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Systematic Sentiment Risk & Market Liquidity: Systematic Liquidity Pricing in Light of the Microblogging Content

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ABSTRACT

Investors are keenly interested in the risk of informed trading, as it can have an immediate impact on transaction costs imposed by liquidity providers. This paper examines microblogging-based informed trading as a systematic risk for liquidity at both market and firm levels. Assets at firm level were categorized into financial and non-financial perspective. In this context, the study constructed a bank index and non-financial firms (NFF) index within the broader market. In a relative market, the liquidity was priced pessimistically and a higher probability for appearance of spread was noted during pessimism environments. The bank index liquidity was significantly responsive towards systematic bearish and bullish sentiments. In addition, the posterior probability of systematic sentiment risk was considerably higher for bank assets' liquidity. The NFF index liquidity was not exposed to the systematic bearish and bullish sentiments. Meantime, the posterior probability of systematic sentiment risk was considerably lower for non-financial assets' liquidity. The relative market's liquidity was not influenced by changes in past series of bearish and bullish sentiments. Similarly, the sentiments' lags were not strong enough to impact the firm index liquidity in the short or long run.

KEYWORDS

Microblogging data; Investor Sentiments; Asset Pricing; Liquidity; Systematic Risk

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1. Introduction

The development in information technologies has enabled access to vast amounts of information without geographical barriers. The emergence of social media has fundamentally transformed the way to study sentiment-driven market participants (Dugast and Foucault, 2018). A rich literature in the behavioral finance has linked social networking to trading activities (Ekinci and Bulut, 2021).

In the context of user-generated information, social media can be particularly important and economically significant (Broadstock and Zhang, 2019). Extracting information from microblogging data provides a deeper understanding of sentiment behavior impelled by financial agents (Sprenger et al., 2014). Microblogging platforms cover almost all aspects of society and can also serve decision-making purposes in multivariate aspects, including the financial sector.

The findings in financial domain are multifaceted, and there is no unified approach to conclusively establish the authoritative role of microblogging-based sentiments on different attributes of financial market (Oliveira et al., 2017; Guijarro et al., 2019). In this debate, there remains room to scrutinize root of microblogging data towards cost-based liquidity. This phenomenon can be even more pivotal whether investor sentiments within a broader market are priced in the systematic liquidity risk. As microblogging data becomes increasingly entwined with financial markets, its impact on the systematic liquidity risk should not be underestimated.

The systematic liquidity risk pertains to the accumulated risk, that affects an entire market or segment of financial markets. The liquidity risk has emerged as a potential area of concern within the financial landscape, specifically confronting the global financial crisis of 2008. Market liquidity, illustrated as the intensity to which an asset can be quickly bought or sold in the market without affecting its price, contributes a critical role in the functioning of financial markets.

In essence, the liquidity risk refers to the substantial difficulty in converting assets into cash without experiencing financial losses. The liquidity facilitators tend to reduce their risk against informed traders (Gorton and Metrick, 2010), leading to costs borne by the counterparty, such as a higher bid-ask spread (Saleemi, 2020). A large spread size indicates illiquidity or higher conditioning costs to facilitate liquidity for financial assets. The informed counterparty impacts trading, and its risk should be priced by liquidity providers (Saleemi, 2022).

This study investigates whether microblogging-based investor sentiments are exposed to the systematic liquidity risk. At the systematic context, commonality in liquidity between the market and its individual entities is often attributed to a common market. Therefore, it is essential to understand the impact of information flow via microblogging platform on liquidity at both market and firm levels. In this work, firm's liquidity is scrutinized in light of financial and non-financial perspective. Thus, two sub-indices are constructed within a broader market using the capitalization weighted average technique: one for banks and another for non-financial firms (NFF). This can better serve to divulge the concept of systematic liquidity risk, particularly in prospect of informed trading via digital communication platform.

The commonality in liquidity between market and its individual entities is a pivotal concern when considering the informed trading. The aptness of social media to promulgate information swiftly, gauge public sentiment, and influence investor behavior indicates its relevance in the study of systematic liquidity conditions. In the perspective of systematic liquidity risk, the astute observer should concede the insights embedded within microblogging opinions. This research strengthens investors' grasp to scrutinize the market liquidity's complexities. In addition, it is the first attempt to cover the systematic liquidity risk, particularly in environments of sentiment behavior driven by microblogging agents.

The investigation of microblog's impact on systematic liquidity risk offers valuable insights for both academics and investors. By scrutinizing digital text, a liquidity facilitator may significantly recognize shifts in the liquidity conditions. Concurrently, understanding liquidity's complexities in the perspective of microblogging-based sentiments can lead to more informed trading strategies. This research contributes to the broader literature on behavioral finance and asset pricing, nurturing a deeper understanding of the reciprocation between social media's opinion and trading.

The paper is structured as follows: Section 2 provides a brief review of the literature; Section 3 discusses the benchmark models and the data collection process; Section 4 presents and discusses the empirical results; finally, Section 5 summarizes the main outcomes of the study.

2. Literature Review

Sentiment analysis is a subfield of natural language processing that can assist in analyzing investor opinions, particularly in the context of binary quantification (bullish vs bearish) or multi-level attributes. The measurement of investor emotions on social media has emerged as a popular research topic in recent years (Oliveira et al., 2013; Poria et al., 2017). The fundamental value of investment is crucial in executing financial transactions (Cervelló-Royo and Guijarro, 2020).

One social media platform that has gained popularity for modeling financial securities is microblogging, particularly Twitter (Sprenger et al., 2014). Quantifying microblogging data can provide insights into market and investor information (Zhang et al., 2022). However, the unstructured nature of microblogging data in its initial stages necessitates the application of sentiment analysis to arrange it for further analysis. Identifying patterns from a large amount of information can be a critical factor for investors (Guijarro et al., 2019).

Microblogging content may also be accessed more conveniently on a real-time basis than traditional sentiment measures (Oliveira et al., 2017). Alleviating rumors related to investment concerns on social media is crucial for the market and investors (Wei et al., 2014). Business engagement on microblogging networks can reduce information asymmetry (Prokofieva, 2015) and mitigate bearish market reactions (Mazboudi and Khalil, 2017). Rumors regarding earning expectations in the market can also influence transaction execution (Chen et al., 2011; Zhang et al., 2022).

Analysis of the extracted content from microblogging network can provide insights into various aspects of the market behavior, including returns (Groß-Klußmann and Hautsch, 2011), price directional movements (Oh and Sheng, 2011; Smailović et al, 2013), market performance (Yu et al., 2013), stock trends (Li et al., 2018), firm's earnings (Bartov et al., 2018; Bank et al., 2019), and market liquidity (Guijarro et al., 2019; Guijarro et al., 2021).

The study by Guijarro, Moya-Clemente, and Saleemi (2019) scrutinizes how investors' moods, as reflected in microblogging sentiment, correlate with liquidity risk. They studied the authoritative role of investor sentiments on market liquidity, employing various financial metrics to measure liquidity risk. Their results guided, that microblogging data can act as a predictive tool for liquidity risk, indicating the significance of considering investor psychology in financial analysis. The research enriches the understanding of behavioral finance by linking microblogging sentiment to traditional financial metrics, arguing that investor emotions play a pivotal role in market functioning.

