

The Impact of Online Word-of-Mouth and Default News on Trading Volumes in Peer-to-Peer Lending Platforms

Yanan Shang
City University of Hong
Kong
Southern University of
Science and Technology
ynshang2-
c@my.cityu.edu.hk

Jin Hu
The University of Hong
Kong
Southern University of
Science and
Technology
jinhu@connect.hku.hk

Cheng Tao
The University of Hong
Kong
Southern University of
Science and Technology
u3008707@connect.hku.
hk

Daning Hu
Southern
University of
Science and
Technology
hdaning@gmai
l.com

Xuan Yang
University of
Zurich
xuanyang06
@gmail.com

Abstract

This study explores the impact of default news of peer-to-peer (P2P) lending platforms on their trading volumes, particularly during a market downturn, and examines the moderating effect of online word-of-mouth (WOM). Using a dataset encompassing 694 P2P lending platforms from P2PEye.com, a premier third-party P2P information portal in China, this study employs advanced econometric techniques such as staggered difference-in-differences and difference-in-difference-in-differences analyses. The results show that default news diminishes trading volumes of P2P platforms, an effect that is more pronounced on platforms with a more positive WOM. Moreover, we find that platforms affiliated with banks or operating without Internet Content Provider (ICP) certification appear to be less susceptible to the negative effects of default news. This study offers novel perspectives on the interplay between default news and online WOM within in a declining market. It contributes to the existing body of literature and provides actionable insights for various stakeholders.

Keywords: peer-to-peer lending platforms, trading volume, default news, online word-of-mouth

1. Introduction

From 2007 to 2020, the peer-to-peer (P2P) lending market experienced a dramatic cycle of expansion and contraction all over the world. These P2P lending markets are typically facilitated via online platforms, which enable individuals to secure investments directly from investors, bypassing traditional financial intermediaries such as banks (Xu et al., 2022). The zenith of this market was reached in 2015 in China when 6,000 lending platforms

constituted the Chinese P2P lending landscape. The total trading volume of these Chinese P2P platforms exceeded the combined volume of eight other nations, including the United States, the United Kingdom, and Japan (Ding et al., 2021).

In the aftermath of stringent regulations implemented by the China Banking Regulatory Commission in late 2017, the Chinese P2P lending industry has experienced a precipitous downturn (He, 2020; Liu, 2018). The market was overwhelmed by news of P2P platform defaults on debts and other financial commitments. This was coupled with alarming reports of platforms absconding with investors' funds and going off the grid entirely. In the month of July 2018 alone, nearly 160 P2P lending platforms were reported to have partially or completely default on their financial obligations. This figure stood in stark contrast to the 217 cases reported for the entirety of 2017 (Liu, 2018). The prevalence of news about default events in a P2P platform can significantly erode investor confidence in this platform. This has the potential to drastically reduce the aggregate value of all loans initiated and executed on this platform within a specific time-period (i.e., trading volume of this platform).

In contrast to traditional financial markets, P2P investors are heavily reliant on the Internet to obtain news and various other information about the P2P platforms they are interested to invest. In particular, the advent of social media has empowered P2P lending platforms and related information portals to facilitate the sharing of opinions and the evaluation of platforms among peer investors. Online word-of-mouth (WOM), defined as the online dissemination of opinions and recommendations, plays a critical role in shaping individuals' investment decisions in P2P lending markets. In these markets, online WOM can offer a more diverse and nuanced array of

information such as user experiences and ratings, elements often absent in traditional financial markets. Therefore, the role of online WOM is more prominent and influential in P2P lending markets as compared to their traditional counterparts.

However, previous literature has primarily centered on online WOM within the confines of traditional financial markets and during standard market conditions (Xie et al., 2020). The role of online WOM during swift market downturns, especially in the context of decentralized financial markets like P2P lending platforms, remains largely unexplored. As a result, our study aims to address the following questions: In a declining P2P lending market, what is the impact of default news of a P2P lending platform on its trading volume? And more importantly, to what extent does the online WOM associated with a platform moderate this effect?

