependent variable:	*Average Sentiment$_{t+1}$*		*Negative Sentiment$_{t+1}$*		*Positive Sentiment$_{t+1}$*	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Trading Volume)	0.0509***	0.0325	-0.0227***	-0.0096	0.0206***	0.0099
	(0.0128)	(0.0245)	(0.0051)	(0.0107)	(0.0051)	(0.0101)
Log(Number of Investors)	0.0018	0.0237	0.0089*	-0.0016	-0.0060	0.0037
	(0.0120)	(0.0231)	(0.0049)	(0.0089)	(0.0049)	(0.0091)
Log(Number of Loans)	0.0005	-0.0203	-0.0037	0.0002	0.0047*	-0.0018
	(0.0059)	(0.0128)	(0.0023)	(0.0056)	(0.0025)	(0.0061)
Average Loan Maturity	0.0003	-0.0054*	0.0005	0.0026**	-0.0010	-0.0028**
	(0.0014)	(0.0031)	(0.0006)	(0.0011)	(0.0006)	(0.0012)
Average Interest Rate	-0.0070*	0.0112*	0.0029**	-0.0034*	-0.0031**	0.0039*
	(0.0039)	(0.0062)	(0.0013)	(0.0020)	(0.0014)	(0.0023)
Log(Number of Reviews)	0.0374***	0.0452***	-0.0165***	-0.0227***	0.0524***	0.0408***
	(0.0103)	(0.0171)	(0.0040)	(0.0081)	(0.0044)	(0.0079)
Log(Outstanding Balance)	-0.0911***	-0.0074	0.0347***	0.0017	-0.0297***	0.0010
	(0.0112)	(0.0294)	(0.0038)	(0.0118)	(0.0039)	(0.0122)
Log(Size)	-0.0054		0.0062		-0.0050	
	(0.0115)		(0.0041)		(0.0045)	
Automatic Investment	-0.0249		0.0155**		-0.0112	
	(0.0209)		(0.0074)		(0.0081)	
Secondary Market	-0.0020		0.0153**		-0.0220***	
	(0.0210)		(0.0078)		(0.0084)	
SOE	-0.0625**		0.0193**		-0.0193*	
	(0.0253)		(0.0094)		(0.0101)	
Age	-0.0245***		0.0061**		-0.0070**	
	(0.0086)		(0.0031)		(0.0033)	
Association	0.0240		-0.0123		0.0118	
	(0.0205)		(0.0076)		(0.0082)	
Risk Control	0.0201		-0.0206***		0.0225***	
	(0.0198)		(0.0073)		(0.0079)	
Log(Risk Reserve)	-0.0134***		0.0026*		-0.0030*	
	(0.0043)		(0.0015)		(0.0016)	
Platform Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,516	3,516	3,516	3,516	3,516	3,516
Adj. R^2	0.053	0.027	0.058	0.016	0.079	0.042

This table presents the coefficients from panel regressions with *Average Sentiment$_{t+1}$*, *Negative Sentiment$_{t+1}$* and *Positive Sentiment$_{t+1}$* as the dependent variables and platform characteristics as the independent variables. *Average Sentiment$_{t+1}$* in column (1) and (2) is defined as the average value of sentiment scores across all the platform reviews posted over the forward month. *Negative Sentiment$_{t+1}$* in column (3) and (4) is defined as the average fraction of negative reviews across all the platform reviews posted over the forward month. *Positive Sentiment$_{t+1}$* in column (5) and (6) is defined as the average fraction of positive reviews across all the platform reviews posted over the forward month. Platform characteristics are defined in Appendix A.3.1. Column (1), (3) and (5) show the regression results without platform and time fixed effects, whereas the column (2), (4) and (6) contain both platform and time fixed effects. The sample covers the period from 2015 to 2019 and consists of 3,516 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5 Empirical Results

5.1 Peer Review and FinTech Platform Performance

We investigate whether peer review signal fundamental performance on the FinTech platform. We conjecture that the information in a review is incorporated into the performance of FinTech platform with a lag, suggesting the predictability of platform financial performance. To examine the relationship between review sentiment and FinTech platform performance, we use panel data regression analysis to the following specification:

$$Performance_{i,t+1} = \alpha + \beta Review_{i,t} + \gamma Controls_{i,t} + FE + \epsilon_{i,t} \tag{1}$$

Where i denotes FinTech platform and t denotes month. The dependent variable, $Performance_{it+1}$ is proxied by $Trading\ Volume_{i,t+1}$, $Number\ of\ Investors_{i,t+1}$ and $Number\ of\ Loans_{i,t+1}$. $Trading\ Volume_{i,t+1}$ is defined as the natural logarithm of the total amount of new loans originated in the platform i in month $t+1$. $Number\ of\ Investors_{i,t+1}$ is defined as the natural logarithm of the total number of investors in the platform i in month $t+1$. $Number\ of\ Loans_{i,t+1}$ is defined as the natural logarithm of the number of new loans originated in the platform i in month $t+1$. Unlike the listed firms, platforms in our sample are relatively young firms and do not publish annual report to disclose the platform performance. We follow Jiang et al. (2018) to use *Trading Volume*, *Number of Investors*, and *Number of Loans* to proxy platform performance. Because the income in a platform primarily relies on the loan origination and service fees which can be observed from the transaction volumes and the user number (borrowers and investors). The primary independent variable, $Review_{i,t}$ is measured by $Negative\ Sentiment_{i,t}$ in baseline regression and $Average\ Sentiment_{i,t}$ and $Positive\ Sentiment_{i,t}$ for robustness check. We will also test the customer ratings as the alternative measure in next section. We estimate all independent variables in month t, which is a one-month lag from the dependent variable, thus allowing us to examine whether customer satisfaction in month *t* can predict the FinTech platform performance in month *t+1*.

To control for time-varying platform characteristics, we include the average value of the loan duration (months) for the platform over the month (*Average Loan Maturity*), the average value of daily loan interest rates for the platform over the month (*Average Interest Rate*), the natural logarithm of the monthly total number of reviews in the platform (*Log(Number of Reviews)*), and the cumulative amount of outstanding balance for all borrowers in the platform (*Log(Outstanding Balance)*). We also include month and platform fixed effects for some of specifications. Standard errors are heteroskedasticity robust and clustered at platform level to account for serial- and cross-correlation, and heteroskedasticity.

Table 3 reports the main regression results of monthly platform-level performance on lagged negative sentiment. Column (1), (3) and (5) show the regression results without fixed effects, whereas the column (2), (4) and (6) contain both platform and month fixed effects. The negative relationship between trading volume in FinTech platform and negative sentiment is both economically and statistically significant. The coefficient of *Negative Sentiment* is -0.7026 in column (2), suggesting that a one-standard-deviation increase in the fraction of negative reviews in month *t* is related to a decrease of 5.57% = (0.7026*0.200/2.525) of a standard deviation in platform trading volume in month *t+1*.Other proxies for platform performance also exhibit a negative relationship with the fraction of negative reviews (Column (2) and (6) respectively).

Table 3 Negative Sentiment and FinTech Platform Performance

Dependent variable:	*Trading Volume$_{t+1}$*		*Number of Investors$_{t+1}$*		*Number of Loans$_{t+1}$*	
	(1)	(2)	(3)	(4)	(5)	(6)
Negative Sentiment	-1.2959***	-0.7026***	-0.9621***	-0.6258***	-1.0729***	-0.5333***
	(0.1925)	(0.2319)	(0.1852)	(0.2143)	(0.1995)	(0.1967)
Average Loan Maturity	-0.0215***	0.0016	0.0288***	0.0361*	0.0820***	0.0548***
	(0.0057)	(0.0231)	(0.0059)	(0.0206)	(0.0064)	(0.0192)
Average Interest Rate	0.2903***	0.3704***	0.2937***	0.3351***	0.1900***	0.2425***
	(0.0235)	(0.0590)	(0.0234)	(0.0545)	(0.0190)	(0.0427)
Log(Number of Reviews)	-0.1793***	-0.3750***	0.0076	-0.2944***	0.1681***	-0.1205**
	(0.0348)	(0.0693)	(0.0362)	(0.0618)	(0.0456)	(0.0610)
Log(Outstanding Balance)	0.9278***	0.8108***	0.8951***	0.7491***	0.8825***	0.7222***
	(0.0320)	(0.1467)	(0.0317)	(0.1291)	(0.0312)	(0.0895)
Platform Fixed Effects	No	Yes	No	Yes	No	Yes
Month Fixed Effects	No	Yes	No	Yes	No	Yes
Obs.	3,686	3,686	3,686	3,686	3,686	3,686
Adj. R^2	0.462	0.490	0.512	0.543	0.461	0.508

This table presents the regression results of monthly platform-level performance on lagged negative sentiment. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variable is *Negative Sentiment*, which is defined as the average fraction of negative reviews across all the platform reviews posted over the month. Variable definitions are provided in Appendix A.3.1. Column (1), (3) and (5) show the regression results without platform and month fixed effects, whereas the column (2), (4) and (6) contain both platform and month fixed effects. The sample covers the period from 2015 to 2019 and consists of 3,686 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

We also find that the average interest rate is positively associated with platform performance. Higher return (interest rates) for investors enlarge the platform performance in future (larger amount of trading activity, more investors participation and higher number of funded loans), suggesting that investors will be attracted to fund loans in the platforms with higher return. The positive relationship between platform performance and average loan maturity (except the specification in column (2) for *Trading Volume$_{t+1}$*) reveals that if the platform can provide longer term loans, will attract more borrowers and boost the trading activities (Hertzberg et al., 2018). Posting more reviews is negatively associated with platform performance if we control the platform and month fixed effects. Increased comments about the platform during a period is considered as the information leakage (often as negative news) and result in crowding discussion. Lastly, outstanding balance can be considered as the platform scale. The results show that the more outstanding principle is related to better future platform performance.

To summary, our finding that a measure of sentiment in commentaries predicts future FinTech performance suggests that the opinions transmitted via this online information outlet channel deliver value-relevant information. Our results suggest that investment-related website provide a meaningful platform for people to help each other make more informed investment decisions for these FinTech platforms (especially for those platforms have less transparency).