A notable research by Guijarro, Moya-Clemente, and Saleemi (2021) investigates the association between market liquidity and investor sentiment, concentrating on how microblogging data can serve to measure liquidity dimensions. The authors utilized natural language processing (NLP) techniques to quantify sentiment expressed in microblogging data. This quantification was linked to various aspects of market liquidity, such as depth, breadth, resilience, and immediacy. The research identifies association between sentiment scores and liquidity metrics, highlighting that positive sentiment improves liquidity by attracting more traders, while negative sentiment leads to reduced liquidity. The study suggests, that microblogging content can act as a beneficial tool for understanding market dynamics and liquidity behavior. The findings have practical implications for both traders and market analysts, specifying that observing sentiment through microblogging platform can provide insights into market liquidity and potential price movements.

The article by Aman and Moriyasu (2022) investigates the correlation between corporate disclosure practices and the role of press media in shaping market liquidity. The authors conduct empirical analysis, employing data from Japanese companies and corresponding media coverage. They evaluate shifts in market liquidity metrics in relation to levels of corporate disclosure and the volume of press reports about these firms. The study revealed, that enhanced transparency through corporate disclosures leads to improved market liquidity. Institutions that ensure more comprehensive financial and operational information attract potential investors, thus improving trading activity. The research indicates the pivotal role of corporate transparency and media in improving market liquidity, recognizing that institutions should prioritize clear communication and engage constructively with media.

Despite the literature provides rich insights into the correlation between social media and market liquidity, a systematic risk for liquidity is still uncovered in light of microblogging-based informed trading. This paper divulges a potential perspective of behavioral finance, establishing a framework for linking microblogging data with systematic liquidity risk. The integration of microblogging sentiment into market liquidity studies offers a novel approach to understanding market behavior, and monitoring systematic risk.

At the foundational level, systematic risk for liquidity is distinguished from idiosyncratic liquidity risk. Recent scholarly work emphasizes how liquidity shortages can aggravate broader financial instability, leading to the systematic liquidity risk (Saleemi, 2020). The study conducted by Brunnermeier and Pedersen (2009) underscores the feedback loop between liquidity and leverage, where deteriorating liquidity conditions can lead to forced deleveraging and further intensifying market stress. This interaction guides, that liquidity risk is not merely an isolated event but can propagate systematic disruption in the financial system.

One critical area of concern in prospect of systematic liquidity risk is the influence of regulatory frameworks on market liquidity. For instance, Dodd-Frank Act in the United States and similar regulatory initiatives globally have foisted higher capital requirements and stricter trading regulations. These measures may lead to a reduction in liquidity provision during times of stressed markets, particularly by limiting the capacity of financial institutions to participate in proprietary trading.

Market liquidity is an essential indicator of asset value in the financial market (Amihud, 2002; Easley and O'Hara, 2004; Corwin and Schultz, 2012). Specialists secure trading against the risk of an informed counterparty (Glosten and Milgrom, 1985; Saleemi, 2020), which is often considered a priced factor (Amihud et al., 2015; Saleemi, 2022). Information transparency about the fundamental value of an asset is critical in determining market liquidity (Gorton and Metrick, 2010).

Market liquidity can impact the cost of capital (Acharya and Pedersen, 2005), corporate investment decisions (Amihud and Mendelson, 2008), funding liquidity (Brunnermeier and Pedersen, 2009), asset prices (Bao et al., 2011), and yields on investment (Amihud et al., 2015). Investors are particularly concerned with uncertainty related to liquidity (Brunnermeier and Pedersen, 2005), and liquidity is considered a priced risk factor in uncertain environments (Saleemi, 2021).

The concept of liquidity is a multidimensional debate and there is currently no unified method for its estimation in the financial market (Goyenko et al., 2009; Abdi and Ranaldo, 2017). Over time, several models focusing either on bid-ask spread or price impact volume have been proposed. The bid-ask spread represents the transaction immediacy at possible trading cost (Roll, 1984; Corwin and Schultz, 2012), while another stream in the field emphasizes the relationship between price variations and trading quantity (Amihud, 2002).

Despite specific assumptions in the construction of different spread models, market frictions are common determinants of liquidity (Degennaro and Robotti, 2007). These frictions can be classified into explicit costs, such as taxes or brokerage fees, and implicit costs. The explicit costs are generally observable in advance of trading. Conversely, the implicit costs are less observable before the transaction takes place and represent a large fraction of total trading cost.

The spread is a popular cost-based liquidity proxy that estimates almost all costs associated with trading (Huang and Stoll, 1997; Sarr and Lybek, 2002). An asset is quoted in two major elements: the ask (high) price and the bid (low) price. Market makers would accept an inventory at lowest bid price and redeem the position at best highest ask price, earning yields on the investment. The spread size indicates the cost that liquidity supplier tends to impose on the counterparty. A higher spread reflects illiquidity in the market (Corwin and Schultz, 2012).

3. Material and Methods

This study contributes to the debate on systematic risk by exploring the potential of microblogging data in determining liquidity-facilitating costs for individual assets and their respective market. The analysis is performed on the Financial Times Stock Exchange (FTSE) 100 index, as this market comprises a list of largest firms whose appearance are also prominent in the global economic perspective. This debate priorities FTSE 100 index over other markets.

A list of assets in the data sampling is delineated in Table 1. The study includes all banks, and creates a financial index using the weighted market capitalization approach. However, a larger sample size of other firms can lead to an error in the construction of index. Thus, a sufficient amount of non-financial firms are selected through a simple random sampling technique. Multiple variety of non-financial assets not only facilitates building a potential index through the weighted market capitalization technique, but also enables a broader study of systematic risk.

Table 1. List of assets in the data sampling.

	Stocks	Symbol	Speciality
Banks	Standard Chartered	STAN.L	Banking & Financial Services
	NatWest Group	NWG.L	Banking & Financial Services
	Lloyds Banking Group	LLOY.L	Banking & Financial Services
	HSBC	HSBA.L	Banking & Financial Services
	Barclays	BARC.L	Banking & Financial Services
Non-Financial Firms (NFF)	Antofagasta	ANTO.L	Mining
	Ashtead Group	AHT.L	Support Services
	Associated British Foods	ABF.L	Food Producers
	AstraZeneca	AZN.L	Pharmaceuticals & Biotechnology
	Auto Trader Group	AUTO.L	Media
	SHELL	SHEL.L	Energy
	BAE Systems	BA.L	Aerospace & Defense
	Barratt Developments	BDEV.L	Household Goods & Home Construction
	Convatec Group	CTEC.L	Health Care

A capitalization-weighted index renders a more factual contemplation of the market's overall dynamics, as the index values shift proportionally to the price changes of each component based on corresponding market capitalization. Thus, this approach permits investors to measure overall market's trends effectively and mitigate potential risks. To establish a link between individual assets and their respective market, the firm index is built following Equation (1).

