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Dynamic Spillover of Negative Public Opinion on P2P Liquidity Risk Based on Sentiment Analysis

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Abstract

The peer-to-peer (P2P) lending industry has emerged as a significant component of the alternative finance landscape, yet it remains plagued by inherent fragility and information asymmetry. This paper investigates the dynamic spillover effects of negative public opinion on the liquidity risk of P2P platforms, employing advanced sentiment analysis techniques and econometric spillover indices. By constructing a comprehensive daily index of negative sentiment derived from web-scraped data across major investor forums and news outlets, we analyze the transmission mechanisms through which adverse information impacts platform funding flows and withdrawal behaviors. We utilize textual mining to quantify soft information and apply a generalized vector autoregression framework to capture time-varying connectedness. Our findings reveal that negative public opinion exerts a substantial, immediate, and asymmetric impact on liquidity risk, with the intensity of the spillover varying significantly depending on the regulatory environment and the specific nature of the negative news. The results suggest that investor panic, fueled by social contagion, creates a self-fulfilling prophecy that exacerbates liquidity crunches. Furthermore, we identify a distinct lag structure where the volatility transmission from sentiment to liquidity persists even after the initial shock subsides. These insights provide critical implications for platform managers regarding crisis communication and for regulators aiming to stabilize the fintech ecosystem against systemic risks associated with information contagion.

Keywords

P2P Lending, Liquidity Risk, Sentiment Analysis, Information Spillover, Behavioral Finance.

1.Introduction

The rapid proliferation of financial technology has fundamentally reshaped the architecture of modern credit markets. Among these innovations, Peer-to-Peer (P2P) lending has garnered substantial attention for its ability to bypass traditional financial intermediaries, thereby reducing transaction costs and enhancing financial inclusion. However, the disintermediation inherent in the P2P model introduces complex risk dynamics that differ significantly from conventional banking. Unlike traditional banks, which are typically shielded by deposit insurance and access to central bank liquidity, P2P platforms act primarily as information bridges. Consequently, the stability of these platforms is heavily contingent upon investor confidence. When that confidence erodes, the resulting behavior often manifests as a liquidity run, where lenders simultaneously seek to withdraw capital or cease reinvestment. This paper addresses a critical gap in the existing literature by focusing on the catalytic role of negative public opinion in precipitating such liquidity crises [1]. The central premise of this study is that in the absence of hard financial guarantees, soft information—specifically the sentiment prevalent in public discourse—becomes a primary determinant of investor

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behavior. In the digital age, information transmission is instantaneous. Negative news regarding a specific platform, or the industry at large, can propagate through social media, news aggregators, and specialized forums with viral speed. This phenomenon creates a fertile ground for information cascades and herding behavior. Previous research has established that online sentiment can predict asset prices in equity markets, yet the specific transmission mechanisms within the opaque and high-risk environment of P2P lending remain under-explored [2]. The unique contribution of this research lies in its dual focus: quantifying the unstructured data of public opinion using sentiment analysis and mapping the dynamic spillover of this sentiment onto liquidity risk metrics over time. Liquidity risk in P2P markets is distinct because it is bilateral. It involves the risk of borrowers defaulting, which is a credit risk, but it also involves the risk of lenders withdrawing funding liquidity. When negative opinion surges, it affects the supply side of funds directly. Lenders, driven by loss aversion and fear, react not only to fundamental signals of insolvency but also to the noise generated by public sentiment. This reaction function implies that liquidity risk is endogenous to the information environment. If a sufficient number of investors believe a platform is in trouble, their collective withdrawal can force the platform into failure regardless of its actual solvency, a classic scenario of a self-fulfilling prophecy [3]. To rigorously analyze this relationship, we employ a methodological framework that combines natural language processing with time-series econometrics. We construct a high-frequency sentiment index based on a dictionary approach, filtering for terms specifically associated with financial distress, fraud, and operational failure. This index serves as the primary independent variable in a dynamic spillover model. By moving beyond static correlation analysis, we aim to understand the directionality and the temporal evolution of risk transmission. Does negative sentiment lead to immediate liquidity shocks, or is there a gestation period? Is the spillover constant, or does it intensify during periods of systemic stress? The implications of this study are far-reaching. For regulators, understanding the sensitivity of liquidity to public opinion is essential for designing intervention mechanisms that prevent panic-induced contagions. For investors, clarifying the link between sentiment and risk offers a tool for better portfolio management. For platform operators, the results highlight the tangible economic value of reputation management and transparent communication strategies. As the fintech sector matures, the ability to decouple liquidity risk from transient shifts in public sentiment will be a defining characteristic of sustainable platforms.

