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Economic Unrest and Investment Perspective on Liquidity in relation to the Investor Sentiments

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ABSTRACT

Liquidity and its associated issues are one of dominant strands in the market microstructure. In this study, microblogging-based behavioral perspective on economic unrest is linked to the market liquidity. The concept of liquidity is examined in terms of price dispersion relative to the quantity traded. The analysis contains the quantification of multiple linear regression, Gaussian distribution technique, and vector error correction methodology. In the economic stability period, the investor's mood, either in positive manner or pessimistic context, had an influential role on the price impact volume-based liquidity. Meantime, the probability was higher for occurrence of price impact volume-based liquidity in response to the sentiment indicators. In the economic unrest environments, the positive bias investor's mood was not vigorous enough to influence the dispersion of asset's prices and trading quantity. Most importantly, the negative bias investor's emotion was linked to increase the dispersion of asset's prices relative to the quantity traded. Investors with a lower amount of trading quantity had declined the liquidity in the market. Additionally, there was a higher probability for occurrence of illiquidity in the pessimistic market periods. However, changes in past sentiment series were not associated with changes in pervious liquidity series, either in short run or long run. The findings may be potentially applicable to manage the behavioral perspective of liquidity risk.

KEYWORDS

Economic crisis; Behavioral analysis; Microblogging-opinionated data; Financial market liquidity

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1. Introduction

Since the dethronement of former government on April 10, 2022, Pakistan's economy has been direly hit by a historic balance of payments crisis, currency depreciation, and crushing inflation. Prior to the initial disbursal of \$1.2 billion by the International Monetary Fund (IMF) on July 12, 2023, the foreign exchange reserves were teetering about \$4 billion. This bailout program may temporarily assist the economy to avoid default. However, Pakistan's economy requires to pay loans with interest around \$21.95 billion in one year. Therefore, the concern is not only related to the arrangement of sufficient funds for payments of debts, but lack of dollars' liquidity is also threatening the import for production sector.

Economy's struggling against a historic currency devaluation is triggering inflation, as well as declining the purchasing power of common man in Pakistan. Apart from incoming debts of the IMF program, the international lending arrangement certainly requires a few potential compliances of spending and structural reforms. Such compliance has sharply escalated prices of petroleum, energy and food. This hike in prices has further surged economic unrest. Additionally, the brain drain phenomenon escalates as more than 1 million people have left the country during the economic uncertainty.

Confronting a historic economic unrest in Pakistan, this study addresses investment perceptive on liquidity in relation to the investor sentiments. Market liquidity depicts the trading environment in terms of easiness with a limited price dispersion (Guijarro et al., 2019). The dispersion of asset price determines traders' movement in the market (Amihud, 2002). Investors would avoid the risk of holding assets in uncertain environments (Cervello-Royo and Guijarro, 2020). This risk leads to illiquidity with a lower number of trading quantity (Guijarro et al., 2021).

Early literature devotes much attention to asset's price dispersion and its trading volume for estimation of market liquidity (Goyenko et al., 2009). The price impact volume-based liquidity depicts the response of an asset's trading quantity against its price dispersion, that in order words, indicates the ease of transaction execution (Amihud et al., 2015). Market liquidity is perceived to be a highly volatile risk in the market (Corwin and Schultz, 2012). Securities sensitive to information can trigger the liquidity risk (Gorton and Metrick, 2010). Therefore, the liquidity providers would secure transaction against the risk of an informed trader (Saleemi, 2022).

Incoming information on social media impacts the investment decision-making process (Nofsinger, 2005), and lead to variations in securities prices (Chen et al., 2011; Li et al., 2018). The escalation of behavior finance literature is ascribable to the authenticity of various information sources in both modeling and predicting financial assets. An abundance of research suggests the significant implications of microblogging data on various variables associated with the efficient functioning of financial markets (Oliveira et al., 2017). The authenticity of microblogging data is demonstrated in mitigating the information asymmetry (Prokofieva, 2015), as well as alleviating the pessimistic market reactions (Mazboudi and Khalil, 2017).