2. Literature Review and Hypothesis Development

2.1. Impact of Default News on P2P Lending Platforms

While the effects of news on traditional financial markets have been widely studied (Clarke et al., 2020; Krüger, 2015; Savor & Wilson, 2013; Tetlock, 2007; Williams, 2015), research on the response of P2P lending markets to negative news remains scarce. Pagnottoni et al. (2021) examined the impact of country-specific socio-economic and political news related to the SARS-CoV-2 outbreak on the volatility of equity and bond markets across six nations. Their investigation reveals that financial markets respond heterogeneously to the news of the epidemic, depending on the reference country and market behaviors before and after the news shock. Knif et al. (2008) showed that news shock related to inflation can significantly influence stock market movements, with the effect hinging on the prevailing economic state and general perception of inflation announcements as either positive or negative news. Moreover, Chen et al. (2021) examined the responses of individual investors to negative news events in the P2P lending industry. Their findings revealed that only incidents involving platform absconding investor funds had a significant negative impact on investor reactions. Our study diverges from theirs by focusing on the platform-level impact of default news shock instead of individual investor-level.

Based on the literature and the unique characteristics of the P2P lending market, we propose that default news has a negative impact on a P2P

platform's trading volume. Firstly, behavioral finance studies (Barberis & Huang, 2001) have shown that individual investors tend to exhibit risk-averse and loss-averse behavior, especially during times of economic downturns (Guiso, 2012). This behavioral bias applies to P2P lending as well, where event risk, such as platform defaults, can be perceived as significant risks in the market (Chen et al., 2021). Negative events in the P2P lending industry, such as platform closure, withdrawal difficulties, and instances of absconding with money, often result in the failure of platforms (Fong, 2018). In response to these negative events, investors may instinctively alter their investment strategies or even withdraw their existing investments to avoid the risk of default or potential losses (Shao & Bo, 2022). Furthermore, new individual investors may hesitate to enter the platform, choosing to remain on the sidelines. Thus, it is reasonable to expect that the occurrence of negative events in P2P platforms will have a subsequent impact on trading volume.

Secondly, the P2P lending market is relatively new and lacks the regulatory oversight seen in traditional financial markets (BBVA, 2015). Consequently, news of a platform default can exacerbate existing concerns and erode investor confidence in the platform. Investors on P2P lending platforms often have limited information about the platform's risk profile (Emekter et al., 2015; Gao et al., 2021; Pokorná & Sponer, 2016). Default news can serve as a signal that the platform's risk management procedures are inadequate, increasing the perceived likelihood of loan defaults. Consequently, investors may feel compelled to withdraw their funds to minimize potential losses. This withdrawal behavior can lead to a decrease in trading volume on the platform.

Thirdly, news of a platform default can have a negative impact on the platform's reputation, deterring potential investors from joining or investing in the platform. This lack of new investment further contributes to a decrease in trading volume. In the P2P lending market, where trust and credibility play significant roles, negative news about a platform default can significantly undermine the platform's reputation and erode investor confidence. Based on these arguments, we hypothesize that:

H1: Default news has a negative impact on a P2P platform's trading volume.

2.2. The Role of Social Media in Financial Markets

Social media's pervasive influence has been rigorously examined across various domains,

unearthing both its advantages and limitations. In health communication, it facilitates targeted message dissemination and enhances user engagement, although issues of information reliability and privacy persist (Moorhead et al., 2013). Similarly, in higher education, platforms like Facebook augment student interaction, but also present privacy challenges (Chugh & Ruhi, 2018). Within marketing, social media has solidified its role as an essential tool for customer outreach and brand development (Alalwan et al., 2017). The tourism sector also leverages social media for influencing travel choices and enhancing industry competitiveness (Leung et al., 2013). Despite these benefits, caution is warranted due to social media's potential negative impact on mental health, particularly among youth (Keles et al., 2020).

Another important stream of literature has explored the impact of social media on financial markets, particularly for the effects of online WOM. In contrast to formal financial news content such as firms' earning reports and regulatory filings, online WOM content, often found on social media, is characterized by a less structured and more informal nature (Xie et al., 2020). Despite this informal character, this type of information content wields a substantial impact on the financial market. It shapes investors' access to information about user experiences, investment decisions, and their social interactions with each another. For instance, Deng et al. (2018) conducted an opinion mining analysis of microblog posts, providing compelling evidence for the predictive power of social media sentiment on stock returns.

Despite the extensive research on the impact of social media on financial markets, there is a noticeable research gap when it comes to its role during periods of financial turbulence. The issue of information asymmetry has been a persistent issue in the P2P lending market even under standard conditions, as lenders frequently lack critical information about borrowers' credit history, employment status, income level, as well as detail information about the P2P platform (Ge et al., 2017). As a result, P2P lenders tend to rely on user reviews from their peer investors, detailing their investment experiences shared on P2P social media platforms, serving as crucial guides for making investment decisions. This reliance becomes especially pronounced during periods of financial instability, as investors tend to seek crisis-related information and communicate with each other through social media channels (Veil et al., 2011).