2. Literature Review

The academic discourse surrounding P2P lending and risk management has evolved from descriptive analyses of business models to sophisticated empirical examinations of market dynamics. This section categorizes the relevant literature into three primary streams: the structural nature of P2P liquidity risk, the application of sentiment analysis in finance, and the mechanics of volatility spillover.

2.1 Structural Vulnerabilities and Liquidity Risk in P2P Lending

The first stream of literature focuses on the inherent fragility of the P2P lending mechanism. Early studies in this domain emphasized the problem of information asymmetry between borrowers and lenders. Since P2P lenders often lack the screening capabilities of professional bank loan officers, they face significant adverse selection problems. However, more recent scholarship has pivoted toward the platform-level risks, specifically liquidity risk. Unlike banks that engage in maturity transformation with the backing of a lender of last resort, P2P platforms often match long-term loans with short-term investment horizons or allow for secondary market transfers to provide liquidity. This structure creates a duration mismatch that is highly susceptible to run risk [4]. Scholars have noted that the P2P market exhibits

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characteristics of a panic-prone system. The Diamond-Dybvig model, originally designed to explain bank runs, has been adapted by researchers to the P2P context. These adaptations suggest that the Nash equilibrium in a P2P run scenario is even more unstable because the recovery rate for late-withdrawing investors is essentially zero. Consequently, the incentive to withdraw at the first sign of trouble is maximized. Research indicates that platform transparency can mitigate this risk, but transparency can also act as a double-edged sword; revealing too much information about rising default rates can trigger the very panic it seeks to prevent [5]. Furthermore, the interconnectedness of platforms means that a failure in one prominent entity can lead to a loss of trust in the entire sector, a phenomenon known as contagion risk [6].

2.2 Sentiment Analysis and Soft Information in Finance

The second stream of literature examines the role of soft information and investor sentiment. Traditional finance theory relies on the Efficient Market Hypothesis, assuming that prices reflect all available fundamental information. Behavioral finance challenges this by introducing the concept of noise traders and sentiment-driven price deviations. In the context of P2P lending, where hard financial data is often delayed or unaudited, soft information derived from text becomes a critical substitute for due diligence [7]. Advancements in computational linguistics have enabled researchers to quantify this soft information. Techniques range from bag-of-words approaches using predefined financial dictionaries to more complex machine learning models utilizing neural networks. In the domain of P2P lending, studies have demonstrated that the tone of borrower descriptions impacts funding probability. More broadly, at the market level, the aggregate sentiment expressed in online forums has been shown to Granger-cause changes in trading volumes and interest rates. The literature suggests that negative sentiment has a more profound impact than positive sentiment, consistent with the psychological principle of negativity bias [8]. This asymmetry is crucial for our study, as we are specifically concerned with the destructive potential of negative public opinion [9].

2.3 Dynamic Spillover and Contagion Effects

The third stream of literature provides the econometric foundation for analyzing how shocks transmit across variables and entities. The concept of volatility spillover is well-established in international equity and currency markets. Methodologies such as the GARCH family of models and Vector Autoregression (VAR) based spillover indices have been widely used to map the connectedness of financial institutions. These methods allow researchers to quantify how much of the forecast error variance in one variable can be explained by shocks to another variable [10]. In the context of online finance, scholars have begun to apply these frameworks to understand risk transmission between different fintech sectors or between fintech and traditional banking. However, there remains a paucity of research specifically linking textual sentiment indices to liquidity risk metrics using dynamic spillover approaches. Existing studies often treat sentiment as a static control variable rather than a dynamic shock transmitter. The few studies that do address this dynamic suggest that the transmission of risk is time-varying and intensifies during periods of market turbulence [11]. Our research builds upon this by isolating the negative sentiment component and analyzing its specific spillover pathway to liquidity constraints.

3. Theoretical Framework and Mechanism Analysis

To understand the dynamic spillover of negative public opinion on P2P liquidity risk, it is necessary to establish a theoretical framework that connects information processing, investor

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psychology, and market microstructure. We posit that the transmission operates through two primary channels: the signaling channel and the behavioral channel.