The concept of liquidity in relation to the microblogging-based sentiments is undoubtedly limited. Therefore, there is still room to investigate the implication of microblogging content on the liquidity and its related aspects. This study understands whether a historic economic unrest in the south Asian country leads to any significant pattern between microblogging data and price impact volume-based liquidity. There is no earlier consideration on how the price impact volume-based liquidity responds to the microblogging-based sentiments, particularly in a historic economic chaos. The work aims to be the first empirical approach in stream of the behavioral domain.

The investment perspective on the liquidity matters to be addressed in Pakistan, as the country is drowning in a historic Rupee depreciation, debts and Forex reserves uncertainty. These challenges may not only affect the efficient functioning of financial system in the long run, but investors' confidence in Pakistan's system seems a major debate across the economy. Thus, the findings may assist investors to measure the transparency of asset's value by the opinionated data, and avoid losses in terms of liquidity risk management.

The rest of the work is structured as follows. The procedure to build models is presented in Section 2. Findings of the paper is presented and discussed in Section 3. Finally, the work is concluded in Section 4.

2. Material and Methods

In this study, the dramatic removal of former government is perceived as a turning point into the economic unrest. The research investigates the implication of economic unrest on behavioral perspective of liquidity. The liquidity is measured using the martin liquidity index (MLI), and covers the period July 26, 2018 – May 18, 2023. The MLI model is potentially competent to estimate the liquidity in light of linkage between price changes and trading quantity (Guijarro et al., 2021). The MLI model is constructed as per Equation (1).

$$MLI_t = \sum_{t=1}^{T} \frac{(TEP_t - TEP_{t-1})^2}{tv_t} \tag{1}$$

where TEP_t (TEP_{t-1}) illustrates executing price of the transaction on day t ($t-1$), and tv_t indicates trading quantity of the asset on day t. A larger price dispersion relative to the quantity traded is guided in light of higher MLI value. The higher price dispersion leads to a decline in the liquidity, and therefore, an illiquid asset would require less trading to move prices.

The next step constructs the sentiment indicators from unstructured microblogging-text. This unstructured information is cleaned through the Text Mining (TM) library. The data mining is performed on R programming language, where participants' opinions are transformed into lower case for construction of sentiment parameters. These sentiments are separated into positive values, and negative values. As a large number of microblogging comments is quantified in each responsive day, the sentiment indicators are built as per Equation (2) and (3).

$$\sum_{t=1}^{T} pos_t = pos_1 + pos_2 + pos_3 + \cdots + pos_T \tag{2}$$

$$\sum_{t=1}^{T} neg_t = neg_1 + neg_2 + neg_3 + \cdots + neg_T \tag{3}$$

where T is the number of positive or negative sentiments on day t, and $\sum_{t=1}^{T} pos_t$ ($\sum_{t=1}^{T} neg_t$) indicates the total positive opinions (negative opinions) on day t.

The multiple linear regression model is first built as per Equation (4), which investigates linear combination between variables.

$$MLI_t = \alpha + \gamma_1 \sum_{t=1}^{T} pos_t + \gamma_2 \sum_{t=1}^{T} neg_t + \epsilon_t \tag{4}$$

where MLI_t depicts the price impact volume-based liquidity on day t, and $\sum_{t=1}^{T} pos_t$ ($\sum_{t=1}^{T} neg_t$) is the accumulation of positive emotions (negative emotions) on same trading day.