$$IC_t = IC_{t-1}(1 + IR_t) \tag{1}$$

where IC_t (IC_{t-1}) refers to the index closing price of day t $(t-1)$, and IR_t states the index yield of day t. IR_t is estimated according to Equation (2).

$$IR_t = \sum_{i=1}^{n} WMC_{i,t} \left[ln \left(\frac{C_{i,t}}{C_{i,t-1}} \right) \right] \tag{2}$$

where $WMC_{i,t}$ indicates the weighted market capitalization of individual stock on day t,and $C_{i,t}$ $(C_{i,t-1})$ represents the closing price of asset on day t $(t-1)$. The weighted market capitalization of stock is computed as Equation (3).

$$WMC_{i,t} = \frac{(S_{i,t} \times C_{i,t})}{\sum_{i=1}^{n} MC_{i,t}} \tag{3}$$

where $S_{i,t}$ indicates the outstanding shares of individual securities on day t; market capitalization, $MC_{i,t}$, is estimated by multiplying the outstanding shares of an asset with its closing price on day t; and $\sum_{i=1}^{n} MC_{i,t}$ depicts accumulated market capitalization of assets on day t.

$$IH_t = \left(\sum_{i=1}^{n} WMC_{i,t} \left[1 + ln \left(\frac{H_{i,t}}{H_{i,t-1}} \right) \right] \right) IC_t \tag{4}$$

$$IL_t = \left(\sum_{i=1}^{n} WMC_{i,t} \left[1 + ln \left(\frac{L_{i,t}}{L_{i,t-1}} \right) \right] \right) IC_t \tag{5}$$

Here, IH_t demonstrates the index highest price of day t; $H_{i,t}$ $(H_{i,t-1})$ shows the highest price of asset i on day t $(t-1)$; IL_t indicates the index lowest price of day t; and $L_{i,t}$ $(L_{i,t-1})$ illustrates the lowest price of asset i on day t $(t-1)$.

The liquidity is estimated using the cost-based market liquidity (CBML) approach. Recognizing the presence of asymmetric information during trading, the CBML model can effectively estimate liquidity and its associated facilitating cost (Saleemi, 2020; Guijarro et al., 2021). The CBML method is formulated according to Equation (6).

$$CBML_t = \sqrt{\left[\left(\frac{Range_{t-1}}{EP_{t-1}} \right) - E_t^S \right]^2} \tag{6}$$

Here, EP_{t-1} refers to the execution price of transaction on day $t-1$, and $Range_{t-1}$ represents the difference between the highest and lowest quoted prices of the previous trading session. Equation (7) models asymmetric information, assuming equal probability for the informed trader.

$$E_t^s = \frac{E[ask_t] - E[bid_t]}{EP_t} \tag{7}$$

where EP_t represents the execution of price of transaction on day t.

The calculation of $E[ask_t]$ is contingent upon a trade, as specified in Equation (8). It explains the expected highest price at which a liquidity provide may be willing to redeem the financial position.

$$E[ask_t] = H_t\theta + \left(\frac{QS_t}{2} \right) \theta \tag{8}$$

where θ depicts the probability of asymmetric information; H_t refers to the highest quoted price of day t; and QS_t is sum of the quoted prices on the same trading session.

The calculation of $E[bid_t]$ is conditioned on a transaction and can be expressed as Equation (9). It illustrates the expected lowest value that a liquidity provider would pay to accept the financial inventory.

$$E[bid_t] = L_t\theta + \left(\frac{QS_t}{2}\right)\theta \tag{9}$$

where L_t represents the lowest quoted price on day t. The liquidity measure is derived from low-frequency data. The attributes of the low-frequency data pertain to the closing, highest, and lowest prices (CHL).

To analyze unstructured microblogging data and gain insights into liquidity-providing costs, the R programming language was employed. The microblogging data was initially organized according to market symbols, such as FTSE 100, and covered the period from June 04, 2020, to November 14, 2023. To prepare the unstructured text for further processing and construct sentiment indicators, the text underwent cleaning using the "NLP" and "tm" libraries. This cleaning process involved removing punctuation, stop words, trailing spaces, and converting the text to lowercase.

Each tweet was classified as either bullish or bearish, and neutral market participants were excluded from the analysis. Given the large volume of data for day t, the process of aggregating sentiments is illustrated in Equations (10) and (11):

$$\sum_{t=1}^{T} Bullish_t = Bullish_1 + Bullish_2 + Bullish_3 + \cdots + Bullish_T \tag{10}$$

$$\sum_{t=1}^{T} Bearish_t = Bearish_1 + Bearish_2 + Bearish_3 + \cdots + Bearish_T \tag{11}$$

where T represents the total number of bullish or bearish sentiments on day t; $\sum_{t=1}^{T} Bullish_t$ denotes the cumulative bullish score on day t; $\sum_{t=1}^{T} Bearish_t$ represents the aggregated bearish score on day t. This aggregation process was performed using the "syuzhet" and "lubridate" libraries.

Furthermore, Equation (12) examines the linear regression relationship between variables. The liquidity cost of the FTSE market is selected as the response variable, while the sentiment indicators serve as explanatory variables.

$$MLC_t = \alpha + \beta_1 Bearish_t + \beta_2 Bullish_t + \epsilon_t \tag{12}$$

MLC_t represents the cost associated with facilitating liquidity for the entire market on day t. $Bearish_t$ reflects the aggregated negative sentiments for same trading day, while $Bearish_t$ represents the accumulated positive sentiments for same trading session. ϵ_t represents the error term. Equation (6) is utilized to estimate market liquidity and its associated facilitating cost.

Additionally, the dataset for the same trading session is examined to determine whether individual assets are exposed to systematic sentiment and liquidity risk. In this context, the dataset is modeled according to Equation (13):

$$ILC_t = \alpha + \beta_1 Bearish_t + \beta_2 Bullish_t + \beta_3 MLC_t + \epsilon_t \tag{13}$$

where ILC_t illustrates the liquidity-facilitating cost of the bank Index or non-financial firm Index on day t.

The Bayesian Theorem is applied to understand the conditional probability between variables. This approach reveals posterior probability of market index spread in relation to sentiments, as per Equation (14):

$$p(MLC|Sen) = \frac{p(MLC \cap Sen)}{p(Sen)} \tag{14}$$

where $p(MLC|Sen)$ suggests eventuality of market index liquidity in relation to bearish and bullish sentiments; $p(Sen)$ assumes the probability of sentiment indicators being true; and $p(MLC \cap Sen)$ explicates the likelihood of all parameters in the Bayesian model being true. $p(MLC \cap Sen)$ can be constructed, as per Equation (15).

$$p(MLC \cap Sen) = p(Sen|MLC)p(MLC) \tag{15}$$

where $p(MLC)$ is the probability of market index liquidity being true, and $p(Sen|MLC)$ assumes the probability of sentiment indicators by conditioning the market index liquidity being true. Thus, Equation (14) is examined as:

$$p(MLC|Sen) = \frac{p(Sen|MLC)p(MLC)}{p(Sen)} \tag{16}$$

Figure 1 illustrates variables' fitting in the Bayesian model. The observed distribution of parameters looks tighter to posterior predictive distribution. Thus, no issue is reported in examining the conditional probability between overall market liquidity and sentiment indicators.