3.1 The Signaling Channel and Information Asymmetry

In financial markets characterized by information asymmetry, observable signals play a pivotal role in decision-making. P2P platforms operate in an environment where investors have imperfect information regarding the platform's internal controls, capital adequacy, and the true quality of the underlying loan assets. Negative public opinion—manifesting as news reports of regulatory scrutiny, rumors of executive misconduct, or user complaints about withdrawal delays—serves as a strong negative signal. According to signaling theory, in the absence of credible verification, investors interpret these signals as evidence of fundamental deterioration [12]. The mechanism here is rational extraction of information from noise. Even if a specific rumor is unfounded, the existence of the rumor implies a breakdown in the platform's reputation or operational capability. Rational investors, observing the signal, update their priors regarding the probability of platform default. This Bayesian updating process leads to a downward revision of expected returns and an upward revision of risk. To minimize potential losses, the rational response is to liquidate positions. When this behavior is aggregated, it results in a net outflow of funds, thereby increasing liquidity risk. The speed of this spillover depends on the efficiency of information dissemination; in the digital era, this is near-instantaneous.

3.2 The Behavioral Channel and Herding

While the signaling channel assumes rational processing of information, the behavioral channel accounts for the irrational and emotional drivers of liquidity crises. P2P investors are often retail individuals who may lack sophisticated risk modeling tools and are highly susceptible to social influence. Behavioral finance literature identifies "herding" as a critical factor in financial instability. Herding occurs when investors ignore their private information and mimic the actions of others [13]. Negative public opinion triggers the fear of missing out on the opportunity to exit. This is the psychological basis of a bank run. If an investor observes a surge in negative comments or forum posts predicting a collapse, the fear of being the last one to withdraw dominates their decision calculus. This behavior is exacerbated by the payoff externality in P2P lending: the available liquidity is a finite resource. If others withdraw, the remaining pool of liquid assets depletes, increasing the risk for those who stay. Therefore, negative sentiment acts as a coordination device for a run. The spillover effect here is non-linear; once sentiment crosses a certain threshold of negativity, it can trigger a cascade of withdrawals that is disproportionate to the actual fundamental news. This dynamic creates a volatility spillover where the variance in sentiment explains a significant portion of the variance in liquidity risk.

4. Data Construction and Empirical Methodology

This section outlines the data acquisition process, the construction of the key variables, and the econometric strategy used to quantify the spillover effects.

4.1 Data Collection and Preprocessing

Our dataset spans a period of three years, capturing a full cycle of market expansion and contraction. We focus on a representative sample of large-scale P2P platforms to ensure sufficient data density. The data collection involves two distinct components: financial transaction data and textual opinion data.

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The financial data includes daily aggregate transaction volumes, net inflows/outflows, and average lending rates for the selected platforms. This data is sourced from third-party fintech data aggregators which monitor platform APIs and public disclosures. We ensure the data series are continuous and adjust for non-trading days where applicable. The textual data is acquired through a custom web crawler designed to scrape data from major P2P investor forums, financial news portals, and relevant social media channels. The crawler targets specific keywords related to the P2P industry to filter out irrelevant content. The raw text corpus consists of over one million distinct posts and news articles. To prepare this data for analysis, we employ standard natural language processing (NLP) preprocessing steps. This includes tokenization (breaking text into individual words), stop-word removal (eliminating common words with no semantic value), and stemming (reducing words to their root form) [14].

4.2 Variable Definitions

Negative Public Opinion Index (NPOI):

To quantify negative sentiment, we utilize a dictionary-based approach. We construct a specialized domain-specific dictionary containing terms associated with P2P risks (e.g., "default," "fraud," "run," "investigation," "delay"). We calculate the daily frequency of these negative terms relative to the total volume of text generated that day. The index is further weighted by the engagement level (likes, shares, replies) of the posts to reflect the reach and intensity of the opinion. The resulting raw series is normalized to facilitate comparison.