The following experiment understands the posterior likelihood of market liquidity against the sentiment parameters. In stream of this field, the Bayesian model is built as per Equation (5).

$$p(MLI|SP) = \frac{p(MLI \cap SP)}{p(SP)} \tag{5}$$

where $p(MLI|SP)$ explicates occurrence of liquidity in response to the sentiment parameters; $p(SP)$ guides the probability of sentiment parameters to being accurate; and $p(MLI \cap SP)$ explains the likelihood of all parameters being true. The term, $p(MLI \cap SP)$, can be explicated as per Equation (6).

$$p(MLI \cap SP) = p(SP|MLI)\, p(MLI) \tag{6}$$

where $p(MLI)$ illustrates the likelihood of price impact volume-based liquidity being true, $p(SP|MLI)$ guides the probable occurrence of sentiment parameters, conditioning the market liquidity being true. The Bayesian model is developed as per Equation (7).

$$p(MLI|SP) = \frac{p(SP|MLI)\, p(MLI)}{p(SP)} \tag{7}$$

Lastly, the change in price impact volume-based liquidity on trading day t is checked as function of its own past series changes, as well as the past series changes of sentiment indicators. In stream of this area, the vector error correction model (VECM) is built as per Equation (8).

$$\Delta MLI_t = \beta_0 + \sum_{i=1}^{n} \emptyset_i \, \Delta MLI_{t-i} + \sum_{i=1}^{n} \delta_i \Delta\, pos_{t-i} + \sum_{i=1}^{n} \vartheta_i \Delta\, neg_{t-i} + \varphi ECT_{t-1} + \epsilon_t \tag{8}$$

where ΔMLI_t (ΔMLI_{t-i}) depicts change in the market liquidity on day t $(t-i)$; Δpos_{t-i} indicates the previous series changes of positive sentiments on day $t-i$; Δneg_{t-i} guides the past series changes of negative sentiments on day $t-i$; and ECT_{t-1} is the error correction term on day $t-1$. The selection of optimal past series is derived through the Akaike information criterion (AIC) technique, and demonstrated as per Equations (9)-(11):

$$\Delta MLI_{t-i} = \emptyset_1 \Delta MLI_{t-1} + \emptyset_2 \Delta MLI_{t-2} + \emptyset_3 \Delta MLI_{t-3} + \emptyset_4 \Delta MLI_{t-4} \tag{9}$$

$$\Delta pos_{t-i} = \delta_1 \Delta pos_{t-1} + \delta_2 \Delta pos_{t-2} + \delta_3 \Delta pos_{t-3} + \delta_4 \Delta pos_{t-4} \tag{10}$$

$$\Delta neg_{t-i} = \vartheta_1 \Delta neg_{t-1} + \vartheta_2 \Delta neg_{t-2} + \vartheta_3 \Delta neg_{t-3} + \vartheta_3 \Delta neg_{t-4} \tag{11}$$

3. Analysis and Discussion

The descriptive quantification of the dataset is exhibited in Table 1. The positive skewness with fat-tailed numerical distribution is noted for the data sampling. This guides, that a larger part of the dataset is located to the right of mean. In addition, the fat-tailed distribution highlights the extreme numerical values in the dataset. The time-varying fluctuation in variables is plotted in Figure 1, where the measurement of corresponding variable changes over time. This fluctuation encourages us to study whether there is a linkage between investor sentiments and price impact volume-based liquidity. Most importantly, the study understands variables' fluctuation in light of the economic unrest.

Table 1. Descriptive summary (daily basis).

Variables	Median	Mean	Standard Deviation	Skewness	Kurtosis
MLI	0.00047	0.0015	0.0032	6.9678	83.4774
neg	0.05	0.0623	0.0540	2.3129	13.5235
pos	0.11	0.1311	0.0971	1.1628	5.2891

Notes: Martin Liquidity Index: MLI; Negative sentiments: neg; Positive sentiments: pos.

The model built in Equation (4) sets the sentiment indicators as predictor variables for price impact volume-based liquidity. This provides a valuable insight into the linear combination between time-varying market liquidity and investors' opinions. The summary of linear relationship between variables is depicted in Table 2. Before the appearance of economic unrest, the market liquidity is significantly linked to both positive and negative opinions. The pessimistic-opinionated data is noted to be positively associated with the liquidity index. This significant relationship guides, that a negative bias investor opinion inclines the MLI value. A higher size of MLI value indicates the greater price dispersion relative to the trading quantity. Therefore, a smaller number of trades moves prices in the bearish market periods. In this debate, a higher price dispersion depicts the lack of market liquidity for the KSE 100 index.