This study aims to address this gap empirically studying the effects of user evaluations of their past investment experiences (i.e., online WOM) in P2P

platforms on investor behaviors during a market crisis. Such evaluation (rating) information are obtained from a major P2P social media information portal called P2PEye.com. Investors in P2P lending platforms may interpret positive user ratings as a reliable indicator of a platform's future resilience, even amidst a market downturn. Such a perception can bolster investors' confidence in this platform's capacity to navigate through the crisis successfully. Consequently, these investors may be less likely to liquidate and withdraw their P2P investments in response to news of default events concerning this platform. Therefore, we propose the following hypothesis:

H2a: The adverse impact of default news on a P2P platform's trading volume is less pronounced for platforms with better online WOM prior to the crisis.

On the other hand, some extant literature and theory challenge H2a by positing that strong online WOM before the crisis could amplify the detrimental effect of default news on a P2P platform. Firstly, the expectancy disconfirmation theory, frequently used in marketing research, suggests that consumers, upon engaging with a product, measure their experience against pre-established expectations (Anderson, 1973; Oliver, 1980; Oliver & DeSarbo, 1988). A positive experience exceeding these expectations often results in consumer satisfaction and increased purchases. On the contrary, if the product fails to meet expectations, it can lead to dissatisfaction and reduced consumer engagement (Rao et al., 2011; Tangari et al., 2019; Wang et al., 2023). Contextualizing this theory, if there are numerous positive reviews from earlier users, potential investors might harbor elevated expectations. Any default by the platform starkly contrasts with this anticipated performance, causing a profound disconfirmation of expectations. This pronounced mismatch can evoke potent negative emotions, like disappointment or betrayal, culminating in a marked decline in trading volume.

Secondly, in markets characterized by significant information asymmetry, such as the P2P lending market, unconventional signals might be construed as insider information. A pertinent study on P2P lending by Zhang and Liu (2012) found that unattractive listing attributes, like poor credit grades and high debt-to-income ratios, could augment herd behavior in P2P investment listings. In this context, such adverse attributes hint at potential hidden advantages, intriguing those investors with access to undisclosed information. This pronounced herd behavior is largely attributed to information asymmetry, as investors frequently do not possess exhaustive data regarding P2P borrowers' creditworthiness. Drawing from this, in our scenario, investors might perceive

default events on platforms with positive online WOM as an indicator of deeper, non-transparent issues. Such a perception could hasten and amplify their fund withdrawal. Consequently, we put forth an alternative hypothesis:

H2b: The adverse impact of default news on a P2P platform's trading volume is more pronounced for platforms with better online WOM prior to the crisis.

3. Data and variables

The Chinese P2P lending market provides an ideal setting for our study, given its remarkable rise and fall. As the largest P2P lending market in the world, China's P2P industry dominated the global market from 2013 to 2018, with trading volume exceeding that of the rest of the world combined (Huang, 2022). However, this market then experienced a prolonged period of extreme downturn, ultimately resulting in the demise of all P2P platforms due to the implementation of strict regulations. This context provides an excellent opportunity to investigate the crash of the P2P lending market.

We collected data from P2PEye, one of the most widely recognized third-party P2P information forums offering P2P lending services in China. Our sample consists of all the 694 P2P platforms that were reported to be in default on P2PEye. We crawled the background information, default details, and transaction data for the 694 platforms from November 2017, when the national P2P rectification campaign began, to March 2021, when we crawled the data. We also crawled the rating information of all the 144,824 user comments for each platform from its launch date to the date of its first default. Finally, we integrated the data into an unbalanced panel at the platform-week level with 207,256 observations. Table 1 shows the list of variables.

One crucial step in the variable construction process is to identify the occurrence of default news for each platform. Fortunately, P2PEye would reports the initial default event of a platform along with its corresponding date at the top of the platform's homepage, as depicted in Figure 1. The default events identified by P2PEye encompass a range of abnormal operation types, such as embezzlement, business termination, withdrawal difficulties, police investigations, lack of communication, disputed transactions, business suspensions, and schedule extensions. Note that the notation and date of the default only appear on the homepage after the platform's first default. Even if the platform encounters subsequent defaults, the displayed

information remains unchanged. This distinct scenario provides an ideal context for employing a difference-in-differences analysis to examine the causal impact of default news.