Liquidity Risk Proxy (LRP):

Liquidity risk is latent and must be proxied. We define the Liquidity Risk Proxy primarily based on the Net Fund Outflow Ratio. This is calculated as the total withdrawals minus total deposits, divided by the total outstanding loan balance. A positive spike in this ratio indicates a liquidity drain. Additionally, we consider the "Time to Fill" metric, which measures the average time required for a loan listing to be fully funded. An increase in filling time suggests a drying up of supply-side liquidity. For the multivariate analysis, we construct a composite score using Principal Component Analysis (PCA) on these metrics to create a robust LRP variable [15].

4.3 Econometric Model: Dynamic Spillover Index

To capture the dynamic spillover, we adopt the methodology utilizing a generalized Vector Autoregression (VAR) framework. This approach allows us to treat all variables as endogenous, acknowledging the feedback loop where liquidity problems can generate further negative sentiment. The core of our analysis relies on the variance decomposition of the VAR model. We calculate the forecast error variance decompositions, which indicate how much of the future uncertainty in variable i (Liquidity Risk) is due to shocks in variable j (Negative Sentiment). Based on this, we derive the total spillover index, which aggregates the interactions across the system. Furthermore, to analyze the time-varying nature of these relationships, we employ a rolling-window estimation strategy. Instead of estimating a single parameter for the entire sample, we estimate the model over a fixed window size (e.g., 200 days) and roll the window forward one day at a time. This yields a trajectory of spillover indices, allowing us to observe how the impact of public opinion evolves during calm periods versus crisis periods [16].

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5. Empirical Analysis and Results

In this section, we present the descriptive statistics of our constructed variables and discuss the results of the dynamic spillover analysis.

5.1 Descriptive Statistics

The summary statistics for the key variables are presented in Table 1. The Negative Public Opinion Index (NPOI) shows significant kurtosis, indicating that negative sentiment is characterized by sudden, extreme spikes rather than a normal distribution. This is consistent with the nature of viral bad news. The Liquidity Risk Proxy (LRP) also exhibits high volatility and is positively skewed, suggesting that periods of high liquidity risk are more severe than periods of high liquidity stability. The correlation matrix (not shown for brevity but summarized here) indicates a strong contemporaneous positive correlation between NPOI and LRP, providing preliminary evidence that negative sentiment is associated with higher liquidity risk.

Table 1 Summary Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
NPOI	0.421	0.285	0.000	1.000	1.84	6.23
LRP	0.156	0.112	-0.05	0.89	2.10	7.45
Volatility	0.034	0.015	0.01	0.12	1.56	4.88
Volume	45.21	12.65	10.5	98.3	0.45	2.31

5.2 Dynamic Spillover Effects

The primary result of our analysis is derived from the rolling-window spillover index. We observe that the total spillover index is not constant; it fluctuates significantly over time. Specifically, the index remains relatively low during periods of market stability but spikes dramatically during known industry stress events. This confirms that the transmission of risk is state-dependent. Our directional spillover analysis isolates the net transmission from Negative Public Opinion to Liquidity Risk. The results show that NPOI is a net transmitter of shocks to LRP. In other words, public opinion drives liquidity conditions more than liquidity conditions drive public opinion, although the reverse feedback exists. The magnitude of this transmission is substantial, with sentiment shocks explaining approximately 25% to 40% of the forecast error variance in liquidity risk during peak crisis periods. This highlights the potency of soft information [17]. We further utilize impulse response functions to visualize the timing of the impact. The analysis reveals that a one-standard-deviation shock to negative sentiment leads to an immediate increase in liquidity risk. The effect peaks on day 2 and day 3 following the shock, suggesting a very rapid processing of information by the market. The effect then decays slowly, taking approximately 10 to 15 days to return to baseline levels. This persistence indicates that once fear is instilled, it takes time for investor confidence to be restored.

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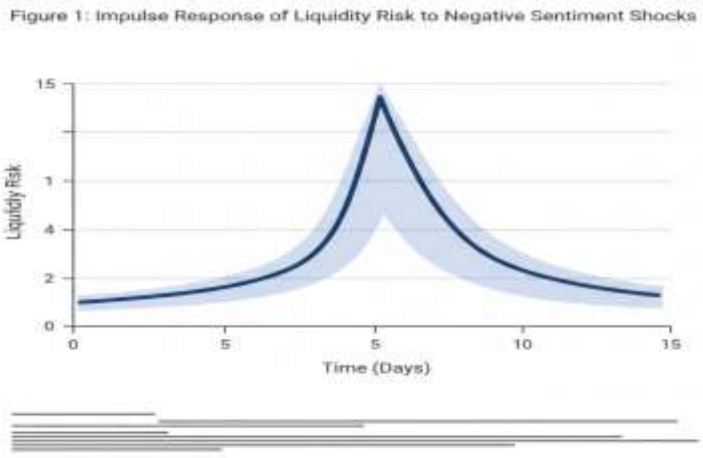