5.2 Robustness Tests

We are aware that our baseline results may be subjected to the following potential issues. First, although sentiment measures are more convincing to help peer's investment decision as it provides informative corpus, we use ratings as alternative measures to test the consistency for the commentator's review sentiment. Table 4, with full control variables and the month and platform fixed effects (the full version of the table is provided in Appendix B Table B.1), presents the regression results of monthly platform-level performance on lagged platform ratings. Panel A reports the results of *Trading Volume*$_{t+1}$ as dependent variable, panel B for *Number of Investors*$_{t+1}$ and panel C for *Number of Loans*$_{t+1}$ respectively. Columns (1), (2), (3), and (4) of all panels shows that all four rating categories (*Pending Investment, Customer Service, Web/App Experience,* and *Funding Withdraw*) are positively related to the platform performance, suggesting that the results are consistent with the base line regressions. The ratings can provide the information for the platform from common experiences, such as a higher rating of *Pending Investment* indicates less waiting time to go through the funding, a higher rating of *Customer Service* indicates better customer service, a higher rating of *Web/App Experience* indicates the better experience of the website or mobile application, and A higher rating of *Funding Withdraw* indicates less waiting time to withdraw the funding.

Column (5) shows the results of *Settlement Dates* that was also consistent with the previous settings. Finally, column (6) reports the impact of whether the commentor is willing to recommend the platform to peers on platform performance. Strong recommendation is positively associated with higher platform's future trading amount, more investors, and number of loans. These findings highlight the importance of crowdsourced reviews on firm performance, which is consistent with Green et al., (2019).

Second, we consider the impact of the positive reviews and the average sentiment score on FinTech platform performance. Table A.2, with full control variables and the month and platform fixed effects, presents the results of monthly platform-level performance on lagged other sentiment measures. Columns (1), (3) and (5) report the regression results that the *Average Sentiment* predicts the positive relationships with the future performance for all three measures (*Trading Volume*$_{t+1}$, *Number of Investors*$_{t+1}$ and *Number of Loans*$_{t+1}$). As a higher sentiment score tends to be positive of cross-sectional reviews, we can confirm that the result is consistent with the main result in the previous section (opposite sign to Negative Sentiment). To rule out the effect of the reviews in larger platforms could shift the results, we further use the measure *Positive Sentiment* to test the specifications in Columns (2), (4) and (6). The results show that the *Positive Sentiment* is positively associated with FinTech platform performance for all three specifications, suggesting that the higher fraction of positive reviews reveal better platform performance.

Third, we consider the reviews from defunct platforms that may be more negative to drift the results, we remove the sample from those defunct platforms to test the same specification as equation (3.1). Also, the new regulation in some provinces implemented at the end of 2018 may discourage platform trading activities. We then remove the 2019 sample to test the same specification as equation (3.1). Furthermore, we use the quarterly sample to test the same specification as equation (3.1). Table A.3, with full control variables and the month and platform fixed effects, presents the regression results of platform-level performance on lagged negative sentiment. Panel A reports the results for excluding defunct platforms sample. The fraction of monthly negative comments predicts less amount of future trading volume, less investors and less loans, suggesting that our results are robustness if we only consider live platforms. Panel B reports the results for excluding 2019 sample and panel C for the quarterly sample, the results are consistent with the main specification.

Lastly, we test the predicting power of review sentiment over a longer period. Table A.4, with full control variables and the month and platform fixed effects, presents the regression results of monthly platform-level performance on lagged negative sentiment from the previous six months. Panel A reports that $\textit{Trading Volume}_{t+1}$ to $\textit{Trading Volume}_{t+6}$ are all negatively affected by negative sentiment. The coefficients are statistically significant but becomes not strong from previous five month. Panel B shows the similar result to the Panel A, there are the less investors if the more negative reviews in past six month for the platform. Panel C also presents consistent findings with other performance measures, but the predicting power does not hold for the negative reviews in six months ago.

Table 4 FinTech Platform Ratings and FinTech Performance

Panel A: Trading Volume$_{t+1}$

Dependent variable:	*Trading Volume$_{t+1}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Pending Investment	0.3713***					
	(0.0927)					
Customer Service		0.3801***				
		(0.0879)				
Web/App Experience			0.3049***			
			(0.0758)			
Funding Withdraw				0.1553**		
				(0.0660)		
Settlement Dates					0.3166***	
					(0.1142)	
Recommended						0.6188***
						(0.1510)

Panel B: Number of Investors$_{t+1}$

Dependent variable:	*Number of Investors$_{t+1}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Pending Investment	0.3360***					
	(0.0859)					
Customer Service		0.3525***				
		(0.0805)				
Web/App Experience			0.2972***			
			(0.0700)			
Funding Withdraw				0.1384**		
				(0.0596)		
Settlement Dates					0.2875***	
					(0.1094)	
Recommended						0.6050***
						(0.1389)

(continue on next page)

Table 4 FinTech Platform Ratings and FinTech Performance (*Continued*)

Panel C: Number of $Loans_{t+1}$

Dependent variable:	*Number of $Loans_{t+1}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Pending Investment	0.2535***					
	(0.0738)					
Customer Service		0.2697***				
		(0.0685)				
Web/App Experience			0.2231***			
			(0.0640)			
Funding Withdraw				0.1471**		
				(0.0624)		
Settlement Dates					0.2704**	
					(0.1050)	
Recommended						0.4283***
						(0.1251)
Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,905	1,964	2,448	2,448	1,021	2,448

This table presents the regression results of monthly platform-level performance on lagged platform ratings. The dependent variables are *Trading* $Volume_{t+1}$, *Number of* $Investors_{t+1}$ and *Number of* $Loans_{t+1}$. *Trading* $Volume_{t+1}$ is defined as the natural logarithm of the total amount of new loans originated in the platform in month $t+1$. *Number of* $Investors_{t+1}$ is defined as the natural logarithm of the total number of investors in the platform in month $t+1$. *Number of* $Loans_{t+1}$ is defined as the natural logarithm of the number of new loans originated in the platform in month $t+1$. The independent variables are *Pending Investment, Customer Service, Web/App Experience, Funding Withdraw, Settlement Dates and Recommended.* Variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading* $Volume_{t+1}$ as dependent variable, panel B for *Number of* $Investors_{t+1}$ and panel C for *Number of* $Loans_{t+1}$ respectively. The sample covers the period from 2015 to 2019 and consists of 1,905 platform-month level observations for *Pending Investment* as the independent variable, 1,964 observations for *Customer Service* as the independent variable, 1,021 for *Settlement Dates* as the independent variable and 2,448 for *Web/App Experience, Funding Withdraw* and *Recommended* as the independent variables. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.5.3 Endogeneity Correction: Difference-in-Differences Design

The previous analysis recognizes a significantly negative relationship between negative review and platform performance. However, although we use trading volume, the number of investors, and the number of loans measures in month *t+1* and negative sentiment measures in month *t* to mitigate the potential reverse causality issue, endogeneity concerns prolong. Specifically, omitted time-varying factors could determine both FinTech platform performance and negative reviews. To address the endogeneity concern, we further employ a difference-in-differences (DID) design in this section.

We identify a series of new regulation adoption as exogenous shocks on FinTech lending businesses during the November 2017 - November 2018 period. As from 2015, the regulation on Chinese FinTech lending tends to be more stringent. The regulation body requests each platform to register in the new framework in late 2016. Thereafter the FinTech marketplace association in some provinces or cities promulgate the guidelines in order to align with the updated regulation framework. The guidelines are relatively the same in the provinces or cities where have adopted. The detailed guideline contains guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in the provinces or cities. Panel A in Table 4 reports the summary information of the regulation adoption in the provinces and cities. With the disruption of the lending business in those locations, FinTech platforms will confront the uncertainty of their business model, which enlarges investor's concerns about the affected platforms. Thus, the distribution of relevant platform reviews could be switching polarity, and the changes in sentiment are exogenous.

We use the staggered DID method to examine the variation in treatment timing and dynamic treatment effects. This empirical framework alleviates the effect of time-invariant unobservable factors on both sentiment and FinTech platform performance and helps address the endogeneity concern. We use the following model:

$$Performance_{(i,t)} = \alpha + \beta Treatment \times Adoption_{i,t} + \gamma Controls_{(i,t)} + FE + \epsilon_{(i,t)} \tag{3.2}$$

Where *Treatment* × *Adoption$_{it}$* is defined as a dummy variable that equals one if starting the month *t* in which the new regulation adoption becomes effective in the province or city of the platform *i*, and zero otherwise. All other variables are defined similarly to the model (3.1). If Hypothesis 1 does hold, i.e., the negative review sentiment is negatively associated with the performance of the FinTech platform, we conjecture a negative relationship between *Treatment* × *Adoption* and platform performance measures, suggesting a reduction in platform performance after adopting the new regulation in those treated platforms. Column (1), (3), and (5) in Panel B of Table 5 presents the estimation results of DID test. The coefficients of *Treatment* × *Adoption* are negative for all performance measures, i.e., *Trading Volume, Number of Investors and Number of Loans.* The DID estimation suggests that our baseline results are robust when we consider the endogeneity issue.

We further consider the validity of DiD results based on the method of Hong and Kacperczyk (2010). Column (2), (4), and (6) in Panel B of Table 5 show the pretreatment trends around the policy adoption (from t-3 to t+3). As from the parallel-trends assumption, we expect a similar trend in performance variables during the pretreatment period for both treated and controlled groups. The coefficients (*Treatment* × *Adoption (t-3), Treatment* × *Adoption (t-2), Treatment* × *Adoption (t-1), and Treatment* × *Adoption (t0)*) are insignificant, suggesting that the parallel-trends assumption of DiD estimation is not violated. Starting from *Treatment* × *Adoption (t+1),* the coefficients are negative and significant (except *Treatment* × *Adoption (t+3)* on *Number of Loans*). This indicates that the negative effects of policy adoption only occurs after it is implemented. These tests strongly confirm the of DiD estimation results and suggest a causal effect of negative sentiment and platform performance.