Equation (17) examines the posterior probability of individual index liquidity in response to sentiment parameters and relative market's liquidity. This may provide insights into the probable occurrence of individual index liquidity against the systematic sentiment or liquidity risk.

$$p(ILC|Sen, MLC) = \frac{p(Sen, MLC|ILC)p(ILC)}{p(Sen, MLC)} \tag{17}$$

where $p(ILC|Sen, MLC)$ exhibits a probable occurrence of bank index liquidity or NFF index liquidity in response to systematic sentiments and overall market's liquidity; $p(ILC)$ specifies the probability of individual index liquidity being true; $p(Sen, MLC)$ presumes the sentiment parameters and market index liquidity being true; and $p(Sen, MLC|ILC)$ suggests the likelihood of sentiments and market index liquidity by conditioning the individual index liquidity being true. Figure 1 suggests, that observed distribution of parameters looks tighter to their corresponding posterior predictive distribution. In this case, there is no issue to apply the conditional probability between individual index liquidity and systematic sentiment indicators.

The Vector Error Correction Model (VECM) explores both long-term and short-term dynamics among the variables. This econometric technique not only provides a clear interpretation of a common trend among the time series variables, but also incorporates error correction mechanisms to measure both short-term and long-term dynamic relationships. Incipiently, the VECM analyzes the effects of changes in market liquidity-facilitating costs on day t, taking into account not only its own lagged changes but also the historical variations in investor sentiments.

$$\Delta MLC_t = \beta_0 + \sum_{i=1}^{n} \delta_i \Delta MLC_{t-i} + \sum_{i=1}^{n} \emptyset_i \Delta Bearish_{t-i} + \sum_{i=1}^{n} \gamma_i \Delta Bullish_{t-i} + \varphi ECT_{t-1} + \epsilon_t \tag{18}$$

where ΔMLC_t (ΔMLC_{t-i}) represents the change in the liquidity-providing cost of the entire market on day t ($t-i$); $\Delta Bearish_{t-i}$ demonstrates the previous changes in bearish sentiments; $\Delta Bullish_{t-i}$ indicates the past changes in bullish sentiments; ECT_{t-1} represents the error correction term of day $t-1$. The Hannan-Quinn (HQ) criterion technique serves to select the optimal lags, and their values are provided in Equations (19) - (21):

$$\Delta MLC_{t-i} = \delta_1 \Delta MLC_{t-1} + \delta_2 \Delta MLC_{t-2} + \delta_3 \Delta MLC_{t-3} + \delta_4 \Delta MLC_{t-4} \tag{19}$$

$$\Delta Bearish_{t-i} = \emptyset_1 \Delta Bearish_{t-1} + \emptyset_2 \Delta Bearish_{t-2} + \emptyset_3 \Delta Bearish_{t-3} + \emptyset_4 \Delta Bearish_{t-4} \tag{20}$$

$$\Delta Bullish_{t-i} = \gamma_1 \Delta Bullish_{t-1} + \gamma_2 \Delta Bullish_{t-2} + \gamma_3 \Delta Bullish_{t-3} + \gamma_4 \Delta Bullish_{t-4} \tag{21}$$

Equation (22) investigates the relationship between the change in liquidity-facilitating cost of individual assets on day t and its corresponding lags, as well as past changes in sentiment indicators and cost-based liquidity for the entire market:

$$\Delta ILC_t = \beta_0 + \sum_{i=1}^{n} \psi_i \Delta ILC_{t-i} + \sum_{i=1}^{n} \emptyset_i \Delta Bearish_{t-i} + \sum_{i=1}^{n} \gamma_i \Delta Bullish_{t-i} + \sum_{i=1}^{n} \delta_i \Delta MLC_{t-i} + \varphi ECT_{t-1} + \epsilon_t \tag{22}$$

where ΔILC_t (ΔILC_{t-i}) represents the change in the cost-based liquidity of the bank index or non-financial firm index on day t ($t-i$). Using the Hannan-Quinn (HQ) criterion approach, the optimal lags are computed using Equation (23):

$$\Delta ILC_{t-i} = \psi_1 \Delta ILC_{t-1} + \psi_2 \Delta ILC_{t-2} + \psi_3 \Delta ILC_{t-3} + \psi_4 \Delta ILC_{t-4} \tag{23}$$

4. Analysis and Discussion

Table 2 displays the descriptive attributes of data sampling. The analysis indicates that variables exhibit positive skewness along with higher kurtosis values. The positive skewness indicates a right-skewed distribution, where the majority of numeric values are situated to the right of mean. The higher kurtosis signifies a fat-tailed distribution within the numerical dataset.

Table 2. Descriptive attributes on a daily basis.

Variables	Min	Median	Mean	Max	SD	Skewness	Kurtosis
MLC	0.000002480	0.0052	0.0067	0.04625	0.0058	1.8039	7.8038
Bearish	0.020	0.810	1.238	14.660	1.3549	3.9808	27.5579
Bullish	0.030	0.950	1.542	30.560	1.8561	6.2098	78.4357
ILC_B	0.0000465	0.0103	0.0133	0.1201	0.0118	3.5357	24.6286
ILC_{NFF}	0.0001658	0.011	0.0126	0.0987	0.0094	3.7028	27.2233

*Notes: Liquidity cost for the entire market (MLC); Bank Index Liquidity cost (ILC_B); Liquidity cost for index of non-financial firms (ILC_{NFF}); Standard deviation (SD); Significance level codes: *** < 0.001; ** < 0.01; * < 0.05.*

The fluctuations observed among variables are first assessed as a linear combination within the same trading session. The model presented in Equation (12) employs the investor sentiments as predictors of liquidity-facilitating cost for the entire market. Table 3 reports a significantly positive association between pessimistic sentiments and cost-based market liquidity. This relationship indicates that an increase in the negative sentiments leads to a wider spread size of market index. A larger spread not only identifies higher transaction costs, but also explains illiquidity in the market. This implies, that the liquidity providers are more hesitant to accept financial inventory without imposing higher costs on the counterparty during periods of pessimism. Thus, the negative sentiments are priced into the overall market liquidity. In other words, a specialist would reduce its risk exposure by pricing the market index liquidity during uncertain environments. Conversely, the underlying drivers of optimistic sentiments towards market index liquidity have not been identified. Therefore, the positive opinion on microblogging platform is not strong enough to decline the trading costs of FTSE market.

To further explore the presence of systematic sentiment risk for liquidity at the individual asset level, stocks are divided into financial and non-financial sectors. In addition, indices as per the sector are constructed using Equations (1) - (5). This approach enables a more comprehensive analysis of systematic risk. The model specified in Equation (13) investigates either the bank index or the NFF index in terms of common market for liquidity and investor sentiments.

Table 3 shows, that the trading costs of bank index is positively connected to the pessimistic sentiments within a broader market. This indicates, that the spread size of bank index increases during bearish market periods. A wider spread signifies the liquidity provider's reluctance to accept bank stocks without imposing higher costs on the counterparty. Thus, the bank index exhibits a significant response to the systematic pessimistic opinions, highlighting the pricing of bearish sentiments in the bank assets' liquidity.