Table 1. Description of variables

Variable	Description
Dependent Variable	
$Volume_{it}$	The trading volume (in Chinese Yuan) of platform i in week t on P2PEye.
Independent Variables	
$DefaultNev$	A dummy that equals 1 when platform i has been reported as defaulting in week t , and 0 otherwise.
WOM_i	Word-of-mouth (expressed through user ratings) of platform i prior to the default news.
Control Variables	
Age_{it}	The number of weeks platform i has been operating up to week t .
$Investor_{it}$	The number of investors who have invested through P2PEye on platform i in week t .
Platform features for heterogeneity analysis	
$List_i$	A dummy that equals 1 if platform i has a listed company background, and 0 otherwise.
$Bank_i$	A dummy that equals 1 if platform i has a bank background, and 0 otherwise.
$State_i$	A dummy that equals 1 if platform i has a state-owned company background, and 0 otherwise.
$Association$	A dummy that equals 1 if platform i belongs to any industry association, and 0 otherwise.
ICP_i	A dummy that equals 1 if platform i has obtained Internet Content Provider (ICP) certification, and 0 otherwise.
$Capital_i$	The registered capital (in Chinese Yuan) of platform i .



Figure 1. Screenshot of a P2P platform on P2PEye

Another significant step involves measuring online WOM generated by investors before the emergence of default news. To achieve this, we utilize user-generated rating information. Users are required to provide an overall rating score when commenting on a platform, reflecting their overall

evaluation as positive, neutral, or negative (see Figure 1). Following the methodologies proposed by Antweiler and Frank (2004) and Sprenger et al. (2014), we calculate the online WOM metric:

$$WOM_i = \ln\left(\frac{1 + \sum_t PN_{it}}{1 + \sum_t NN_{it}}\right), \quad t < \text{default week} \quad (1)$$

where WOM_i is a proxy for the online WOM of platform i before platform i was first exposed by the news for its risk of default, $\sum_t PN_{it}$ sums the total number of positive comments for i before its first default, and $\sum_t NN_{it}$ sums the total number of neutral and negative comments for i before its first default.

4. Empirical models and results

4.1. Empirical models

To test H1, considering that different platforms experience default events at different times, we employ a staggered difference-in-differences and two-way fixed effect framework:

$$\ln(\text{Volume}_{it}) = \alpha + \beta \text{DefaultNews}_{it} + \gamma \text{Age}_{it} + \delta \text{Investor}_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

where i indexes the platforms and t indexes the weeks. The dependent variable, Volume_{it} , is the weekly trading volume of each platform on P2PEye. To facilitate analysis, we add one to this measure and take the logarithm. DefaultNews_{it} is a dummy variable that equals 1 if t is after the week when platform i was first reported to be in default, and 0 otherwise. Additionally, we incorporate Age_{it} , measured as the number of weeks since the launch of platform i , and Investor_{it} , measured as the number of investors participating on platform i during week t . To account for potential influences from platform-specific characteristics and macro-level changes over time, we introduce platform fixed effects μ_i and time fixed effects θ_t . These fixed effects help control for unobserved heterogeneity and time-varying factors that may affect our analysis. Of particular interest is the coefficient β , which indicates the impact of default news on platform trading volume.

To test H2, we use the following difference-in-difference-in-differences model:

$$\begin{aligned} \ln(\text{Volume}_{it}) = & \alpha + \beta_1 \text{DefaultNews}_{it} \\ & + \beta_2 \text{DefaultNews}_{it} \\ & \times \text{WOM}_i + \gamma \text{Age}_{it} \\ & + \delta \text{Investor}_{it} + \mu_i + \theta_t \\ & + \varepsilon_{it} \end{aligned} \quad (3)$$

where WOM_i indicates platform i 's online WOM before its first default, as defined in Equation (1). All other variables are the same as those in Equation (2). The parameter of our interest is β_2 , which captures the moderating effect of platform WOM on the impact of default news on platform trading volume.

4.2. Estimation results

Table 2 shows the estimation results of Equations (2) and (3) in Columns (1) and (2), respectively. From Column (1), we can find that the coefficient of DefaultNews_{it} is significantly negative, which suggests that news of platform default has a negative effect on the trading volume of P2P platforms. Specifically, the trading volumes of P2P platforms experience a substantial decline of 52.8% ($= e^{-0.751} - 1$) after being reported defaults. Therefore, H1 is supported. It is natural and reasonable that P2P investors will reduce investment to a platform after seeing the default news of the platform because they lose trust in the platform.