Table 5 Negative Sentiment and FinTech Platform Performance: Difference-in-Differences Approach

Panel A: New FinTech Lending Regulation Adoption across Province or City

Province/City	Adoption Date	Description
Jinan, Shandong	24 November 2017	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Jinan.
Shenzhen	16 July 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Shenzhen.
Zhejiang	25 July 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Zhejiang.
Beijing	20 July 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Beijing.
Anhui	02 August 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Anhui.
Shanghai	03 August 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Shanghai.
Jiangxi	16 November 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Jiangxi.
Dalian, Liaoning	10 October 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Dalian.
Guangdong	13 October 2018	Provide guidelines on terminating FinTech lending business and going into administration for those bankruptcy platforms registered in Guangdong.

(continue on next page)

Table 5 Negative Sentiment and FinTech Platform Performance: Difference-in-Differences Approach (*Continued*)

Panel B: Difference-in-Differences Analysis

Dependent variable:	*Trading Volume*		*Number of Investors*		*Number of Loans*	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Adoption	-0.6358***		-0.4846***		-0.3569**	
	(0.1787)		(0.1595)		(0.1735)	
Treatment × Adoption (t-3)		0.1096		0.0404		0.1879*
		(0.1122)		(0.1230)		(0.1030)
Treatment × Adoption (t-2)		0.0232		0.0461		0.0953
		(0.1130)		(0.1198)		(0.1080)
Treatment × Adoption (t-1)		-0.0778		-0.0983		-0.0473
		(0.1499)		(0.1438)		(0.1455)
Treatment × Adoption (t0)		-0.1521		-0.1579		-0.0359
		(0.1654)		(0.1632)		(0.1602)
Treatment × Adoption (t+1)		-0.4850**		-0.4159**		-0.2163*
		(0.1898)		(0.1767)		(0.1791)
Treatment × Adoption (t+2)		-0.3402**		-0.2969**		-0.0515**
		(0.2128)		(0.1999)		(0.2033)
Treatment × Adoption (t+3)		-0.6302***		-0.5464***		-0.3201
		(0.2175)		(0.2061)		(0.2036)
Average Loan Maturity	0.0168	0.0178	0.0480***	0.0488***	0.0593***	0.0596***
	(0.0190)	(0.0193)	(0.0181)	(0.0182)	(0.0178)	(0.0178)
Average Interest Rate	0.3741***	0.3740***	0.3528***	0.3526***	0.3000***	0.2998***
	(0.0462)	(0.0464)	(0.0438)	(0.0440)	(0.0385)	(0.0386)
Log(Number of Reviews)	-0.0265	-0.0258	0.0108	0.0118	0.0088	0.0084
	(0.0527)	(0.0526)	(0.0494)	(0.0495)	(0.0537)	(0.0541)
Log(Outstanding Balance)	0.6574***	0.6682***	0.6458***	0.6523***	0.4637***	0.4706***
	(0.1630)	(0.1638)	(0.1515)	(0.1516)	(0.1308)	(0.1312)
Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,789	4,789	4,789	4,789	4,789	4,789
Adj. R^2	0.548	0.545	0.526	0.525	0.400	0.399

This table reports Difference-in-Differences (DID) tests of examining how exogenous changes in new FinTech lending regulation adoption across province affect FinTech platform performance. Panel A provides a summary of judicial new regulation adoption by province over August 2017 to December 2018. Panel B presents the results of DID analysis and pretreatment trends for testing the impact of exogenous regulation changes on FinTech platform performance. The dependent variables are *Trading Volume*, *Number of Investors* and *Number of Loans*. *Trading Volume* is defined as the natural logarithm of the monthly total amount of new loans originated in the platform. *Number of* Investors is defined as the natural logarithm of the monthly total number of investors in the platform. *Number of Loans* is defined as the natural logarithm of the monthly total number of new loans originated in the platform. The independent variables are *Treatment × Adoption*, which is defined as a dummy variable that equals one if starting the month in which the new regulation adoption becomes effective in the province or city, and zero otherwise. *Treatment × Adoption (t-3),… Treatment × Adoption (t+3)* are dummy variables that equals one in the specific time (t-3, t-2, t-1, t=0, t+1, t+2 and t+3) generated by observing the new regulation has ever adopted in the province or city, and zero otherwise. Variable definitions are provided in Appendix A.3.1. Time and platform fixed effects are included in all specifications. The sample covers the period from 2015 to 2019 and consists of 4,789 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.5.4 The Informativeness of Crowdsourced Review: Considering Value-Relevant Information

Although in previous sections we establish the association between sentiment and FinTech platform performance, we cannot conclude with confidence whether the platform reviews include value-relevant information (predictability channel). Because the variation in the review quality raises concerns on the effective use of the reviews (Liu et al., 2008). The helpfulness reviews can provide more accurate reputation information, more trust in product market settings (Bolton et al., 2013). Thus, we further consider the informativeness of the crowdsourced reviews in platform performance. To examine the effect of helpfulness reviews, we use *High Positive, High Negative, Low Positive* and *Low Negative* to proxy the review Informativeness. We first calculate the number of *Net Useful* for each review.[8] *High Positive* is the average fraction of positive reviews with positive *Net Useful* across all the platform reviews posted over the month. *High Negative* is the average fraction of negative reviews with positive *Net Useful* across all the platform reviews posted over the month. *Low Positive* is the average fraction of positive reviews with negative *Net Useful* across all the platform reviews posted over the month. *Low Negative* is the average fraction of negative reviews with negative *Net Useful* across all the platform reviews posted over the month.

Table 6 reports the regression results of monthly platform-level performance on lagged review informativeness. Column (1) in Panel A shows the positive relationship between of *High Positive* and trading volume, but it is not statistically significant. Column (2) in Panel A presents that *High Negative* is negatively associated with trading volume and the coefficient is both statistically and economically significant. Column (3) in Panel A reports a positive coefficient

[8] All registered users in *Wdzj.com* are able to click a *Useful* button if they think this review is helpfulness and click *Not Useful* if they think the review is useless, no action otherwise. We observe that the most of reviews have neither *Useful* nor *Not Useful. Net Useful* is calculated by the number of *Useful* for a review minus the number of *Not Useful*. If a review without *Useful* or *Not Useful*, we set the *Net Useful* as zero. According to review sample in our analysis, the mean for *Useful* is 1.54 with standard deviation 3.84, and the mean value for *Not Useful* is 0.76 with standard deviation 2.92, the sample size is 152,676 reviews.

of *Low Positive* but shows a weaker significance. Column (4) in Panel A reports a negative coefficient of *Low Negative* but it is not statistically significant. These results suggest that more informative negative reviews have a strong predicting power on future trading volume, which is consistent with Hypothesis 2b. However, the result for less informative negative reviews is insignificant. Surprisingly, more informative positive reviews are not related to trading volume although the coefficient on less informative positive reviews is positively associated with trading volume but the result is not strong. The Hypothesis 2a is not valid in our empirical test, suggesting that informative positive reviews do not matter. Other performance measures in Panel B (*Number of Investors* $_{t+1}$) and Panel C (*Number of Loans*$_{t+1}$) have similar results to Panel A. These findings support the view that more informative review has better outcome than less informative one, which is consistent with prior studies, such as Green et al. (2019), Liu et al. (2008) and Chen et al. (2014). Mover, our results uncover the novel evidence that more informative negative review matters, but informative positive review is not helpful for predicting performance, which supports the Hypothesis 2b. This can be explained by marketing theory that negative word of mouth can more accurately predict decreases in firm performance than positive word of mouth predicts the growth of firm revenue (Kirby and Marsden, 2006; Ferguson, 2008).

Table 6 The Informativeness of Crowdsourced Review and FinTech Platform Performance

Panel A: Trading Volume$_{t+1}$				
Dependent variable:	*Trading Volume$_{t+1}$*			
	(1)	(2)	(3)	(4)
High Positive	0.1101			
	(0.1623)			
High Negative		-0.5810***		
		(0.1902)		
Low Positive			0.5112*	
			(0.3079)	
Low Negative				-0.0467
				(0.2516)
Panel B: Number of Investors $_{t+1}$				
Dependent variable:	*Number of Investors $_{t+1}$*			
	(1)	(2)	(3)	(4)
High Positive	0.0643			
	(0.1538)			
High Negative		-0.4893***		
		(0.1806)		
Low Positive			0.6132**	
			(0.2757)	
Low Negative				0.0994
				(0.2265)
Panel C: Number of Loans$_{t+1}$				
Dependent variable:	*Number of Loans$_{t+1}$*			
	(1)	(2)	(3)	(4)
High Positive	0.1366			
	(0.1525)			
High Negative		-0.2993*		
		(0.1655)		
Low Positive			0.3575	
			(0.2426)	
Low Negative				0.0457
				(0.2356)
Obs.	3,197	3,197	3,197	3,197

This table presents the regression results of monthly platform-level performance on lagged review informativeness. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *High Positive, High Negative, Low Positive* and *Low Negative. High Positive* is the average fraction of positive reviews with positive *Net Useful* across all the platform reviews posted over the month. *High Negative* is the average fraction of negative reviews with positive *Net Useful* across all the platform reviews posted over the month. *Low Positive* is the average fraction of positive reviews with negative *Net Useful* across all the platform reviews posted over the month. *Low Negative* is the average fraction of negative reviews with negative *Net Useful* across all the platform reviews posted over the month. *Net Useful* is calculated by the number of *Useful* for a review minus the number of *Not Useful*. Other variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 3,197 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.5.5 Review Sentiment, Defunct Platforms and Interest Rates

i. Review Sentiment and Defunct Platforms: Survival analysis

As yet, our empirical evidence uncovers that review sentiment (especially negative) can predict the FinTech platform performance. Unlike other industries, the FinTech marketplace is still facing a high failure rate. In this section, we investigate the role of sentiment on platform survivals through Cox model to examine the impact of changes in review sentiment on the survival probability of FinTech lending platforms. We follow Seru et al. (2010) to use Cox proportional hazard regression model is as follows:

$$h(t) = h_0(t)\exp(\beta \Delta Sentiment_i + \gamma Controls_i + Location_i), \quad (2)$$

where $h(t)$ is the expected hazard at time t, $h_0(t)$ is the baseline hazard when all the predictors are qual to zero. *ΔSentiment*$_i$ is measured by *ΔNegative Sentiment* and *ΔPositive Sentiment. ΔNegative Sentiment* is defined as the *Negative Sentiment* in month *t* minus the *Negative Sentiment* in month *t-1. ΔPositive Sentiment* is defined as the *Positive Sentiment* in month *t* minus the *Positive Sentiment* in month *t-1.* The coefficient β represents the effect of change in sentiment on the change in the hazard rate. We conjecture a positive sign of beta for change in negative sentiment and a negative sign for change in positive sentiment. Since an increase in the change of negative sentiment are more likely to be considered as a signal of failure, and vice versa. As our data records the precise defunct time for a platform, we employ Cox analysis and we do not control the platform fixed effects as the platforms will be survival if no recorded failure date.

