Data Science in Finance and Economics

DSFE, 3 (2): 196–207.
DOI: 10.3934/DSFE.2023012
Received: 01 May 2023
Revised: 03 June 2023
Accepted: 07 June 2023
Published: 19 June 2023

http://www.aimspress.com/journal/dsfe

Research article

Political-obsessed environment and investor sentiments: pricing liquidity through the microblogging behavioral perspective

Jawad Saleemi*

Business School, Universitat Politècnica de València, 46022, València, Spain

* **Correspondence:** Jasa1@doctor.upv.es; j.saleemi@yahoo.com.

Abstract: Pakistan's political instability has pushed its economic system to the brink of collapse. Considering this political turmoil, this study addresses the behavior of liquidity providers against microblogging-opinionated information. The behavioral perspective was quantified through multiple linear regressions, the Bayesian theorem, and the vector error correction technique. Before this political crisis, sentiment indicators were linked to the liquidity-conditional cost for the same trading session. In the political uncertainty environment, pessimistic opinions were the sole concern of the liquidity providers during the same trading session. The liquidity facilitator was observed to price the liquidity in light of pessimistic sentiments. The Bayesian theorem suggested a higher posterior probability for the occurrence of the liquidity-facilitating cost in response to the pessimistic sentiments. Nevertheless, the past time series changes for the sentiment indicators were irrelevant in determining changes in cost-based liquidity for the next trading session.

Keywords: political dilemma; investor behavior; microblogging-opinionated data; asset pricing

JEL Codes: G10, G41

1. Introduction

The governing coalition of a dozen parties in Pakistan are facing drastic stress including, but not limited to, triggering inflation and falling foreign exchange reserves. Meantime, the economic activities are pressurized by a consistent depreciation in currency. The future economic perspective may seem like a wider concern to the stakeholders. The political change phenomenon is under discussion as the source of the economic chaos in Pakistan.

Since the dismissal of the ruling party on April 10, 2022, the country has turned into a censorious polarization. This has triggered a relentless campaign against the handlers of the political-change operation in Pakistan. In addition, two provincial assemblies were dissolved to force a governing coalition for early general elections. However, the incumbent government was not willing to allow for early national polls and openly denied holding elections for the dissolved assemblies as per constitution.

Pakistan's constitution permits new polls within ninety days after the dissolution of the assembly. In this debate, the supreme court intervened for constitutional compliance and rescheduled provincial polls on May 14, 2023. Nevertheless, the governing coalition clearly denied acting as per the guidelines of the supreme court. The constitutional crisis may not be limited to political instability, but has the scope to trigger havoc on an extensive scale.

In environments of economic chaos, the International Monetary Fund (IMF) can certainly facilitate the economy to avoid default and bolster the market confidence for other inflows. The political-obsessed environment in Pakistan may be a major concern in delaying the agreement of $1.1 billion with the IMF. Meanwhile, the IMF seems unsure that the future governing setup may be compliant with its current agreement.

Considering the widespread root of political instability within Pakistan's economy, this study prices liquidity in response to the investor sentiments. Whether the behavioral perspective of liquidity providers to impose the conditional cost on counterparty has impacted due to the political uncertainty is certainly a matter for investigation. The behavioral element has been examined using microblogging data. The opinion analysis of the microblogging text is not only a cost-effective technique, but also provides useful real-time content by eliminating geographical limitations (Guijarro et al., 2021).

Microblogging data is considerably applied to the behavioral domain (Oliveira et al., 2013). This behavioral phenomenon is not only linked to financial perspectives (Sprenger at al., 2014; Prokofieva, 2015; Oliveira et al., 2017; Bartov et al., 2018; Broadstock and Zhang, 2019; Bank et al., 2019), but has created serious concerns across diversified subjects (Guijarro et al., 2019). The proliferation of microblogging-opinionated content is attributable to its authentic role on the investor's emotions (Guijarro et al., 2021).