Table 2. Main results

	(1)	(2)
DefaultNews_{it}	-0.751*** (-4.69)	-0.635*** (-4.15)
$\text{DefaultNews}_{it} \times \text{WOM}_i$		-0.118*** (-4.34)
Age_{it}	0.003*** (11.76)	0.003*** (11.73)
Investor_{it}	0.012*** (4.01)	0.012*** (4.01)
Constant	-0.223** (-2.92)	-0.231** (-3.05)
Platform FE	Yes	Yes
Time FE	Yes	Yes
R-squared	0.358	0.359
Observations	207,256	207,256

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Column (2) of Table 2, while the coefficient of DefaultNews_{it} is still significantly negative, the coefficient of $\text{DefaultNews}_{it} \times \text{WOM}_i$ is significantly negative. This means that P2P platforms' online WOM negatively moderates the negative impact of default news on platform trading volume, supporting H2a. The better the WOM of the platform, the more money the platform is withdrawn by investors after the news of the platform default. This

phenomenon can be explained by the fact that during an extremely negative market situation, investors are more sensitive to negative information circulating on social media (Zhang & Liu, 2012). Investors may interpret a platform with positive WOM defaulting as a sign of insurmountable and severe issues. As a result of feeling panicked and betrayed, investors may withdraw more investments from platforms with better WOM.

5. Heterogeneity analysis and robustness checks

5.1. Heterogeneity analysis

To gain further insights into the impact of default news on users' trading decisions, we extend our analysis to examine whether the sensitivity to default news varies across P2P lending platforms with different characteristics. We consider six platform features: (1) whether platforms are established by listed companies, (2) whether platforms receive investments from commercial banks, (3) whether platforms are owned by state-owned companies, (4) whether platforms are members of the Internet Banking Association (IBA), (5) whether platforms have obtained Internet Content Provider (ICP) certification, and (6) the registered capital of platforms (see Table 1). We explore the heterogeneity of reactions to default news using Equation (4), where the coefficient of the interaction term, calculated as the product of the $DefaultNews_{it}$ and $Feature_i$, becomes the focal point of our analysis. By examining this coefficient, we can assess whether different platform characteristics lead to varying responses to default news.

$$\ln(\text{Volume}_{it}) = \alpha + \beta_1 \text{DefaultNews}_{it} + \beta_2 \text{DefaultNews}_{it} \times \text{Feature}_i + \gamma \text{Age}_{it} + \delta \text{Investor}_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (4)$$

Table 3 presents heterogeneous reactions to default news among platforms with different backgrounds. Platforms with a banking background show a smaller negative impact on trading volume, while platforms with ICP certification experience a greater negative impact. Other platform features do not moderate the effect of default news. The observed empirical results can be attributed to the varying levels of reputational endorsement associated with different platform background. The banking background serves as a tangible and practical

endorsement, which can provide a sense of stability and reliability to investors. As a result, when default news emerges, the negative impact on trading volume is mitigated for platforms with a banking background. Conversely, the ICP certification represents a more abstract form of endorsement. When default events occur, this relatively intangible indicator may generate a sense of betrayal or disappointment among investors. The perceived vulnerability of this virtual indicator may intensify investor reactions, leading to a greater negative impact on trading volume.

Table 3. Heterogeneity results

	(1)	(2)	(3)
$DefaultNews_{it}$	-0.751*** (-4.73)	-0.752*** (-4.69)	-0.746*** (-4.65)
$DefaultNews_{it} \times List_i$	0.007 (0.05)		
$DefaultNews_{it} \times Bank_i$		0.588*** (19.82)	
$DefaultNews_{it} \times State_i$			-0.062 (-0.64)
Age_{it}	0.003*** (11.76)	0.003*** (11.76)	0.003*** (11.77)
$Investor_{it}$	0.012*** (4.01)	0.012*** (4.01)	0.012*** (4.01)
Constant	-0.223** (-2.91)	-0.223** (-2.92)	-0.223** (-2.92)
Platform FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R-squared	0.358	0.358	0.358
Observations	207,256	207,256	207,256
	(4)	(5)	(6)
$DefaultNews_{it}$	-0.745*** (-4.71)	-0.709*** (-4.51)	-0.749*** (-4.68)
$DefaultNews_{it} \times Association_i$	-0.071 (-0.55)		
$DefaultNews_{it} \times ICP_i$		-0.208** (-2.84)	
$DefaultNews_{it} \times Capital_i$			-0.000 (-0.66)
Age_{it}	0.003*** (11.26)	0.003*** (11.65)	0.003*** (11.76)
$Investor_{it}$	0.012*** (4.01)	0.012*** (4.02)	0.012*** (4.01)
Constant	-0.230** (-3.06)	-0.240** (-3.16)	-0.221** (-2.88)
Platform FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R-squared	0.358	0.359	0.359
Observations	207,256	207,256	206,957