Table 3. Linear regression results on a daily basis.

Variables		Estimate	p-value
MLC (I)	Intercept	0.6037	0.000 ***
	Bearish	0.0565	0.018 *
	Bullish	0.0032	0.854
ILC_B (II)	Intercept	0.6469	0.000 ***
	Bearish	0.2248	0.000 ***
	Bullish	-0.1240	0.000 ***
	MLC	0.8956	0.000 ***
ILC_{NFF} (III)	Intercept	0.8305	0.000 ***
	Bearish	-0.0152	0.672
	Bullish	0.0212	0.417
	MLC	0.6185	0.000 ***

Notes: (I) Adjusted R-squared: 0.017; F-statistic: 8.18; p-value: 0.000; (II) Adjusted R-squared: 0.226; F-statistic: 81.47; p-value: 0.000; (III) Adjusted R-squared: 0.144; F-statistic: 47.62; p-value: 0.000.

Meantime, the bank index spreads are negatively explained by optimistic sentiments within a broader market. This relationship suggests, that the spread size of financial assets decreases in response to the systematic positive opinions. As the FTSE market enters optimistic periods, liquidity providers seem more willing to execute the bank index transactions at a lower cost, resulting in increased liquidity for bank stocks. Additionally, the liquidity of bank index is positively influenced by liquidity of its corresponding market index. Thus, the bank stocks are exposed to both systematic sentiment risk and systematic liquidity risk.

A systematic sentiment review for banks' liquidity may indicate the exposure of financial sector to the Basel implementation. Before the financial crisis 2007-2009, the banking sector was actively engaged in the market making using consumers' deposits. However, this activity was discouraged by the Basel committee on banking supervision. Nowadays, the baking system is more regulated over other industries, and obliged to maintain a higher liquid ratio. A considerable amount of liquid assets in banks can not only assist them to meet obligations during environments of financial stress, but also restrict them from participating in certain earning areas. Thereby, a positive or negative opinion on microblogging platform may guide liquidity providers to determine the spread size of bank stocks.

The transaction costs of non-financial firm index is not significantly explained by bearish and bullish sentiments. In other words, a positive or pessimistic opinion on microblogging platform is not strong enough to estimate the spread size of non-financial stocks. Consequently, the systematic investor sentiments are not priced in the liquidity of non-financial assets. Nevertheless, the liquidity of non-financial assets is positively associated with the liquidity of their corresponding market. A common market is one major feature for commonality in liquidity between individual stocks and market index. The result suggests, that non-financial firms are not influenced by systematic sentiment risk, but exposed to the systematic liquidity risk.

Equation (14) unveils posterior probability of overall market liquidity during pessimism environments. Table 4 reports a 99.10% likelihood for appearance of market index spread against the pessimistic investor opinions. This suggests, that an incline in negative emotions would increase the probability for a wider spread of market index. Consequently, the negative opinions are priced into overall market liquidity. Conversely, the posterior likelihood of overall liquidity in relation to optimistic opinions is 57.73 percent. A lower posterior probability guides, that the market index liquidity is less probable to be influenced by underlying drivers of optimistic sentiments.

Table 4. Summary of Bayesian model on a daily basis.

Variables	Parameters	Median	PD	% in Rope	Rhat	ESS
MLC	Intercept	0.60	100%	0%	1.000	3401
	Bearish	0.06	99.10%	52.74%	1.001	2238
	Bullish	0.0033	57.73%	100%	1.001	2267
Bank Index	Intercept	0.65	100%	0%	1.000	3987
	Bearish	0.22	100%	0%	1.000	2759
	Bullish	-0.12	100%	42.79%	1.000	2798
	MLC	0.90	100%	0%	1.000	3226
NFF	Intercept	0.83	100%	0%	1.000	3837
	Bearish	-0.01	65.77%	100%	1.000	2316
	Bullish	0.02	78.77%	100%	1.000	2372
	MLC	0.62	100%	0%	1.000	3625

Notes: Probability of Direction: PD; Region of Practical Equivalence: ROPE; Effective Sample Size: ESS.

Equation (17) examines whether there is a probable occurrence of individual index liquidity due to the systematic sentiment or liquidity risk. Table 4 exhibits a 100% relevance between bank index spread and systematic negative sentiments. During uncertain environments, liquidity providers would likely accept the bank stocks on a condition of higher costs, i.e., a wider spread. This highlights the pricing of negative opinions in liquidity of bank assets. Similarly, a 100% eventuality is noted between bank index liquidity and systematic optimistic sentiments. Thus, the spread size would likely be decreased in environments of optimism. This leads to a higher probability of liquidity for bank stocks. The finding reports, that the financial assets' liquidity is more likely exposed to the systematic sentiment risk. In addition, the posterior probability for eventuality of bank index liquidity in relation to its corresponding market liquidity is 100%. This guides, that the liquidity of bank assets is more probable to be impacted by systematic liquidity risk.