Table 7 reports the coefficients and hazard rate from the Cox-proportional hazard model of the FinTech platform become defunct on lagged changes in sentiment. Column (1) shows the result for *ΔNegative Sentiment* as independent variable. The coefficient on *ΔNegative Sentiment* is 0.139, with a significant standard error of 0.014 and clustered at platform level. The positive sign suggests that an increase in changes of negative sentiment rises the risk of platform collapse, which is consistent with the Hypothesis 3b. The hazard ratio of 1.15 indicates that conditional failure probability for the FinTech platforms with more negative reviews have 15% more further failure risk. However, Column (2) presents the result for *ΔPositive Sentiment* as independent variable. The coefficient on *ΔPositive Sentiment* is 0.0567 and insignificant, suggesting that the change in positive reviews will not indicate a higher survival rate for the platforms, which have no evidence to support our Hypothesis 3a. These findings further support the view that predicting power of negative review is more accurate (Kirby and Marsden, 2006; Ferguson, 2008).

Table 7 Changes in Sentiment and Defunct Platforms

Dependent variable:	*Defunct Platform (1=Yes)*	
	(1)	(2)
ΔNegative Sentiment	0.1390***	
	(0.0387)	
ΔPositive Sentiment		0.0567
		(0.0373)
Log(Trading Volume)	0.2777***	0.2784***
	(0.0988)	(0.0990)
Log(Number of Investors)	0.2502**	0.2484**
	(0.1090)	(0.1090)
Log(Number of Loans)	-0.4112***	-0.4102***
	(0.0557)	(0.0556)
Average Loan Maturity	-0.0721***	-0.0721***
	(0.0210)	(0.0211)
Average Interest Rate	0.0734***	0.0713***
	(0.0175)	(0.0176)
Log(Number of Reviews)	-0.2553***	-0.2684***
	(0.0837)	(0.0830)
Log(Outstanding Balance)	-0.0790	-0.0783
	(0.0596)	(0.0603)
Log(Size)	0.1948*	0.1926*
	(0.1140)	(0.1145)
Automatic Investment	-0.0301	-0.0318
	(0.1915)	(0.1918)
Secondary Market	-0.1044	-0.1019
	(0.2265)	(0.2264)
SOE	0.0732	0.0697
	(0.2683)	(0.2694)
Association	-0.2561	-0.2636
	(0.2011)	(0.2016)
Risk Control	-0.0483	-0.0471
	(0.2116)	(0.2122)
Log(Risk Reserve)	0.1265***	0.1247***
	(0.0319)	(0.0319)
Log(Risk Reserve)	0.1265***	0.1247***
Province Fixed Effects	Yes	Yes
Hazard Ratio	1.1491***	1.0584
Obs.	4,508	4,508

This table presents the coefficients and hazard rate from the Cox-proportional hazard model of the FinTech platform become defunct on lagged changes in sentiment. The dependent variable is *Defunct Platform,* defined as a dummy variable that equals 1 if the platform has ceased to exist for any reason (e.g., has gone bankrupt; fraud, etc.), and zero otherwise. The independent variables are *ΔNegative Sentiment* and *ΔPositive Sentiment*. *ΔNegative Sentiment* is defined as the *Negative Sentiment* in month *t* minus the *Negative Sentiment* in month *t-1*. *ΔPositive Sentiment* is defined as the *Positive Sentiment* in month *t* minus the *Positive Sentiment* in month *t-1.* Variable definitions are provided in Appendix A.3.1. Province fixed effects is included in all specifications. The sample covers the period from 2015 to 2019 and consists of 4,508 platform-month level observations for 428 unique platforms. *Hazard Ratio* is reported for *ΔNegative Sentiment* and *ΔPositive Sentiment* respectively. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

ii. Review Sentiment and Interest Rate

As from our previous analysis in Chapter 2, interest rate is the most important variable in marketplace lending. In this platform level study, the interest rate is aggerated by each platform and exposes the pricing information of the platform. Table 3.8 reports the regression results of monthly platform-level interest rate on lagged sentiment. The dependent variable is *Interest* $Rate_{t+1}$, defined as the average value of daily loan interest rates for the platform over the month. Column (1) presents that average sentiment positively associated with future interest rate, suggesting that investors post more positive reviews will have an increase in the average return (interest rate). But this result is more likely to be affected by larger platforms with more reviews, as the sentiment scores may shift. We then use the fraction of positive reviews and negative reviews each month to mitigate the bias. Column (2) and (3) reports the regression results that shows the insignificant coefficient for both *Positive Sentiment* and *Negative Sentiment,* indicating that it is not convincing that the review sentiment will influence the interest rate, as this rate purely depends on what kind of borrowers and the distribution of borrowers in a platform will not change too much in a short period.

Table Error! No text of specified style in document.**.1 Sentiment and Interest Rate**

Dependent variable:	*Interest Rate$_{t+1}$*		
	(1)	(2)	(3)
Average Sentiment	0.1691**		
	(0.0715)		
Positive Sentiment		0.1161	
		(0.1995)	
Negative Sentiment			-0.1932
			(0.2117)
Log(Trading Volume)	0.2685***	0.2700***	0.2697***
	(0.0916)	(0.0923)	(0.0922)
Log(Number of Investors)	0.0242	0.0264	0.0263
	(0.0683)	(0.0681)	(0.0680)
Log(Number of Loans)	-0.0904**	-0.0904**	-0.0906**
	(0.0413)	(0.0416)	(0.0416)
Average Loan Maturity	0.0145	0.0141	0.0143
	(0.0182)	(0.0182)	(0.0182)
Average Interest Rate	0.6213***	0.6228***	0.6223***
	(0.0895)	(0.0902)	(0.0902)
Log(Number of Reviews)	-0.0539	-0.0524	-0.0486
	(0.0543)	(0.0600)	(0.0557)
Log(Outstanding Balance)	-0.0370	-0.0328	-0.0331
	(0.0987)	(0.0986)	(0.0986)
Platform Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Obs.	3,686	3,686	3,686
Adj. R^2	0.414	0.413	0.413

This table presents the regression results of monthly platform-level interest rate on lagged sentiment. The dependent variable is *Interest Rate$_{t+1}$*, defined as the average value of daily loan interest rates for the platform over the month. The independent variables are *Average Sentiment*, *Negative Sentiment* an*d Positive Sentiment*. *Average Sentiment* is defined as the average value of sentiment scores across all the platform reviews posted over the month. *Negative Sentiment* is defined as the average fraction of negative reviews across all the platform reviews posted over the month. *Positive Sentiment* is defined as the average fraction of positive reviews across all the platform reviews posted over the month. Month and platform fixed effects are included in all specifications. Variable definitions are provided in Appendix A.3.1. The sample covers the period from 2015 to 2019 and consists of 3,686 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6 Conclusion

To understand the growth, failure and regulation in the Chinese FinTech marketplace, we explain whether peer platform reviews are related to the performance and survival dynamics. We use data of over 152,676 customer-level platform reviews for 428 unique platforms between 2015 and 2019 obtained from the FinTech platform review website Wdzj.com and merged with the FinTech platform characteristics and performance data from the China Stock Market &

Accounting Research (CSMAR) database. We find a negative relationship between negative sentiment and the trading volume for the FinTech platform, a one-standard-deviation increase in the fraction of negative reviews is associated with a decrease of 5.57% of the future trading volume for the FinTech platform.

Further, we expand the analysis by exploring whether the review informativeness adds value to the predicting power. Our results suggest that more informative negative reviews have a strong predicting power on future trading volume and informative positive reviews do not matter. In addition, we explore the role of sentiment on platform survivals through the Cox model to examine the impact of changes in review sentiment on FinTech lending platforms' survival probability. We document that excess negative sentiment is associated with a lower probability of the survival of the FinTech platform.

We contribute to the FinTech lending literature by providing novel evidence that examines the FinTech performance and crowdsourced reviews at the platform level. This interdisciplinary research is important given that FinTech innovations pose many challenges for firm performance and survival and mitigate the information asymmetry through the new crowdsourced channel. In particular, this is the first study that links the role of peer-based reviews and the FinTech marketplace.

Our study also provides policy implications that crowdsourced reviews can be crucial for regulation on the FinTech platforms. Compared with traditional information channels such as news media and expert opinions, consumer reviews can convey more timely information on platforms' products and potential issues. Particularly, most FinTech platforms are start-ups, the transparency of the products and services is the key issue for its success to obtain public acceptance and economic growth. Regulators can take advantage of the customer intelligence to identify those "bad" platforms, and ultimately protect investors' welfare.