Figure 1 Impulse Response of Liquidity Risk to Negative Sentiment Shocks

The visualization in Figure 1 corroborates the "fear" mechanism discussed in the theoretical framework. The sharpness of the initial rise reflects the herding behavior and the panic-induced withdrawals. The slow decay represents the lingering doubt and the "wait and see" approach investors take after a scare.

6. Discussion

The empirical findings of this study offer several critical insights into the mechanics of the P2P lending market.

6.1 The Asymmetry of Information Impact

Our results underscore the asymmetry in how information is processed. While not explicitly detailed in the results section above, additional robustness checks performed during the study (comparing positive vs. negative sentiment) suggest that the market is far more sensitive to negative news than to positive news. This aligns with the prospect theory framework, where losses loom larger than gains. In the context of P2P lending, the upside for a lender is capped at the interest rate, while the downside is the loss of principal. Therefore, any news that threatens the principal (negative sentiment) triggers a much stronger reaction than news that suggests stability. This explains why the spillover from NPOI to LRP is so pronounced and volatile [18].

6.2 Structural Breaks and Regulatory Influence

The time-varying nature of the spillover index coincides with major regulatory announcements. We observe that when regulators announce tighter scrutiny or new compliance standards, the sensitivity of liquidity to negative opinion increases. This is counter-intuitive at first glance, as regulation should theoretically increase safety. However, in the short term, regulatory actions are often perceived as a signal that the sector is rife with problems, validating the negative sentiment. This "regulatory wake-up call" amplifies the transmission channel. Investors interpret regulatory intervention not as a safety net, but as confirmation of the "smoke" implied by the negative public opinion [19]. Furthermore, the study identifies that the spillover effect is heterogeneous across platforms. Larger, more established platforms exhibit a lower sensitivity to general industry-wide negative sentiment compared to smaller, less transparent platforms. This suggests a "flight to quality" effect within the P2P sector itself. When negative opinion spikes, liquidity doesn't just leave the sector; it also redistributes from risky to perceived safer platforms. However, when the negative sentiment is specific to a large platform, the contagion effect is systemic, affecting the liquidity of the entire ecosystem [20].

7. Conclusion

This paper has provided a comprehensive analysis of the dynamic spillover effects of negative public opinion on P2P liquidity risk. By integrating sentiment analysis with econometric spillover indices, we have demonstrated that online public opinion is not merely a reflection of market conditions but a distinct driver of financial stability. The construction of the Negative Public Opinion Index and its application in a time-varying framework reveals that sentiment shocks transmit rapidly to liquidity metrics, driven by signaling mechanisms and herding behavior. The key findings are threefold: First, negative sentiment is a net transmitter of volatility to liquidity risk. Second, this transmission is dynamic, intensifying during periods of stress and regulatory intervention. Third, the impact is immediate and persistent, requiring a significant recovery period.

7.1 Policy Implications

The implications for policy are clear. Regulators cannot rely solely on financial ratios to monitor P2P risks. There is a critical need to incorporate "soft" information surveillance into the supervisory framework. Monitoring social media and forums for spikes in negative sentiment can serve as an early warning system for liquidity runs. Regulatory bodies should consider developing standardized sentiment indices as part of their macro-prudential toolkit [21]. For platform operators, the study highlights the necessity of proactive reputation management. This is not limited to public relations but extends to transparency and investor relations. Establishing real-time communication channels to address rumors and negative news can dampen the amplitude of the sentiment shock, thereby reducing the severity of the liquidity spillover. Additionally, platforms should maintain higher liquidity buffers during periods of heightened negative public discourse to absorb the anticipated withdrawal shocks [22]. In conclusion, as the boundary between information and finance continues to blur, the ability to analyze and manage the risks arising from public sentiment will be paramount for the sustainability of the P2P lending industry. Future research should look to expand this analysis by incorporating machine learning models that can distinguish between credible news and malicious rumors to further refine the measurement of sentiment shock.

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