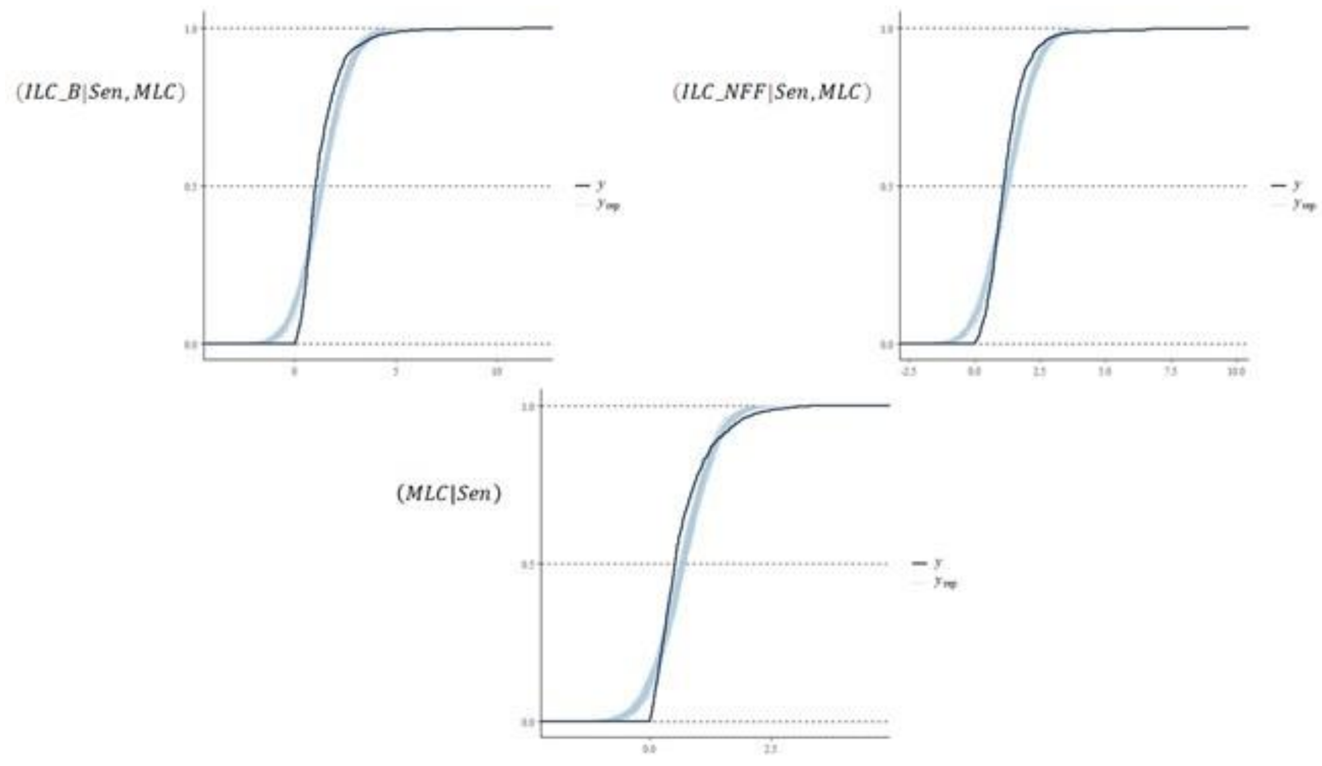

Figure 1. Dataset fitting in the Bayesian model.

The Bayesian Theorem reports a 65.77% posterior probability for eventuality of NFF index spread during pessimism environments. This indicates, that the liquidity of non-financial firms is less probable to be controlled by systematic negative opinions. Similarly, a lower posterior probability, i.e., 78.77%, is found between NFF index liquidity and optimistic opinions. The analysis guides, that non-financial assets' liquidity is less likely to be influenced by systematic positive sentiments. However, a higher posterior probability, i.e., 100%, is observed for appearance of NFF index liquidity in response to the market index liquidity. This suggests a higher likelihood of systematic liquidity risk for non-financial assets.

The probability of direction for Bayesian parameters is graphically demonstrated in Figure 2. A large proportion of bearish parameter values is positively linked to the market index spread. This demonstrates, that a wider market spread is more probable to appear during pessimistic periods. Conversely, a small number of optimistic sentiment drivers is negatively allied to the market index spread. Thus, the trading cost of market index is less probable to decline against the bullish investor opinions.

An enlarge positive relation is observed between bank index spread and systematic bearish sentiments. Thereby, the liquidity-facilitating cost for bank stocks would likely be increased in the pessimistic market periods. Similarly, the possible parameter values of overall market liquidity is positively linked to the bank index liquidity. This graphical demonstration guides, that the systematic liquidity risk is more probable to appear for bank stocks. A negative connection of bullish parameter with the bank index spread suggests, that the bank stocks' liquidity would likely be inclined in the optimism environments.

The NFF index spread is positively allied to a small number of negative sentiment drivers. Consequently, an incline in the trading cost of non-financial stocks is less probable against the systematic pessimistic sentiments. Likewise, a small proportion of the bullish parameter values is negatively associated with the NFF index spread. This guides, that non-financial assets' liquidity is less probable to incline in the systematic optimism environments. A positive connection of market index parameter with the NFF index spread indicates, that non-financial stocks' liquidity would possibly be exposed towards systematic liquidity risk.

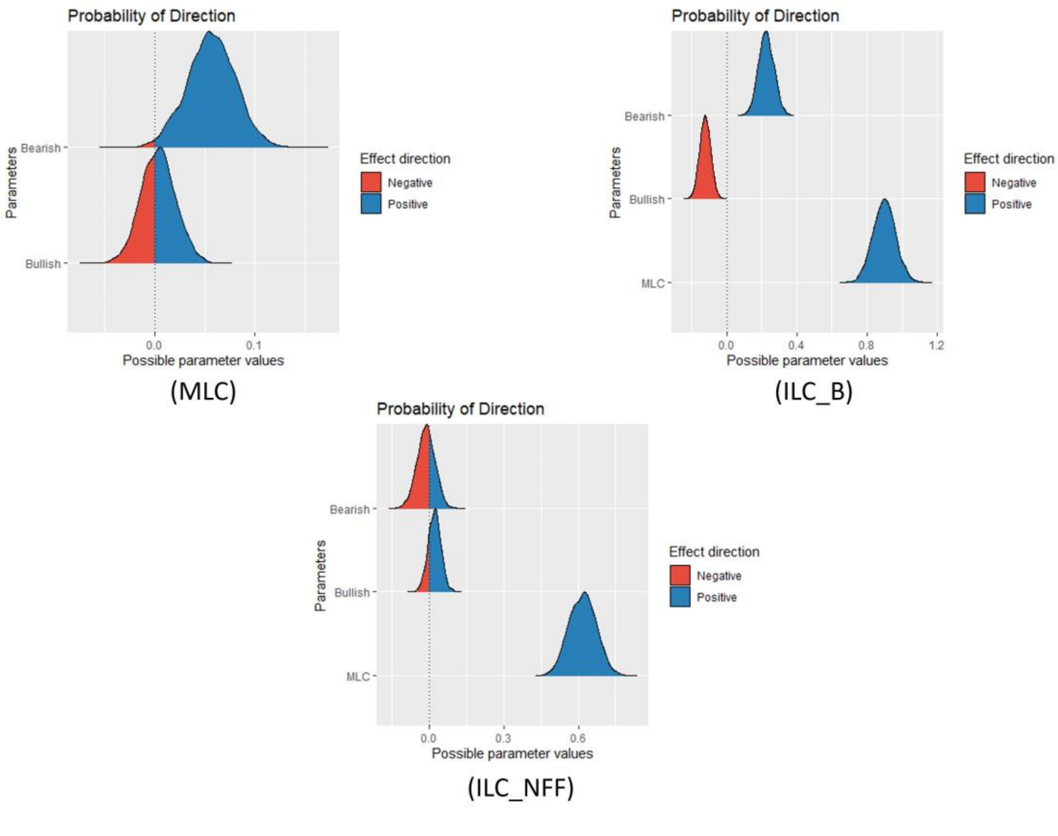

Figure 2. Bayesian parameters' probability of direction.

A VECM approach is utilized to examine the relationship dynamics, starting with the assessment of unit roots and cointegration in the system. The Augmented Dickey-Fuller (ADF) test, shown in Table 5, indicates stationarity in the time series. Cointegration, denoted as term c in Table 6, is analyzed using Johansen technique. Trace statistics exceeding the critical values suggest the presence of cointegration among time series variables.

Table 5. Unit roots test.

Variables	ADF Statistics	p-value	1% CV	5% CV	10% CV
MLC	-8.1194	0.000	-2.58	-1.95	-1.62
Bearish	-6.8423	0.000	-2.58	-1.95	-1.62
Bullish	-8.0116	0.000	-2.58	-1.95	-1.62
ILC_B	-8.4242	0.000	-2.58	-1.95	-1.62
ILC_{NFF}	-7.747	0.000	-2.58	-1.95	-1.62

Notes: Critical value (CV).