However, the optimistic mood of investors is negatively associated with the price impact volume-based liquidity. This significant linkage guides, that a positive bias investor opinion leads to a lower MLI value. A smaller size of MLI value illustrates the lower price dispersion relative to the trading volume. Thus, investors would require a larger number of trades to move prices in the bullish market periods. In this context, the lower price dispersion suggests a higher market liquidity for the KSE 100 index. During the economic stability, the analysis reasonably addresses the fundamental role of both negative and positive opinions in the time-varying market liquidity. In addition, the analysis opens door to investigate the exposure of market liquidity towards the opinionated data during the economic instability environments.

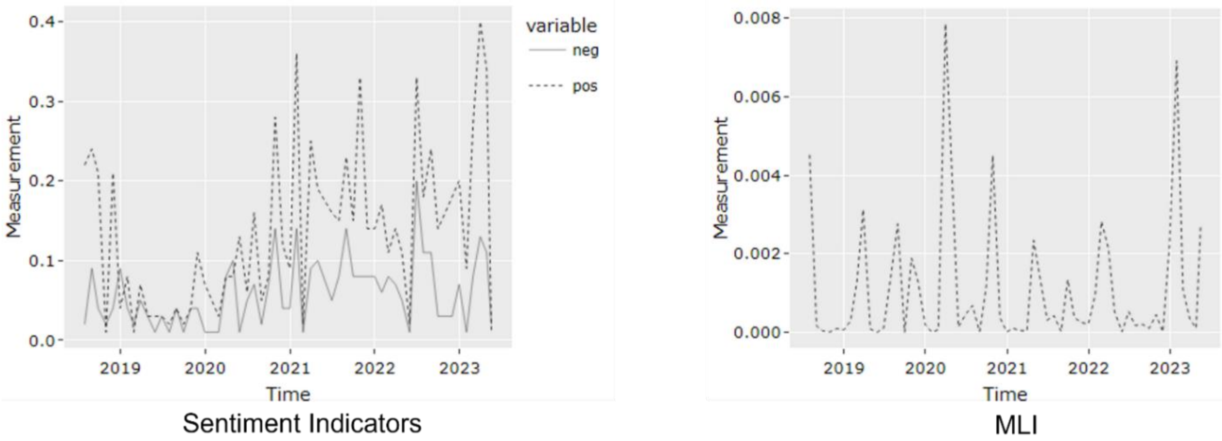

Figure 1. Time-varying variables (monthly basis).

Table 2. Quantification of regression model (daily basis).

Variables		Estimate	p-value
Economic stability MLI (a)	Intercept	0.000496	0.0105 *
	neg	0.0264959	0.000 ***
	pos	-0.002807	0.0495 *
Economic unrest MLI (b)	Intercept	0.0007910	0.0208 *
	neg	0.0115344	0.000 ***
	pos	-0.0016103	0.4789

Notes: (a) Adjusted R-squared: 0.0989; F-statistic: 50.7; p-value: 0.000; (b) Adjusted R-squared: 0.0604; F-statistic: 9.71; p-value: 0.000.

The economic unrest is observed to affect the linear combination between variables. In the economic uncertainty environments, the optimistic-opinionated content is not significantly associated with the liquidity index. This suggests that investors are certainly concerned with the economic stake in Pakistan. This concern may not only be limited to a historic inflation or currency devaluation, but the future economic perspective seems a major debate among the potential investors. Therefore, the positive opinions are disregarded by the risk-aversion behavior of investors. However, the price impact volume-based liquidity is positive and significantly explained by the pessimistic sentiments. This relationship guides, that a negative bias investor emotion inclines the MLI value. The higher MLI value illustrates the greater price dispersion of KSE 100 index relative to its trading quantity. In this case, investors would require a smaller number of trading volume to move prices in the bearish market period. Thus, a higher price dispersion exhibits the illiquidity during the economic instability periods.