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Appendix A

Table A.1 Variable definitions

Variable	Definition	Source
Dependent variables		
Trading Volume	The monthly total amount of new loans originated in the platform. We use the natural log of this amount in our regression analysis.	CSMAR
Number of Investors	The monthly total number of investors in the platform. We use the natural log of this amount in our regression analysis.	CSMAR
Number of Loans	The monthly total number of new loans originated in the platform. We use the natural log of this amount in our regression analysis.	CSMAR
Defunct Platform	A dummy variable that equals 1 if the platform has ceased to exist for any reason (e.g., has gone bankrupt; fraud, etc.), and zero otherwise.	CSMAR
Independent variables		
Average Sentiment	The average value of sentiment scores across all the platform reviews posted over the month. The sentiment score for an individual review is calculated by *BaiduAI* with value ranged (0, 1 or 2). 0 means that this textual information indicates negative sentiment, 1 represents neutral and 2 reflects positively. See section 3.3 for more details.	*Wdzj.com*
Negative Sentiment	The average fraction of negative reviews across all the platform reviews posted over the month.	*Wdzj.com*
Positive Sentiment	The average fraction of positive reviews across all the platform reviews posted over the month.	*Wdzj.com*
Pending Investment	The subcategory one-to-five star platform rating from the *Wdzj.com*, measured monthly using the average of the reviews submitted that month. The rating represents the pending period between the reviewer transfer the fund to the platform and fulfilled to the loans. A higher rating indicates less waiting time to go through the funding (1 means that the period is over two weeks; 2 indicates between one and two weeks; 3 indicates between three days and one week; 4 indicates between one day and three days; and 5 indicates less than one day).	*Wdzj.com*
Customer Service	The subcategory one-to-five star platform rating from the *Wdzj*.com, measured monthly using the average of the reviews submitted that month. The rating yields from the evaluation of the platform customer service. A higher rating indicates better customer service (1 means extremely unhappy about the service; 2 indicates unhappy; 3 indicates neutral; 4 indicates happy; and 5 indicates extremely happy).	*Wdzj.com*
Web/App Experience	The subcategory one-to-five star platform rating from the *Wdzj.com*, measured monthly using the average of the reviews submitted that month. The rating yields from the evaluation of the platform website or mobile application. A higher rating indicates the better experience of the website or mobile application (1 means extremely unhappy about the service; 2 indicates unhappy; 3 indicates neutral; 4 indicates happy; and 5 indicates extremely happy).	*Wdzj.com*
Funding Withdraw	The subcategory one-to-five star platform rating from the *Wdzj.com*, measured monthly using the average of the reviews submitted that month. The rating represents the pending period between the reviewer withdraw her/his fund from the platform. A higher rating indicates less waiting time to withdraw the funding (1 means that the period is over 30 days; 2 indicates between 7 days and 30 days; 3 indicates between 3 days and 7 days; 4 indicates between 1 day and 3 days; and 5 indicates less than 1 day).	*Wdzj.com*

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Table A.1 (*Continued*))

Settlement Dates	The overall one-to-five star platform rating from the *Wdzj.com*, measured monthly using the average of the reviews submitted that month. The rating represents settlement dates of funding withdraw transactions that occur on a transaction date plus days. 1 means that the settlement dates are over 30 days from the transaction occurs. 2 indicates that the settlement dates are between 7 days and 30 days from the transaction occurs; 3 indicates that the settlement dates are between 1 days and 7 days from the transaction occurs; 4 indicates that the settlement date is 1 day from the transaction occurs; and 5 indicates that the settlement date is less than 1 day from the transaction occurs).	*Wdzj.com*
Recommended	Whether the reviewer is willing to recommend the platform to peers with value ranged (0, 1 or 2). 0 means that the reviewer is not willing to recommend the platform, 1 represents neutral and 2 reflects recommend.	*Wdzj.com*
Other variables		
Average Loan Maturity	The average value of the loan duration (months) for the platform over the month.	CSMAR
Average Interest Rate	The average value of daily loan interest rates for the platform over the month. The daily interest rate is loan amount-weighted average percentage rate of all facilitated loans for the platform during the day.	CSMAR
Number of Reviews	The monthly total number of reviews in the platform.	CSMAR
Outstanding Balance	The cumulative amount of outstanding balance for all borrowers in the platform (measured by the average amount of daily based cumulative outstanding balance over the month). We use the natural log of this amount in our regression analysis.	CSMAR
Size	The registered capital of the platform measured in Chinese RMB. We use the natural log of this amount in our regression analysis.	CSMAR
Automatic Investment	A dummy variable that equals one if the platform provides the automatic investing function, and zero otherwise.	*Wdzj.com*
Secondary Market	A dummy variable that equals one if the platform provides the secondary market, and zero otherwise.	*Wdzj.com*
SOE	A dummy variable that equals 1 if the platform is affiliated with State-Owned Enterprises (SOEs), and zero otherwise.	*Wdzj.com*
Age	The number of years since inception for the platform.	*Wdzj.com*
Association	A dummy variable that equals 1 if the platform is affiliated with a FinTech industry association, and zero otherwise.	*Wdzj.com*
Risk Control	A dummy variable that equals 1 if the platform has an independent risk management team, and zero otherwise.	*Wdzj.com*
Risk Reserve	The amount of the safeguard fund measured in Chinese RMB that the platform takes advantage of the reserve to cover defaulted loans. We use the natural log of this amount in our regression analysis.	*Wdzj.com*

Table A.2 Average Sentiment, Positive Sentiment and FinTech Platform Performance

Dependent variable:	*Trading Volume$_{t+1}$*		*Number of Investors$_{t+1}$*		*Number of Loans$_{t+1}$*	
	(1)	(2)	(3)	(4)	(5)	(6)
Average Sentiment	0.3010***		0.2687***		0.2190***	
	(0.0857)		(0.0771)		(0.0712)	
Positive Sentiment		0.6935***		0.6261***		0.5062***
		(0.2165)		(0.2019)		(0.1881)
Average Loan Maturity	0.0009	0.0017	0.0355*	0.0363*	0.0543***	0.0549***
	(0.0231)	(0.0230)	(0.0206)	(0.0205)	(0.0193)	(0.0192)
Average Interest Rate	0.3692***	0.3710***	0.3341***	0.3357***	0.2418***	0.2432***
	(0.0586)	(0.0588)	(0.0541)	(0.0543)	(0.0425)	(0.0426)
Log(Number of Reviews)	-0.3689***	-0.4174***	-0.2890***	-0.3330***	-0.1151*	-0.1506**
	(0.0684)	(0.0747)	(0.0610)	(0.0665)	(0.0598)	(0.0680)
Log(Outstanding Balance)	0.8023***	0.8118***	0.7416***	0.7499***	0.7163***	0.7231***
	(0.1442)	(0.1463)	(0.1272)	(0.1289)	(0.0886)	(0.0894)
Obs.	3,686	3,686	3,686	3,686	3,686	3,686
Adj. R^2	0.286	0.285	0.293	0.292	0.229	0.228
r2_b	0.489	0.491	0.542	0.544	0.509	0.509

This table presents the regression results of monthly platform-level performance on lagged sentiment. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *Average Sentiment*, *Negative Sentiment* and *Positive Sentiment*. *Average Sentiment* is defined as the average value of sentiment scores across all the platform reviews posted over the month. *Negative Sentiment* is defined as the average fraction of negative reviews across all the platform reviews posted over the month. *Positive Sentiment* is defined as the average fraction of positive reviews across all the platform reviews posted over the month. Month and platform fixed effects are included in all specifications. Variable definitions are provided in Appendix A.3.1. The sample covers the period from 2015 to 2019 and consists of 3,686 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.3 Negative Sentiment and FinTech Platform Performance: Sub Sample Analysis

Panel A: Excluding Defunct Platforms Sample			
Dependent variable:	*Trading Volume$_{t+1}$*	*Number of Investors$_{t+1}$*	*Number of Loans$_{t+1}$*
	(1)	(2)	(3)
Negative Sentiment	-0.6641**	-0.5530**	-0.4349*
	(0.2600)	(0.2549)	(0.2407)
Average Loan Maturity	-0.0139	0.0304*	0.0504***
	(0.0205)	(0.0163)	(0.0159)
Average Interest Rate	0.4494***	0.3906***	0.3066***
	(0.0393)	(0.0410)	(0.0354)
Log(Number of Reviews)	-0.2826***	-0.1838***	-0.0200
	(0.0737)	(0.0646)	(0.0676)
Log(Outstanding Balance)	0.9582***	0.8756***	0.7149***
	(0.1195)	(0.1026)	(0.1103)
Platform Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Obs.	2,348	2,348	2,348
Adj. R^2	0.348	0.341	0.281

Panel B: Excluding 2019 Sample			
Dependent variable:	*Trading Volume$_{t+1}$*	*Number of Investors$_{t+1}$*	*Number of Loans$_{t+1}$*
	(1)	(2)	(3)
Negative Sentiment	-0.6247***	-0.5760***	-0.5470***
	(0.2205)	(0.1950)	(0.1925)
Average Loan Maturity	-0.0155	0.0138	0.0320
	(0.0223)	(0.0196)	(0.0203)
Average Interest Rate	0.2925***	0.2736***	0.1882***
	(0.0608)	(0.0569)	(0.0432)
Log(Number of Reviews)	-0.3972***	-0.3060***	-0.1350**
	(0.0719)	(0.0651)	(0.0633)
Log(Outstanding Balance)	0.7241***	0.6823***	0.7268***
	(0.1632)	(0.1473)	(0.1034)
Obs.	3,253	3,253	3,253
Adj. R^2	0.205	0.213	0.154

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Table A.3 Negative Sentiment and FinTech Platform Performance: Sub Sample Analysis (*Continued*)

Panel C: The Quarterly Sample

Dependent variable:	*Trading Volume$_{t+1}$*	*Number of Investors$_{t+1}$*	*Number of Loans$_{t+1}$*
	(1)	(2)	(3)
Negative Sentiment	-1.1449***	-1.0336***	-0.7598**
	(0.3902)	(0.3754)	(0.3786)
Average Loan Maturity	-0.0199	0.0275	0.0307
	(0.0374)	(0.0376)	(0.0361)
Average Interest Rate	0.3841***	0.2961***	0.2876***
	(0.0783)	(0.0773)	(0.0699)
Log(Number of Reviews)	-0.5784***	-0.4912***	-0.3223***
	(0.1123)	(0.1058)	(0.1140)
Log(Outstanding Balance)	0.0154	0.0052	0.0153
	(0.0767)	(0.0734)	(0.0630)
Platform Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Obs.	794	794	794
Adj. R^2	0.220	0.191	0.153