Table 6. Cointegration analysis results.

Cointegrated Relationship	Trace Statistics	10% CV	5% CV	1% CV
MLC & Sentiments				
$c > 2$	34.92	7.52	9.24	12.97
$c > 1$	134.83	17.85	19.96	24.60
$c > 0$	257.37	32.00	34.91	41.07
ILC_B, Sentiments & MLC				
$c > 3$	34.78	7.52	9.24	12.97
$c > 2$	135.34	17.85	19.96	24.60
$c > 1$	254.90	32.00	34.91	41.07
$c > 0$	439.34	49.65	53.12	60.16
ILC_{NFF}, Sentiments & MLC				
$c > 3$	34.95	7.52	9.24	12.97
$c > 2$	137.33	17.85	19.96	24.60
$c > 1$	260.61	32.00	34.91	41.07
$c > 0$	439.81	49.65	53.12	60.16

Notes: $c > 0$*: cointegration exists at least one in the system;* $c > 1$*: cointegrated relationship between two series;* $c > 2$*: three cointegrated vectors;* $c > 3$*: cointegration is greater than 3.*

Equation (18) investigates whether changes in the cost against accepting positions of the market index on day t are explained by its own previous changes, as well as past changes in the sentiment indicators. The results for the optimal lags, based on Equations (19) - (21), are reported in Table 7. ΔMLC_t is not significantly influenced by previous changes in the investor optimistic and pessimistic sentiments. This suggests, that changes in the market index liquidity on day t are not allied to the past series changes of sentiment indicators, in either the short or long run. However, changes in liquidity-facilitating costs for market index on day t are correlated with its own past series, with exception of lag $t-4$.

Equation (22) is employed to examine the systematic risk, where changes in individual index liquidity for the following trading period are analyzed in relation to corresponding lags and past series changes of other variables. The results, presented in Table 7, show that $\Delta ILC_{B,t}$ is not significantly correlated with changes in past series of bearish and bullish sentiments. This implies, that changes in the bank stocks' liquidity on day t are not influenced by past series changes of systematic sentiments, in either the short or long run. Conversely, $\Delta ILC_{B,t}$ is linked to changes in the past series of market index liquidity, except for lags $t-3$ and $t-4$. This indicates a short-run relationship between bank index liquidity and its corresponding market liquidity. Furthermore, changes in the cost of providing liquidity for bank index on day t are significantly explained by changes in its own past series.

Table 7. VECM results.

ΔMLC_t	Estimates	$\Delta ILC_{B,t}$	Estimates	$\Delta ILC_{NFF,t}$	Estimates
ECT	-0.4441 (0.0563)***	ECT	-0.6684 (0.0778)***	ECT	-0.5652 (0.0709)*** 0.1519
Intercept	0.1430 (0.0266)***	Intercept	0.1353 (0.0432)**	Intercept	(0.0383)*** -0.4067
ΔMLC_{t-1}	-0.5595 (0.0569)***	$\Delta ILC_{B,t-1}$	-0.3825 (0.0711)***	$\Delta ILC_{NFF,t-1}$	(0.0665)*** 0.0274 (0.0411)
$\Delta Bearish_{t-1}$	0.0274 (0.0269)	$\Delta Bearish_{t-1}$	-0.0671 (0.0543)	$\Delta Bearish_{t-1}$	-0.0131 (0.0297)
$\Delta Bullish_{t-1}$	0.0058 (0.0178)	$\Delta Bullish_{t-1}$	0.0675 (0.0368)	$\Delta Bullish_{t-1}$	-0.4361 (0.0904)*** -0.3096
ΔMLC_{t-2}	-0.4274 (0.0555)***	ΔMLC_{t-1}	-0.6149 (0.1124)***	ΔMLC_{t-1}	(0.0610)*** -0.0202 (0.0468)
$\Delta Bearish_{t-2}$	0.0042 (0.0291)	$\Delta ILC_{B,t-2}$	-0.3058 (0.0640)***	$\Delta ILC_{NFF,t-2}$	0.0070 (0.0328)
$\Delta Bullish_{t-2}$	-0.0003 (0.0196)	$\Delta Bearish_{t-2}$	-0.0611 (0.0600)	$\Delta Bearish_{t-2}$	-0.3184 (0.094) ***
ΔMLC_{t-3}	-0.1945 (0.0488)***	$\Delta Bullish_{t-2}$	0.0668 (0.0402)	$\Delta Bullish_{t-2}$	-0.1930 (0.0516)***
$\Delta Bearish_{t-3}$	0.0263 (0.0285)	ΔMLC_{t-2}	-0.4189 (0.1167)***	ΔMLC_{t-2}	-0.0331 (0.0465)
$\Delta Bullish_{t-3}$	-0.0006 (0.0196)	$\Delta ILC_{B,t-3}$	-0.1987 (0.0538)***	$\Delta ILC_{NFF,t-3}$	0.0395 (0.0328)
ΔMLC_{t-4}	-0.0402 (0.0341)	$\Delta Bearish_{t-3}$	-0.0853 (0.0584)	$\Delta Bearish_{t-3}$	-0.1807 (0.0858)*
$\Delta Bearish_{t-4}$	0.0104 (0.0247)	$\Delta Bullish_{t-3}$	0.0631 (0.0402)	$\Delta Bullish_{t-3}$	-0.1600 (0.0367)*** -0.0762
$\Delta Bullish_{t-4}$	0.0121 (0.0176)	ΔMLC_{t-3}	-0.1604 (0.1061)	ΔMLC_{t-3}	(0.0410) 0.0448
		$\Delta ILC_{B,t-4}$	-0.1754 (0.0378)***	$\Delta ILC_{NFF,t-4}$	(0.0295) -0.0742
		$\Delta Bearish_{t-4}$	0.0790 (0.0513)	$\Delta Bearish_{t-4}$	(0.0612)
		$\Delta Bullish_{t-4}$	0.0194 (0.0362)	$\Delta Bullish_{t-4}$	
		ΔMLC_{t-4}	0.0562 (0.0762)	ΔMLC_{t-4}	

Table 7 also reveals that changes in the trading cost for non-financial firm index on day t are not significantly linked to changes in past series of negative and positive sentiments. Thus, previous changes in sentiments' series, whether in the short or long run, are not applicable for estimating $\Delta ILC_{NFF,t}$. However, changes in the cost of facilitating liquidity for NFF index on period t are associated with past series changes in the market index liquidity, except for lag $t-4$. This suggests a short-run linkage of commonality in liquidity between non-financial stocks and corresponding market index. Additionally, changes in NFF index liquidity for the next trading period are significantly influenced by changes in its own past series.

Finally, this study conducts an impulse response analysis using the Bootstrap 95% confidence interval, as illustrated in Figure 3. The cost of facilitating liquidity for market index responds to shocks in the optimistic and pessimistic sentiments. Thus, standard deviation shocks in the investor sentiments can impact market index liquidity during the observed responsive periods. Similarly, the trading cost of bank index is influenced by shocks in both systematic sentiments and market index liquidity. In this regard, standard deviation shocks in investor sentiments and market index liquidity play a significant role in changing bank index liquidity during each responsive period. Likewise, the liquidity-facilitating cost for NFF index shows considerable responsiveness to standard deviation shocks in systematic sentiments and market index liquidity.