Table 3. Summary of Bayesian model (daily basis).

Variables	Parameters	Median	PD	ESS
Economic stability MLI	Intercept	0.00049	99.58%	3044
	neg	0.03	100%	1830
	pos	-0.0028	97.28%	1645
Economic unrest MLI	Intercept	0.000778	98.72%	2573
	neg	0.01	99.98%	1453
	pos	-0.00152	74.98%	1450

Notes: Probability of Direction: PD; Effective Sample Size: ESS.

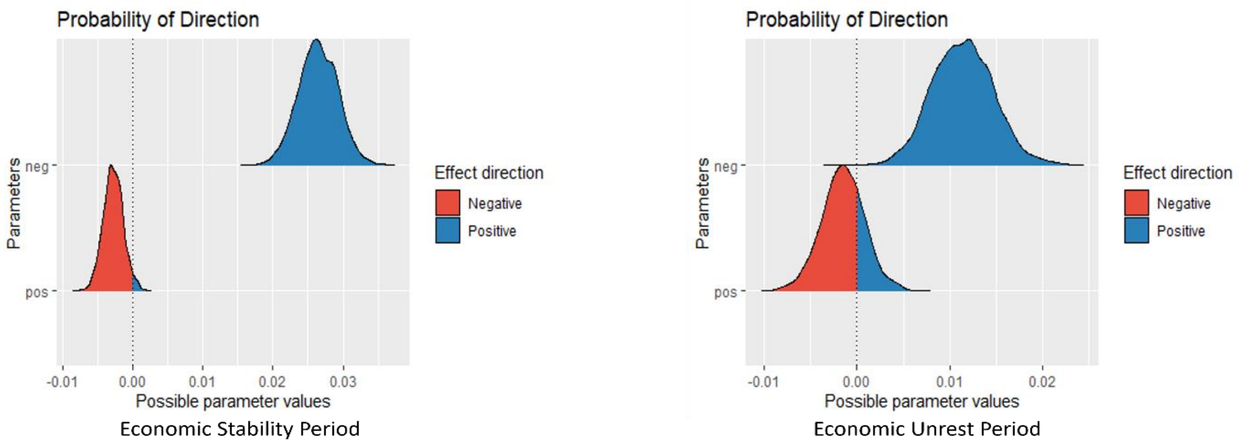

Figure 2. Probability of direction for parameters.

The Bayesian model constructed in Equation (7) uncovers the posterior likelihood of price impact volume-based liquidity in relation to the sentiment parameters. This empirical methodology is quantified in Table 3 using the Gaussian distribution technique. During the economic certainty environments, the Bayesian Theorem reports an occurrence of price impact volume-based liquidity in response to the sentiment parameters. The posterior probability suggests a 100% positive relatedness between MLI and negative sentiments. This measurement guides, that the greater price dispersion of KSE 100 Index is more probable relative to its trading quantity in the pessimistic market period. Therefore, a negative bias investor emotion inclines the probability of market illiquidity. Conversely, the posterior likelihood reports a 97.28% negative relativeness between MLI and positive sentiments. This quantification suggests that the lower price dispersion of KSE 100 Index is more probable relative to its trading quantity during the optimistic market period. Thus, a positive bias investor emotion inclines the probability of market liquidity. The Bayesian Theorem analysis endorses the linear regression results, where a potential exposure of market liquidity towards the sentiment indicators are addressed during the economic stability environment.

The outcomes are changed in the economic unrest environments. The Bayesian Theorem reports a 74.98% negative relativeness between MLI and positive sentiments. This quantification indicates that the lower price dispersion of KSE 100 Index is less probable relative to its trading quantity. Therefore, a positive bias investor emotion fails to increase the probability of market liquidity. These findings may raise serious concerns on the future perspective of Pakistan's economy. As far a historic political unrest in Pakistan is the major hurdle in its economy, the policy makers should take immediate actions to avoid a full-blown market meltdown. Most importantly, the Bayesian Theorem suggests a 99.98% positive relatedness between MLI and negative sentiments. This quantification guides, that the greater price dispersion of KSE 100 Index is more probable relative to its trading quantity. Thereby, a negative bias investor emotion inclines the probability of market illiquidity.