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Robustness checks

5.2.1. Multicollinearity. Multicollinearity poses a challenge in regression modeling as it leads to unstable and ambiguous interpretation of estimated

coefficients. To identify multicollinearity, the variance inflation factor (VIF) is computed for each independent variable, where a VIF value exceeding 5 indicates multicollinearity. Upon examination of the results presented in Table 4, no evidence of multicollinearity is observed in our analysis.

Table 4. Multicollinearity test

Variable	VIF
<i>DefaultNews_{it}</i>	1.67
<i>WOM_i</i>	1.00
<i>Age_{it}</i>	1.68
<i>Investor_{it}</i>	1.01
Mean VIF	1.28

5.2.2. Parallel trends. The validity of an unbiased estimate in the difference-in-differences model relies on the assumption that the trading volume trends for both control and treatment groups exhibit parallel paths before the occurrence of default news. Given the staggered nature of default news in P2P lending platforms, we employ an event study approach to examine the assumption of parallel pretreatment trends. Following the methodology of Jacobson et al. (1993) and He and Wang (2017), we estimate the following equation:

$$\begin{aligned}
 Volume_{it} = & \sum_{k \geq -10, k \neq -1}^{k=10} D_{it}^k \times \tau_k \\
 & + \gamma Age_{it} + \delta Investor_{it} \\
 & + \mu_i + \theta_t + \varepsilon_{it}
 \end{aligned} \tag{5}$$

where the dummy variables D_{it}^k collectively indicate the assignment of default news. We define s_i as the week when platform i was assigned its default news. $D_{it}^k = 1$ if $t - s_i = k$, and 0 otherwise, where k ranges from -10 to 10, excluding -1. Note that the dummy for if $k = -1$ is omitted in Equation (5) so that the post-treatment effects are relative to the period immediately prior to the start of default news. The parameter of interest, τ_k , estimates the effect of default news k weeks following its occurrence. The results, as shown in Figure 2, indicate that the estimated coefficients of the lead periods of treatment (τ_k for all $k \leq -2$) are statistically insignificant. Consequently, we conclude that the trading volume trends prior to treatment are comparable for both groups of platforms.

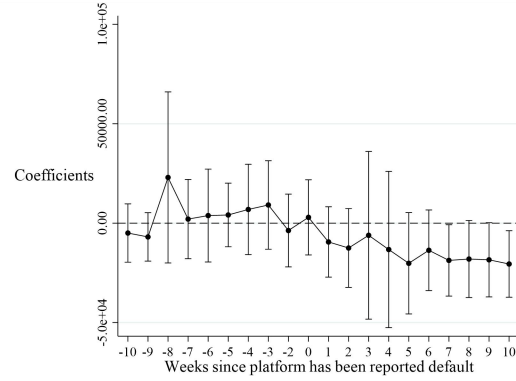


Figure 2. Parallel trends assumption test

5.2.3. Placebo test. To provide further evidence that our findings are not mere coincidences, we conduct a placebo test following the approach of Li et al. (2018) and Bae et al. (2021). Firstly, we randomly select a set of P2P lending platforms to the treatment group and assign pseudo weeks for the appearance of default news to these selected platforms. Next, using Equation (2), we perform the difference-in-differences analysis using this artificially generated sample, repeating the process 500 times. We plot the density of the coefficients of *DefaultNews_{it}* and the corresponding p-values. Figure 3 illustrates that the distribution of placebo coefficients is centered around zero, while the actual coefficient significantly deviates from the mean of placebo coefficients. This provides compelling evidence that our main finding is highly unlikely to be attributable to random chance.