This table presents the regression results of monthly platform-level performance on lagged negative sentiment. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variable is *Negative Sentiment*, which is defined as the average fraction of negative reviews across all the platform reviews posted over the month. Panel A reports the results for excluding defunct platforms sample, panel B for excluding 2019 sample and panel C for the quarterly sample. Month and platform fixed effects are included in all specifications. Variable definitions are provided in Appendix A.3.1. The excluding defunct platforms sample covers the period from 2015 to 2019 and consists of 2,348 platform-month level observations for 198 unique platforms. The excluding 2019 sample covers the period from 2015 to 2018 and consists of 3,253 platform-month level observations for 421 unique platforms. The quarterly sample covers the period from 2015 to 2018 and consists of 794 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.4 Negative Sentiment and FinTech Platform Performance: Considering the Previous Six Months

Panel A: Trading Volume						
Dependent variable:	*Trading Volume$_{t+1}$* (1)	*Trading Volume$_{t+2}$* (2)	*Trading Volume$_{t+3}$* (3)	*Trading Volume$_{t+4}$* (4)	*Trading Volume$_{t+5}$* (5)	*Trading Volume$_{t+6}$* (6)
Negative Sentiment	-0.6258***	-0.7070***	-0.5962**	-0.8213***	-0.6433**	-0.5739*
	(0.2143)	(0.2692)	(0.2798)	(0.2851)	(0.3027)	(0.3085)
Average Loan Maturity	0.0361*	0.0225	0.0158	0.0061	0.0019	0.0095
	(0.0206)	(0.0225)	(0.0256)	(0.0227)	(0.0243)	(0.0229)
Average Interest Rate	0.3351***	0.2685***	0.1951***	0.1657***	0.1967***	0.0906*
	(0.0545)	(0.0556)	(0.0526)	(0.0374)	(0.0440)	(0.0474)
Log(Number of Reviews)	-0.2944***	-0.3125***	-0.2669***	-0.3444***	-0.3751***	-0.4019***
	(0.0618)	(0.0710)	(0.0737)	(0.0848)	(0.0953)	(0.1026)
Log(Outstanding Balance)	0.7491***	0.5621***	0.2342	0.1274	0.0464	0.0913
	(0.1291)	(0.1391)	(0.1596)	(0.1494)	(0.1520)	(0.1395)
Obs.	3,686	3,251	2,931	2,729	2,553	2,393
Adj. R^2	0.292	0.157	0.073	0.048	0.050	0.029

Panel B: Number of Investors						
Dependent variable:	*Number of Investors$_{t+1}$* (1)	*Number of Investors$_{t+2}$* (2)	*Number of Investors$_{t+3}$* (3)	*Number of Investors$_{t+4}$* (4)	*Number of Investors$_{t+5}$* (5)	*Number of Investors$_{t+6}$* (6)
Negative Sentiment	-0.6258***	-0.7070***	-0.5962**	-0.8213***	-0.6433**	-0.5739*
	(0.2143)	(0.2692)	(0.2798)	(0.2851)	(0.3027)	(0.3085)
Average Loan Maturity	0.0361*	0.0225	0.0158	0.0061	0.0019	0.0095
	(0.0206)	(0.0225)	(0.0256)	(0.0227)	(0.0243)	(0.0229)
Average Interest Rate	0.3351***	0.2685***	0.1951***	0.1657***	0.1967***	0.0906*
	(0.0545)	(0.0556)	(0.0526)	(0.0374)	(0.0440)	(0.0474)
Log(Number of Reviews)	-0.2944***	-0.3125***	-0.2669***	-0.3444***	-0.3751***	-0.4019***
	(0.0618)	(0.0710)	(0.0737)	(0.0848)	(0.0953)	(0.1026)
Log(Outstanding Balance)	0.7491***	0.5621***	0.2342	0.1274	0.0464	0.0913
	(0.1291)	(0.1391)	(0.1596)	(0.1494)	(0.1520)	(0.1395)
Obs.	3,686	3,251	2,931	2,729	2,553	2,393
Adj. R^2	0.292	0.157	0.073	0.048	0.050	0.029

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Table A.4 Negative Sentiment and FinTech Platform Performance: Considering the Previous Six Months (*Continued*)

Panel C: Number of Loans

Dependent variable:	*Number of Borrowers$_{t+1}$*	*Number of Borrowers$_{t+2}$*	*Number of Borrowers$_{t+3}$*	*Number of Borrowers$_{t+4}$*	*Number of Borrowers$_{t+5}$*	*Number of Borrowers$_{t+6}$*
	(1)	(2)	(3)	(4)	(5)	(6)
Negative Sentiment	-0.5333***	-0.6634**	-0.5662**	-0.7738***	-0.5011*	-0.4425
	(0.1967)	(0.2575)	(0.2543)	(0.2710)	(0.3008)	(0.3174)
Average Loan Maturity	0.0548***	0.0376*	0.0286	0.0203	0.0209	0.0272
	(0.0192)	(0.0214)	(0.0240)	(0.0235)	(0.0225)	(0.0188)
Average Interest Rate	0.2425***	0.1983***	0.1405***	0.1186***	0.1446***	0.0518
	(0.0427)	(0.0452)	(0.0440)	(0.0395)	(0.0457)	(0.0412)
Log(Number of Reviews)	-0.1205**	-0.1411**	-0.1151*	-0.2283***	-0.2823***	-0.2975***
	(0.0610)	(0.0674)	(0.0688)	(0.0811)	(0.0917)	(0.0938)
Log(Outstanding Balance)	0.7222***	0.5540***	0.3041*	0.2087	0.1482	0.1567
	(0.0895)	(0.0866)	(0.1559)	(0.1498)	(0.1493)	(0.1169)
Obs.	3,686	3,251	2,931	2,729	2,553	2,393
Adj. R^2	0.228	0.128	0.059	0.038	0.040	0.021

This table presents the regression results of monthly platform-level performance on lagged negative sentiment from the previous six months. The dependent variables are *Trading Volume*, *Number of Investors* and *Number of Loans*. *Trading Volume* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1 to t+6*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1 to t+6*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1 to t+6*. The independent variable is *Negative Sentiment*, which is defined as the average fraction of negative reviews across all the platform reviews posted over the month. Variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 3,68 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.5 Negative Sentiment and FinTech Platform Performance over Negative Sentiment Ratio Changes

Dependent variable:	*Trading Volume$_{t+1}$*			*Number of Investors$_{t+1}$*			*Number of Loans$_{t+1}$*		
	Low	Middle	High	Low	Middle	High	Low	Middle	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Negative Sentiment	-0.9857*	-0.1033	-1.3528***	-1.0150*	-0.0443	-1.0798***	-1.3503***	0.2131	-0.6204*
	(0.5161)	(0.3220)	(0.4143)	(0.5160)	(0.3337)	(0.3531)	(0.4332)	(0.3027)	(0.3231)
Average Loan Maturity	-0.0198	0.0265	0.0150	0.0171	0.0672**	0.0396*	0.0430*	0.0731***	0.0616***
	(0.0251)	(0.0372)	(0.0252)	(0.0252)	(0.0312)	(0.0204)	(0.0249)	(0.0266)	(0.0223)
Average Interest Rate	0.4434***	0.2958***	0.4352***	0.4109***	0.2473***	0.4194***	0.2875***	0.1962***	0.3061***
	(0.0573)	(0.1043)	(0.0429)	(0.0601)	(0.0866)	(0.0406)	(0.0553)	(0.0726)	(0.0354)
Log(Number of Reviews)	-0.4180***	-0.2706***	-0.4628***	-0.3529***	-0.1757**	-0.3773***	-0.1818*	-0.0132	-0.1496
	(0.1037)	(0.0882)	(0.1174)	(0.1069)	(0.0808)	(0.1017)	(0.0986)	(0.0768)	(0.0961)
Log(Outstanding Balance)	0.7457***	0.8801***	0.7307***	0.7017***	0.8228***	0.6319***	0.4268***	0.6246***	0.7771***
	(0.1455)	(0.1314)	(0.2423)	(0.1489)	(0.0941)	(0.2036)	(0.1398)	(0.0934)	(0.1456)
Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	899	1,692	1,095	899	1,692	1,095	899	1,692	1,095
Adj. R^2	0.315	0.249	0.341	0.318	0.254	0.359	0.218	0.197	0.300

This table presents the regression results of monthly platform-level performance on lagged negative sentiment. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variable is *Negative Sentiment*, which is defined as the average fraction of negative reviews across all the platform reviews posted over the month. Variable definitions are provided in Appendix A.3.1 Month and platform fixed effects are included in all specifications. Column (1), (4) and (7) report the regression results for the *Low* negative sentiment changes group; Column (2), (5) and (8) report the regression results for the *Middle* negative sentiment change group; Column (3), (6) and (9) report the regression results for the *High* negative sentiment change group. *Low* denotes the lowest change in *Negative Sentiment* (reductions in the fraction of negative reviews), *High* denotes the highest change in *Negative Sentiment* (increments in the fraction of negative reviews), and *Middle* denotes the group between *High* and *Low*. The breakpoints for partitioning the groups are based on the bottom 25%, the middle 50%, and the top 25% change in *Negative Sentiment* in month *t* minus month *t-1*. The sample covers the period from 2015 to 2019 and consists of 899, 1,692

Appendix B

Table B.1 FinTech Platform Ratings and Performance

Panel A: Trading Volume$_{t+1}$

Dependent variable:	*Trading Volume$_{t+1}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Pending Investment	0.3713***					
	(0.0927)					
Customer Service		0.3801***				
		(0.0879)				
Web/App Experience			0.3049***			
			(0.0758)			
Funding Withdraw				0.1553**		
				(0.0660)		
Settlement Dates					0.3166***	
					(0.1142)	
Recommended						0.6188***
						(0.1510)
Average Loan Maturity	0.0185	0.0169	0.0190	0.0164	-0.0108	0.0201
	(0.0383)	(0.0378)	(0.0351)	(0.0355)	(0.0301)	(0.0350)
Average Interest Rate	0.3185***	0.3141***	0.3503***	0.3613***	0.2446**	0.3454***
	(0.0849)	(0.0811)	(0.0736)	(0.0753)	(0.1083)	(0.0731)
Log(Number of Reviews)	-0.4267***	-0.4484***	-0.4808***	-0.4691***	-0.4710***	-0.4947***
	(0.1027)	(0.1032)	(0.0894)	(0.0912)	(0.1294)	(0.0901)
Log(Outstanding Balance)	0.8123***	0.8192***	0.7820***	0.8047***	1.0172***	0.7862***
	(0.1540)	(0.1432)	(0.1875)	(0.1883)	(0.2033)	(0.1899)
Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,905	1,964	2,448	2,448	1,021	2,448
Adj. R^2	0.315	0.310	0.330	0.320	0.271	0.333