The measurement of the Bayesian Theorem is visually plotted in Figure 2. The left-hand plot in Figure 2 demonstrates the probability of direction during the economic stability environments. The graphical demonstration reports an increased positive relation between price impact volume-based liquidity and negative sentiments. This implies, that a negative bias investor emotion increases the probability of market illiquidity. Meantime, an increased, but negative relatedness is noted between price impact volume-based liquidity and positive sentiments. This relation guides, that a positive bias investor emotion inclines the probability of market liquidity.

The right-hand plot in Figure 2 demonstrates the probability of direction during the economic unrest environments. A decreased, but negative relation is observed between price impact volume-based liquidity and positive sentiments. In this case, the posterior probability is lower for occurrence of market liquidity in response to the positive sentiments. Conversely, an increased positive relation is reported between price impact volume-based liquidity and negative sentiments. This quantification suggests a higher posterior probability for occurrence of illiquidity in response to the negative sentiments.

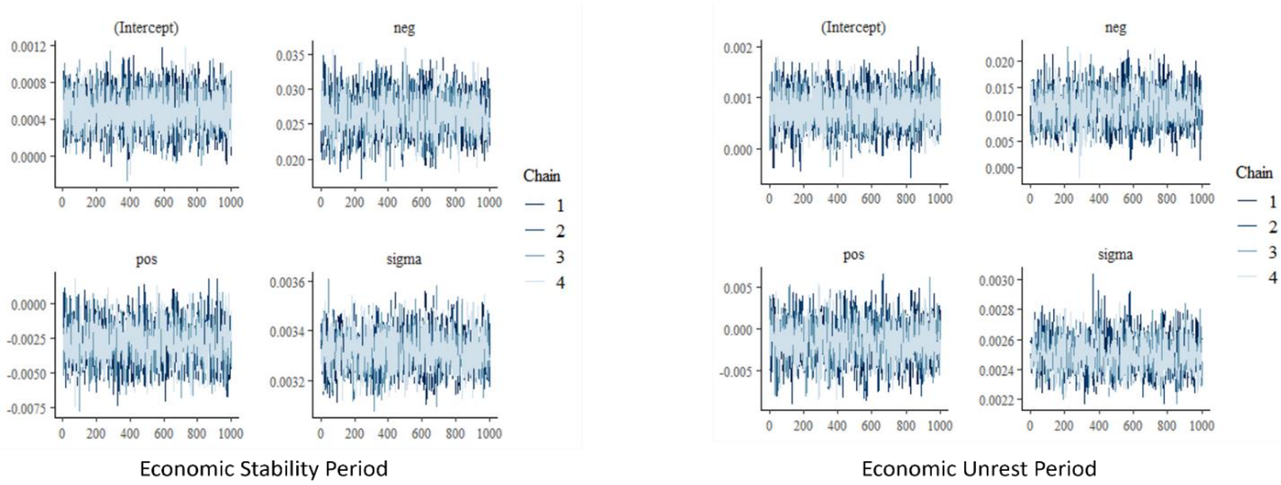

Figure 3. Assessing convergence in the Bayesian model.

The convergence issue in the Gaussian distribution is assessed using the trace plots in Figure 3. The left-hand graphical presentation in Figure 3 depicts the convergence concerns in parameters during the economic stability period. As parameters do not suffer from breaks or gigantic spikes in the trace plots, there is no convergence issue in the adopted model. This argument can also be supported by the ESS values, which are greater than 400. The right-hand graphical presentation in Figure 3 checks the convergence problems in parameters during the economic uncertainty period. There is no convergence issue in the Bayesian model, as breaks or gigantic spikes are not noted in all relevant parameters. This debate can also be endorsed by the corresponding ESS values.