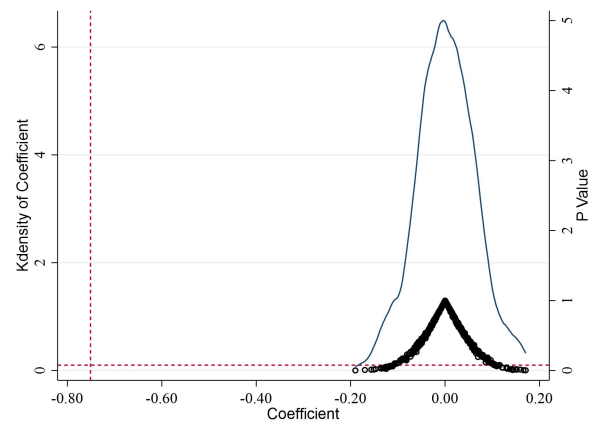


Figure 3. Placebo test

5.2.4. Lagged dependent variable as a control. As a platform's current trading volume may be influenced by its past trading volume, we include the lagged trading volume, $\ln Volume_{i,t-1}$, as an additional control variable in the regression model. By incorporating this variable, we aim to capture any

potential influence of past trading volume on the current outcome variable. The results of the regression analysis, as shown in Table 5, consistent with the findings from Table 2 and demonstrate the robustness of our results after controlling the lagged trading volume.

Table 5. Results: lagged dependent variable as a control

	(1)	(2)
<i>DefaultNews_{it}</i>	-0.352*** (-5.28)	-0.295*** (-4.64)
<i>DefaultNews_{it} × WOM_i</i>		-0.0585*** (-4.76)
<i>Age_{it}</i>	0.001*** (13.44)	0.001*** (13.36)
<i>Investor_{it}</i>	0.006*** (3.78)	0.006*** (3.77)
<i>lnVolume_{i,t-1}</i>	0.563*** (39.33)	0.563*** (39.23)
Constant	-0.084* (-2.47)	-0.088** (-2.61)
Platform FE	Yes	Yes
Time FE	Yes	Yes
R-squared	0.564	0.564
Observations	206,562	206,562

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusion

This study investigates how news of default events in a P2P platform affects its trading volume and how WOM may moderate this effect. We used a dataset comprising 694 P2P lending platforms and information gathered from P2PEye.com, a major social media information portal for P2P investors. Our findings show that default news generally reduce the trading volume on these platforms. Interestingly, this negative effect is even more pronounced on platforms with better online WOM prior to the default news. In addition, we found that platforms with certain features, such as those backed by a bank or operating without ICP certification, demonstrate a less negative response to default news. We have corroborated these findings through various robustness checks to ensure their reliability.

Our study contributes to the literature on the impact of news on financial markets by examining the effect of default news on the trading volume of P2P platforms during an industry-wide recession. Our findings highlight the importance of managing negative news events for the sustainability of such decentralized internet finance platforms like the popular smart contract-based lending platforms on major blockchains. Additionally, our study broadens the scope of the social media literature by

demonstrating that the impact of default news on a P2P platform's trading volume is influenced by its prior online WOM. We are among the first to demonstrate that P2P platforms with better WOM will experience a greater negative impact on trading volume in response to default news compared to those with worse WOM.

Our findings have important implications for the P2P industry and its stakeholders. Specifically, P2P lending platforms should acknowledge that having better online WOM among users does not necessarily shield them from the negative repercussions of default news. Platforms with a more favorable WOM reputation may actually face a more substantial adverse impact on trading volume in the wake of default news, as demonstrated in our study. Consequently, P2P lending platforms should employ proactive measures to manage the impact of default news on their trading volume, particularly those platforms with better WOM. These measures can include transparent communication with investors, offering additional incentives or benefits to investors, or developing a crisis management plan to cope with the aftermath of default news.

Although this study provides valuable insights, it also has several limitations. First, our empirical context is confined to P2PEye, one of the most widely recognized third-party P2P information forums offering P2P lending services in China. Despite its popularity, the results derived from this setting may not be generalized to other P2P platforms. Future research could benefit from replicating our analyses across different P2P platforms and within various cultural and regulatory frameworks. Second, we only focus on the impact of default news on trading volume, and we do not explore other potential outcomes such as changes in loan quality or shifts in borrower behavior. Third, we only consider online WOM and do not examine other types of reputation signals, such as ratings from third-party reputable agencies. Future research could address these limitations and provide a more comprehensive understanding of the impact of default news on Internet-based financial platforms.

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