This table presents the regression results of monthly platform-level performance on lagged platform ratings. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *Pending Investment, Customer Service, Web/App Experience, Funding Withdraw, Settlement Dates and Recommended.* Variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 1,905 platform-month level observations for *Pending Investment* as the independent variable, 1,964 observations for *Customer Service* as the independent variable, 1,021 for *Settlement Dates* as the independent variable and 2,448 for *Web/App Experience, Funding Withdraw* and *Recommended* as the independent variables. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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Table B.1 FinTech Platform Ratings and Performance (*Continued*)

Panel B: Number of Investors$_{t+1}$

Dependent variable:	*Number of Investors$_{t+1}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Pending Investment	0.3360***					
	(0.0859)					
Customer Service		0.3525***				
		(0.0805)				
Web/App Experience			0.2972***			
			(0.0700)			
Funding Withdraw				0.1384**		
				(0.0596)		
Settlement Dates					0.2875***	
					(0.1094)	
Recommended						0.6050***
						(0.1389)
Average Loan Maturity	0.0282	0.0258	0.0319	0.0293	0.0057	0.0329
	(0.0308)	(0.0303)	(0.0288)	(0.0293)	(0.0287)	(0.0286)
Average Interest Rate	0.3041***	0.2978***	0.3309***	0.3417***	0.2274**	0.3260***
	(0.0801)	(0.0761)	(0.0687)	(0.0707)	(0.0988)	(0.0682)
Log(Number of Reviews)	-0.3798***	-0.3905***	-0.4078***	-0.3944***	-0.4249***	-0.4215***
	(0.0878)	(0.0892)	(0.0820)	(0.0840)	(0.1117)	(0.0821)
Log(Outstanding Balance)	0.7324***	0.7513***	0.6927***	0.7165***	0.9342***	0.6967***
	(0.1291)	(0.1209)	(0.1592)	(0.1602)	(0.1926)	(0.1616)
Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,905	1,964	2,448	2,448	1,021	2,448
Adj. R^2	0.332	0.326	0.337	0.326	0.279	0.341

This table presents the regression results of monthly platform-level performance on lagged platform ratings. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *Pending Investment, Customer Service, Web/App Experience, Funding Withdraw, Settlement Dates and Recommended.* Variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 1,905 platform-month level observations for *Pending Investment* as the independent variable, 1,964 observations for *Customer Service* as the independent variable, 1,021 for *Settlement Dates* as the independent variable and 2,448 for *Web/App Experience, Funding Withdraw* and *Recommended* as the independent variables. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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Table B.1 FinTech Platform Ratings and Performance (*Continued*)

Panel C: Number of Loans$_{t+1}$

Dependent variable:	*Number of Loans$_{t+1}$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Pending Investment	0.2535***					
	(0.0738)					
Customer Service		0.2697***				
		(0.0685)				
Web/App Experience			0.2231***			
			(0.0640)			
Funding Withdraw				0.1471**		
				(0.0624)		
Settlement Dates					0.2704**	
					(0.1050)	
Recommended						0.4283***
						(0.1251)
Average Loan Maturity	0.0625**	0.0580*	0.0642**	0.0624**	0.0260	0.0648**
	(0.0306)	(0.0300)	(0.0282)	(0.0285)	(0.0336)	(0.0281)
Average Interest Rate	0.1879***	0.1873***	0.2144***	0.2220***	0.1502**	0.2115***
	(0.0546)	(0.0528)	(0.0505)	(0.0516)	(0.0707)	(0.0503)
Log(Number of Reviews)	-0.1929**	-0.1958**	-0.1693**	-0.1658**	-0.2329*	-0.1776**
	(0.0906)	(0.0914)	(0.0821)	(0.0834)	(0.1398)	(0.0820)
Log(Outstanding Balance)	0.7364***	0.7339***	0.6932***	0.7055***	0.9694***	0.6977***
	(0.1452)	(0.1391)	(0.1066)	(0.1060)	(0.2060)	(0.1081)
Platform Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,905	1,964	2,448	2,448	1,021	2,448
Adj. R^2	0.235	0.229	0.239	0.233	0.205	0.240

This table presents the regression results of monthly platform-level performance on lagged platform ratings. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *Pending Investment, Customer Service, Web/App Experience, Funding Withdraw, Settlement Dates and Recommended.* Variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 1,905 platform-month level observations for *Pending Investment* as the independent variable, 1,964 observations for *Customer Service* as the independent variable, 1,021 for *Settlement Dates* as the independent variable and 2,448 for *Web/App Experience, Funding Withdraw* and *Recommended* as the independent variables. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table B.2 The Review Quality and FinTech Platform Performance

Panel A: Trading Volume$_{t+1}$				
Dependent variable:	*Trading Volume$_{t+1}$*			
	(1)	(2)	(3)	(4)
High Positive	0.1101			
	(0.1623)			
High Negative		-0.5810***		
		(0.1902)		
Low Positive			0.5112*	
			(0.3079)	
Low Negative				-0.0467
				(0.2516)
Average Loan Maturity	-0.0011	0.0006	-0.0014	-0.0012
	(0.0237)	(0.0233)	(0.0236)	(0.0236)
Average Interest Rate	0.3735***	0.3680***	0.3743***	0.3740***
	(0.0565)	(0.0563)	(0.0558)	(0.0565)
Log(Number of Reviews)	-0.3878***	-0.4322***	-0.3438***	-0.3921***
	(0.0728)	(0.0756)	(0.0760)	(0.0773)
Log(Outstanding Balance)	0.9397***	0.9391***	0.9501***	0.9391***
	(0.1148)	(0.1143)	(0.1158)	(0.1145)
Platform Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Obs.	3,197	3,197	3,197	3,197
Adj. R^2	0.273	0.278	0.275	0.273

This table presents the regression results of monthly platform-level performance on lagged review quality. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *High Positive, High Negative, Low Positive* and *Low Negative*. *High Positive* is the average fraction of positive reviews with positive *NetUseful* across all the platform reviews posted over the month. *High Negative* is the average fraction of negative reviews with positive *NetUseful* across all the platform reviews posted over the month. *Low Positive* is the average fraction of positive reviews with negative *NetUseful* across all the platform reviews posted over the month. *Low Negative* is the average fraction of negative reviews with negative *NetUseful* across all the platform reviews posted over the month. *NetUseful* is calculated by the number of *Useful* for a review minus the number of *Not Useful* for the review. Other variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 3,197 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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Table B.2 The Review Quality and FinTech Platform Performance (*Continued*)

Panel B: Number of Investors $_{t+1}$

Dependent variable:	*Number of Investors $_{t+1}$*			
	(1)	(2)	(3)	(4)
High Positive	0.0643			
	(0.1538)			
High Negative		-0.4893***		
		(0.1806)		
Low Positive			0.6132**	
			(0.2757)	
Low Negative				0.0994
				(0.2265)
Average Loan Maturity	0.0345	0.0360*	0.0342	0.0343
	(0.0212)	(0.0209)	(0.0211)	(0.0212)
Average Interest Rate	0.3346***	0.3298***	0.3353***	0.3349***
	(0.0529)	(0.0526)	(0.0520)	(0.0528)
Log(Number of Reviews)	-0.2995***	-0.3368***	-0.2465***	-0.2913***
	(0.0645)	(0.0670)	(0.0678)	(0.0684)
Log(Outstanding Balance)	0.8830***	0.8825***	0.8956***	0.8836***
	(0.0919)	(0.0904)	(0.0928)	(0.0923)
Platform Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Obs.	3,197	3,197	3,197	3,197
Adj. R^2	0.279	0.283	0.281	0.279

This table presents the regression results of monthly platform-level performance on lagged review quality. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *High Positive, High Negative, Low Positive* and *Low Negative*. *High Positive* is the average fraction of positive reviews with positive *NetUseful* across all the platform reviews posted over the month. *High Negative* is the average fraction of negative reviews with positive *NetUseful* across all the platform reviews posted over the month. *Low Positive* is the average fraction of positive reviews with negative *NetUseful* across all the platform reviews posted over the month. *Low Negative* is the average fraction of negative reviews with negative *NetUseful* across all the platform reviews posted over the month. *NetUseful* is calculated by the number of *Useful* for a review minus the number of *Not Useful* for the review. Other variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 3,197 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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Table B.2 The Review Quality and FinTech Platform Performance (*Continued*)