Table 4. Checking stationarity in the dataset.

Variables	ADF Statistics	p-value	1 PCV	5 PCV	10 PCV
Economic stability					
MLI	-13.87	0.000	-2.58	-1.95	-1.62
neg	-7.76	0.000	-2.58	-1.95	-1.62
Pos	-5.27	0.000	-2.58	-1.95	-1.62
Economic unrest					
MLI	-8.04	0.000	-2.58	-1.95	-1.62
Neg	-3.71	0.000	-2.58	-1.95	-1.62
Pos	-2.73	0.000	-2.58	-1.95	-1.62

Notes: Percent Critical Value: PCV.

Table 5. Cointegration results using Johansen technique.

	Trace Statistics	10% CV	5% CV	1% CV
Cointegration between MLI & Sentiments in the economic stability period				
$r > 2$	35.56	7.52	9.24	12.97
$r > 1$	122.36	17.85	19.96	24.60
$r > 0$	235.12	32.00	34.91	41.07
Cointegration between MLI & Sentiments in the economic unrest period				
$r > 2$	26.71	7.52	9.24	12.97
$r > 1$	71.50	17.85	19.96	24.60
$r > 0$	132.08	32.00	34.91	41.07

Notes: $r > 0$: Cointegration exists at least one in the system; $r > 1$: Indication of cointegrated relationship between two series; $r > 2$: Presence of three cointegrated vectors.

Before this study performs VECM technique on the data sampling, a concern related to the stationarity is first addressed in the system. The Augmented Dickey-Fuller (ADF) test, quantified in Table 4, suggests that the time series is featured with the stationarity. Additionally, the cointegration, indicated as term r in Table 5, is noted between the time series. The VECM model structured in Equation (8) examines changes in the price impact volume-based liquidity on day t as function of own past changes, as well as previous changes in negative and positive sentiments. The findings for optimal lags, derived as per Equations (9)-(11), are presented in Table 6.

In the economic stability period, changes in the price impact volume-based liquidity on day t are not significantly determined by changes in the previous sentiment series. This guides that the ΔMLI_t is not impacted by past series changes in the sentiments, either in the short or long run. Meantime, changes in the price impact volume-based liquidity on day t are significantly associated with own lags, both in the short and long run. Thus, changes in the liquidity for trading session are influenced by its own previous serious changes. In the economic unrest environments, the ΔMLI_t is not significantly explained by changes in the past sentiment series, as well as changes in own previous series.

Table 6. Summary of vector error correction model.

ΔMLI_t	Estimates	ΔMLI_t	Estimates
Economic stability		Economic unrest	
ECT	-0.4188(0.0589)***	ECT	-0.7738(0.1306)***
Intercept	0.000063(0.0001)	Intercept	0.000096(0.0002)
ΔMLI_{t-1}	-0.6176(0.0584)***	ΔMLI_{t-1}	-0.0630(0.1185)
Δneg_{t-1}	-0.0053(0.0033)	Δneg_{t-1}	-0.0052(0.0035)
Δpos_{t-1}	-0.0011(0.0020)	Δpos_{t-1}	-0.0027(0.0024)
ΔMLI_{t-2}	-0.5448(0.0568)***	ΔMLI_{t-2}	-0.0680(0.1039)
Δneg_{t-2}	-0.0022(0.0038)	Δneg_{t-2}	-0.0033(0.0040)
Δpos_{t-2}	-0.0027(0.0024)	Δpos_{t-2}	-0.0033(0.0027)
ΔMLI_{t-3}	-0.3209(0.0496)***	ΔMLI_{t-3}	-0.0326(0.0861)
Δneg_{t-3}	-0.0003(0.0037)	Δneg_{t-3}	-0.0041(0.0039)
Δpos_{t-3}	-0.0011(0.0024)	Δpos_{t-3}	-0.0011(0.0027)
ΔMLI_{t-4}	-0.1931(0.0353)***	ΔMLI_{t-4}	-0.0214(0.0635)
Δneg_{t-4}	-0.0014(0.0030)	Δneg_{t-4}	-0.0034(0.0033)
Δpos_{t-4}	0.0012(0.0020)	Δpos_{t-4}	-0.0013(0.0024)