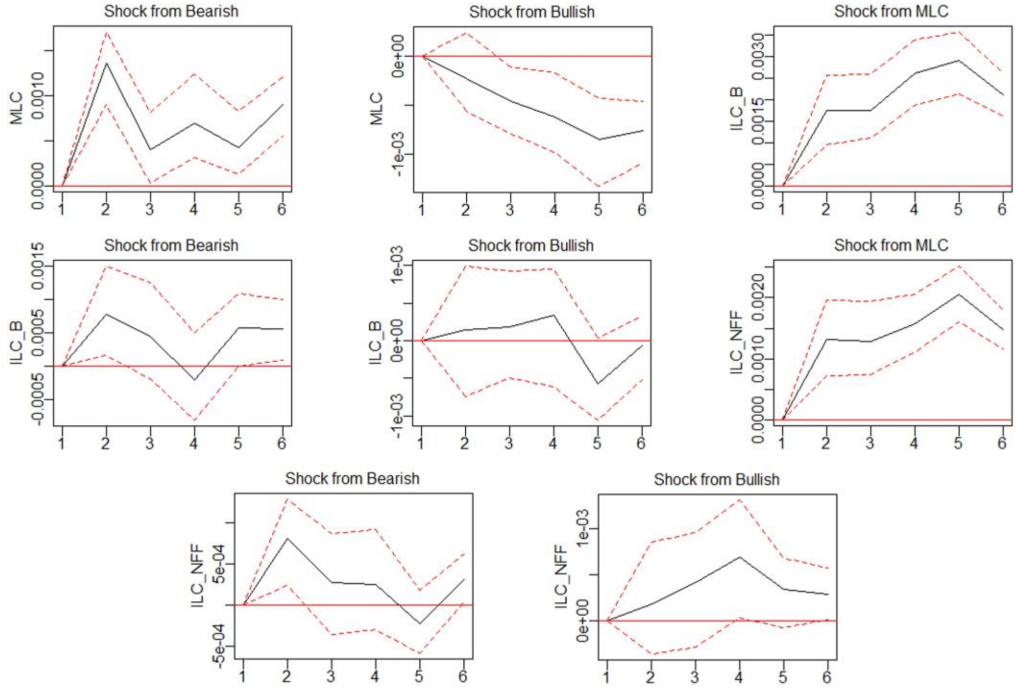

Figure 3. Impulse Response analysis.

5. Conclusion

This research focuses on analyzing the systematic risk for liquidity across the market, particularly in environments of information flow via digital conversations. The sentiment indicators were built by utilizing the microblogging data as a source of investor sentiments. The assets were categorized by industry, and comprised the construction of corresponding index. The outcomes aimed to understand the systematic sentiment risk for liquidity at both market and firm levels.

During the same trading sessions, the cost of accepting positions in FTSE index was positively influenced by pessimistic investor sentiments. This suggests higher transaction costs or illiquidity in response to the negative opinions. Consequently, market index liquidity appears to be priced by bearish sentiments. In addition, eventuality of market index spread in relation to the pessimistic opinions was noticed on a conditional probability. The Bayesian methodology guides us, that the cost of accepting positions in the market index would probably be increased against the pessimistic sentiments. Thus, market index liquidity would likely decline in the pessimism environments.

However, no association was observed between market index spread and bullish sentiments within the same trading periods. This identifies, that positive opinions on microblogging platform are not strong enough to increase the liquidity for market index. The posterior probability for appearance of market index spread was also lower in the optimism environments. This highlights, that market index liquidity is less probable to be influenced by underlying drivers of positive sentiments.

The bank index liquidity was significantly related to the sentiment indicators during the same trading periods. The cost of facilitating liquidity for bank stocks was positively associated with bearish sentiments, indicating higher transaction costs and illiquidity. Thus, bank index liquidity was priced based on systematic negative sentiments. In addition, the posterior probability for occurrence of bank index liquidity was considerably higher in relation to the pessimistic opinions. A large size of bearish parameter values were positively connected to the bank index spread. This indicates, that the bank assets' liquidity is more probable to decrease in light of systematic pessimistic sentiments. The bank index spread showed a negative correlation with systematic optimistic sentiments, implying that bullish market leads to a decrease in the trading cost of bank index. Meantime, the posterior probability for appearance of bank index spread was considerably higher in response to the positive opinions. Thus, the liquidity-facilitating cost for bank stocks is more probable to decrease in the systematic optimism environments. A positive connection between bank index spread and spread of its corresponding market exhibits, that bank assets' liquidity would probably be exposed to the systematic liquidity risk.

Nevertheless, no significant relationship was observed between systematic sentiments and trading cost of non-financial firm index. The posterior probability for eventuality of NFF index spread was considerably lower in relation to the investor sentiment parameters. This lower conditional probability informs us, that the liquidity cost of non-financial assets would not possibly be exposed to the bearish or bullish sentiment parameters. The liquidity of non-financial firm index was positively linked to corresponding market index liquidity. The posterior probability of systematic liquidity risk was further higher for non-financial assets.

The VECM analysis indicated, that changes in market index liquidity for the following trading session were not significantly explained by past series changes in bearish and bullish sentiments. This suggests, that these variables are not associated in the short or long run. Similarly, changes in the firm index liquidity for the next trading period were not significantly explained by previous series changes in bearish and bullish sentiments. However, changes in bank index liquidity on day t were linked to changes in the past series of market index liquidity, excluding lags t-3 and t-4. This indicates a short-run linkage of liquidity commonality between financial assets and market index. Meantime, changes in the non-financial firm index liquidity on day t were significantly explained by changes in previous series of market index liquidity, excluding lag t-4.

The findings have identified significant correspondence between microblogging activity and market liquidity on a daily basis, recognizing that increased engagement on microblogging platform can trigger investor interest, enhance trading activity, and lessen price impact. This permits investors to mitigate systematic risk for liquidity within a broader market. Comprehensively, microblogging platform facilitates swift dissemination of information about individual entities and their corresponding market. Thus, the systematic flow of information can improve market liquidity by allowing quicker decisions among traders.

However, the correspondence between social media and systematic liquidity risk may be intrinsically constrained by a few limitations. Predominantly, the heterogeneity of microblogging platform and participant's demographics can complicate the generalization of results. The behavioral biases of social media participants may skew information diffusion, obstructing the decision-making process among investors. Further research should quantify the influence of microblogging sentiment on systematic liquidity risk across diverse markets. Combining an interdisciplinary approach including finance, psychology, and technological advancements in microblogging platforms may provide comprehensive insights into how microblogging-based informed trading influences the systematic liquidity risk.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Author contributions

Conceptualization: Jawad Saleemi; Investigation: Jawad Saleemi; Methodology: Jawad Saleemi; Formal analysis: Jawad Saleemi; Writing – original draft: Jawad Saleemi; Writing – review & editing: Jawad Saleemi.

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