Panel C: Number of Loans$_{t+1}$

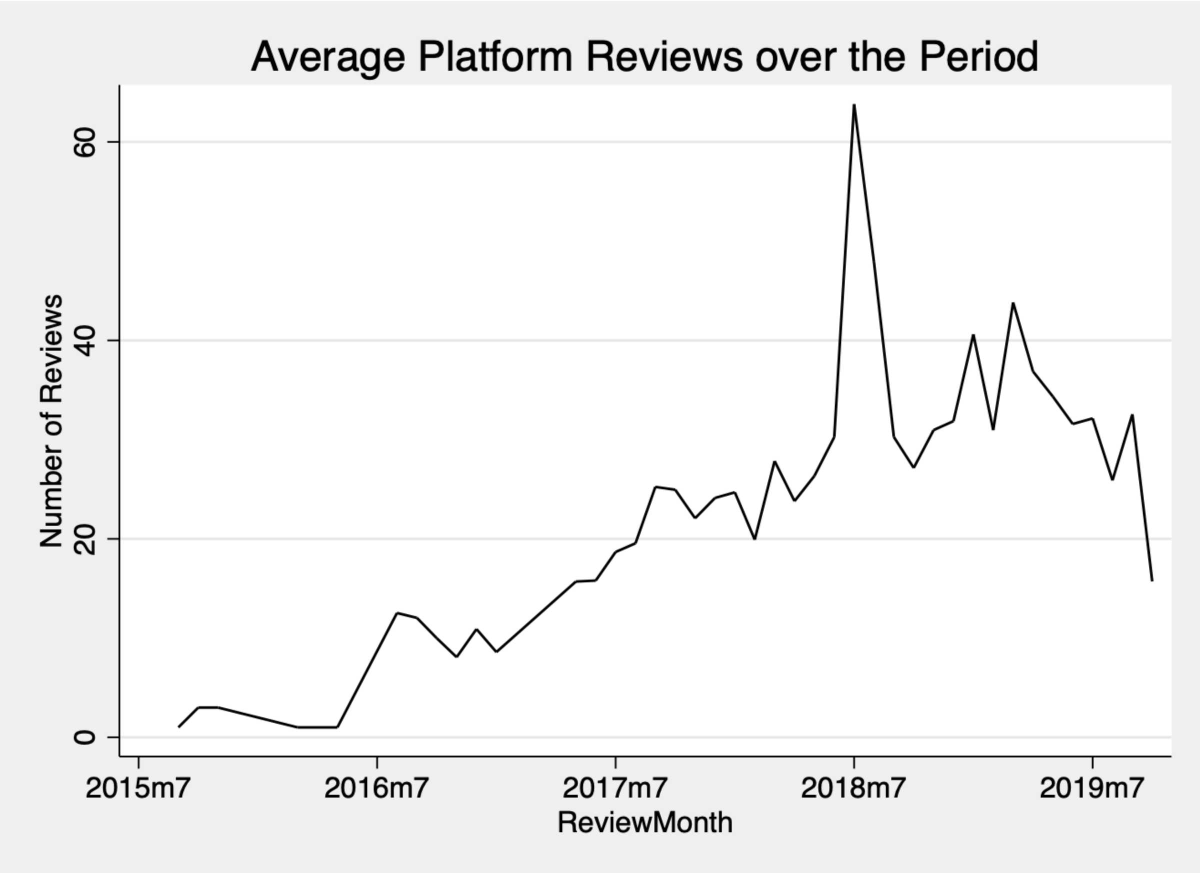
Dependent variable:	*Number of Loans$_{t+1}$*			
	(1)	(2)	(3)	(4)
High Positive	0.1366			
	(0.1525)			
High Negative		-0.2993*		
		(0.1655)		
Low Positive			0.3575	
			(0.2426)	
Low Negative				0.0457
				(0.2356)
Average Loan Maturity	0.0526**	0.0534***	0.0523**	0.0524**
	(0.0206)	(0.0204)	(0.0206)	(0.0205)
Average Interest Rate	0.2500***	0.2475***	0.2509***	0.2507***
	(0.0429)	(0.0427)	(0.0424)	(0.0428)
Log(Number of Reviews)	-0.0966	-0.1198*	-0.0661	-0.0932
	(0.0642)	(0.0691)	(0.0668)	(0.0715)
Log(Outstanding Balance)	0.7865***	0.7860***	0.7936***	0.7865***
	(0.1091)	(0.1085)	(0.1104)	(0.1096)
Platform Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Obs.	3,197	3,197	3,197	3,197
Adj. R^2	0.224	0.225	0.225	0.224

This table presents the regression results of monthly platform-level performance on lagged review quality. The dependent variables are *Trading Volume$_{t+1}$*, *Number of Investors$_{t+1}$* and *Number of Loans$_{t+1}$*. *Trading Volume$_{t+1}$* is defined as the natural logarithm of the total amount of new loans originated in the platform in month *t+1*. *Number of Investors$_{t+1}$* is defined as the natural logarithm of the total number of investors in the platform in month *t+1*. *Number of Loans$_{t+1}$* is defined as the natural logarithm of the number of new loans originated in the platform in month *t+1*. The independent variables are *High Positive, High Negative, Low Positive* and *Low Negative*. *High Positive* is the average fraction of positive reviews with positive *NetUseful* across all the platform reviews posted over the month. *High Negative* is the average fraction of negative reviews with positive *NetUseful* across all the platform reviews posted over the month. *Low Positive* is the average fraction of positive reviews with negative *NetUseful* across all the platform reviews posted over the month. *Low Negative* is the average fraction of negative reviews with negative *NetUseful* across all the platform reviews posted over the month. *NetUseful* is calculated by the number of *Useful* for a review minus the number of *Not Useful* for the review. Other variable definitions are provided in Appendix A.3.1. Month and platform fixed effects are included in all specifications. Panel A reports the results of *Trading Volume$_{t+1}$* as dependent variable, panel B for *Number of Investors$_{t+1}$* and panel C for *Number of Loans$_{t+1}$* respectively. The sample covers the period from 2015 to 2019 and consists of 3,197 platform-month level observations for 428 unique platforms. Standard errors are heteroskedasticity robust and clustered at platform level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 1 Submitting a Review for a platform on Wdzj.com

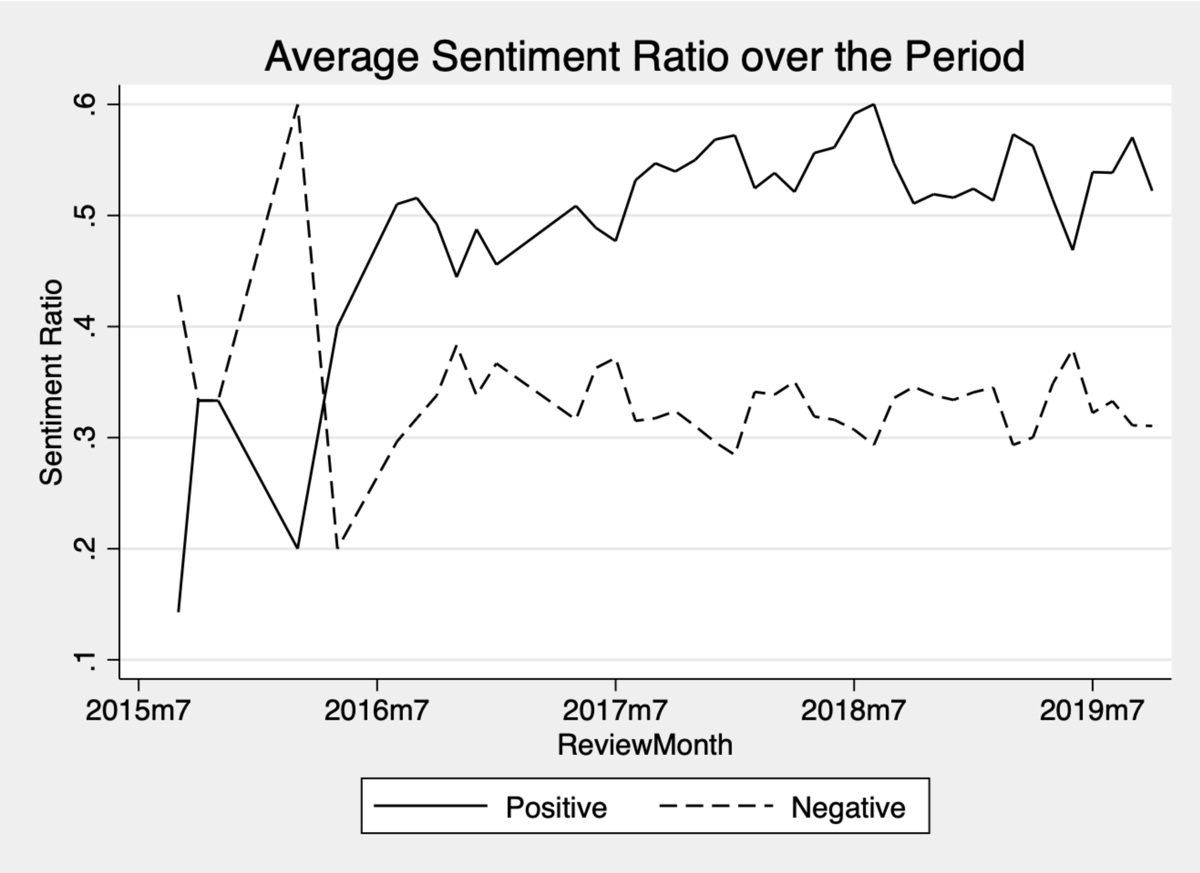
This figure shows the review process through Wdzj.com. A contributor should be registered as a user of *Wdzj.com* with an email verification from an active email address or a valid mobile number. The site administrator also moderates content through manual censorship or reported by other users for specific reviews to avoid potential fraud or self-promotion. The review process contains two parts. First, the contributor should enter the one-to-five star of platform ratings of *Pending Investment*, *Customer Service*, *Web/App Experience*, *Funding Withdraw, Settlement Dates* and *overall Recommended* (Variable definitions are provided in Appendix A.3.1). This part is not compulsory to complete. Second, the contributor is required to input the textual comments for their investing/borrowing experience in the FinTech platform at least 15 characters (compulsory). Finally, the contributor can submit the review that will be publicly shown on the platform column of *Wdzj.com*.

Figure 2 Average FinTech Platform Reviews



This figure shows the average FinTech platform reviews over the period. The general trend of reviews is increasing from 2015 and suddenly rising around June 2018 due to the online attention of some defunct FinTech platforms. The trend is going down from mid-2019 due to new regulation adoption for discouraging FinTech lending business.

Figure 3 Average Sentiment Ratio



This figure shows the average positive and negative sentiment ratio for all FinTech platforms over the period. The positive sentiment ratio is the average fraction of positive reviews across all the platform reviews posted over the month. The negative sentiment ratio is the average fraction of negative reviews across all the platform reviews posted over the month. The positive sentiment ratio is higher than the negative one from early 2016 and remains steady around at 0.5 (50% of the monthly fraction of positive reviews), while the positive sentiment ratio fluctuates from 0.3 to 0.4 (30% and 40% the monthly fraction of negative reviews).