On a daily basis, the work undoubtedly endorses the literature that highlights the microblogging-opinionated content in the efficient functioning of financial markets. Additionally, this study uncovers a potential relationship of investor sentiments with the price impact volume-based liquidity in light of the economic unrest. The findings may not only aid us to alleviate the adverse selection issues during the uncertain environments, but the liquidity suppliers may also reduce their risk exposure against the riskier investment.

4. Conclusion

Market liquidity in terms of price dispersion relative to the quantity traded is examined as the behavioral pattern of economic unrest. The findings, based on the KSE 100 Index, are derived through the multivariate analysis approach. In the economic stability period, the microblogging-opinionated information, either in positive context or negative domain, played a significant role on the price impact volume-based liquidity. The negative bias investor's mood was noted to lead a greater price dispersion relative to the trading quantity. Therefore, a smaller number of trades in the pessimistic period depicted a lack of market liquidity. Meantime, the positive sentiments were noticed to lead a lower price dispersion relative to the trading volume. This implies, that a larger number of trades in the optimistic period exhibited a higher market liquidity.

In the economic unrest environments, the optimistic opinions were not strong enough to influence the price and trading quantity. This undoubtedly raises concerns on current economic situation in Pakistan, where the optimistic-opinionated information is avoiding by investors. Conversely, the pessimistic opinions were vigorous enough to impact the market liquidity. The pessimistic bias investor's mood was reported to lead a greater price dispersion relative to the trading quantity. In this discussion, a smaller amount of trading volume was required by investors. Therefore, liquidity declined in the market.

Before the economic unrest occurs in Pakistan, the Bayesian Theorem analysis suggested the implication of microblogging sentiments, either in positive form or negative perspective, on the liquidity. The negative bias investor's sentiment was noticed to incline the probability of greater price dispersion relative to the trading quantity. Therefore, investors with smaller trades in the pessimistic period increased the likelihood of market illiquidity. Meanwhile, the positive bias investor's sentiment was reported to increase the probability of lower price dispersion relative to the trading volume. This implies, that a larger amount of trading volume in relation to the optimistic opinions was more probable, which as a result, increased the expectation of higher liquidity in the market.

During the economic uncertainty environments, the optimistic sentiments were not strong enough to predict the price impact volume-based liquidity. However, the pessimistic sentiments were potentially vigorous to forecast the market liquidity. The pessimistic bias investor's mood was observed to incline the probability of greater price dispersion in comparison to the trading volume. Therefore, a lower amount of trading quantity in relation to the negative sentiments was more probable, which as a result, increased the likelihood of illiquidity in the market.

The analysis of VECM reported, that changes in the price impact volume-based liquidity for next trading day were not significantly associated with changes in past sentiment series. Thereby, the variables were not linked either in the short or long run. These results were consistent in both economic stability and uncertainty periods. During the economic stability period, changes in the price impact volume-based liquidity for following trading session were significantly explained by changes in own past series. Therefore, these variables were linked in short and long run. However, same findings were not found in economic uncertainty period.

This research suggests a potential inference of microblogging-opinionated information on the price impact volume-based liquidity. The sentiment analysis of microblogging opinions can make the asset's value more transparent. Therefore, incoming information from microblogging platform is suggested to be addressed by investors for portfolio construction and liquidity risk management. Nevertheless, it matters to address that there may be limitations related to market aspects in this research. Therefore, the research encourages other researchers to expand study at the firm level. This may provide additional insights into the implication of economic unrest on relationship dynamics between market liquidity and microblogging opinions.

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Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

Author contributions

The author contributed to all aspects, including conceptualization, methodology, software, resources, data curation, writing-original draft preparation, and writing-review and editing.

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