Microblogging-opinionated content may eliminate the expected asymmetric information in the market more effectively (Mazboudi and Khalil, 2017). Incoming information from microblogging comments influences the market performance more than a traditional source of news (Yu et al., 2013). Microblogging-based investment interest contributes a potential role to generate reliable content (Sprenger at al., 2014). This content can predict price movements (Smailović et al., 2013), asset trends (Li et al., 2018), investors' earnings (Bartov et al., 2018; Bank et al., 2019), and dimensions of market liquidity (Guijarro et al., 2021) ahead of time.

The investor is undoubtedly concerned with the lucidity of their investment's value (Cervelló-Royo and Guijarro, 2020), and the market frictions (Roll, 1984; Huang and Stoll, 1997; Sarr and Lybek, 2002; Acharya and Pedersen, 2005; Amihud and Mendelson, 2008; Corwin and Schultz, 2012; Amihud et al., 2015). Liquidity reflects the transparency of an asset's value more broadly, as it is a source of various market frictions within uncertainty environments (Saleemi, 2022). The friction refers to a conditional cost that the liquidity provider demands against facilitating the liquidity (Saleemi, 2020).

In contrast to earlier research, this study uncovers the political perspective regarding the behavior of liquidity providers using microblogging-opinionated information. The current political dilemma in Pakistan needs to be addressed within behavioral finance literature, as its roots have expanded to the constitutional crisis and a full-blown economic collapse. Incoming news from microblogging comments gains considerable attention in broadly understanding the investors' behavior. Therefore, the study aims to unfold the authoritative role of political uncertainty on liquidity by means of the microblogging-behavioral perspective.

There is no earlier consideration on how the liquidity supplier responds to microblogging-opinionated content during the political uncertainty era. Thereby, this paper is the first empirical attempt to fill this gap within behavioral finance literature and helps us to understand the microblogging-based behavior of liquidity suppliers throughout the political uncertainty environment.

The rest of the manuscript is arranged as follows. The procedure to build the model is illustrated in Section 2. The empirical findings are depicted and discussed in Section 3. Finally, the main achievements of this research are highlighted in Section 4.

2. Materials and methods

The multivariate analysis is performed on data from the Karachi Stock Exchange 100 Index (KSE 100), where the sentiment indicators are built using microblogging data. The collection of opinionated data is facilitated by the R statistical language and covers the period from January 01, 2018 – March 31, 2023. The root of the political-obsessed environment is linked to a dramatic removal of the ruling government on April 10, 2022. In this debate, the dynamic of political instability in the area of research was investigated for the period from April 11, 2022 – March 31, 2023.

A text mining (TM) library is applied to clean the unstructured text. This process converts the text into lower case to identify the valuable content. The extracted information is quantified in various opinions, such as pessimistic, optimistic, or neutral. Neutral data is not included in the analysis. The sentiment indicators are constructed, as per Equation (1) and (2):

$$\sum_{t=1}^{T} PS_t \;=\; PS_1 + PS_2 + PS_3 + \cdots + PS_T \tag{1}$$

$$\sum_{t=1}^{T} OS_t \;=\; OS_1 + OS_2 + OS_3 + \cdots + OS_T \tag{2}$$

where T demonstrates the number of pessimistic or optimistic sentiments on day t and $\sum_{t=1}^{T} PS_t$ ($\sum_{t=1}^{T} OS_t$) narrates the total pessimistic sentiments (optimistic sentiments) of day t.

The liquidity-associated cost is measured through the effective spread (ES) and the quoted spread (QS). This combination may reflect a more comprehensive insight into the topic. The ES method is empirically demonstrated, as per Equation (3):

$$ES_t = \frac{2\left|cp_t - \left[(h_t + l_t)\left(\frac{1}{2}\right)\right]\right|}{(h_t + l_t)\left(\frac{1}{2}\right)} \tag{3}$$

where h_t shows the highest quoted value of day t, l_t refers to the lowest quoted value of day t, and cp_t represents the closing value of the transaction on day t. Considering the executing price in buying and selling quotes, the ES model is a useful liquidity proxy (Guijarro et al., 2019). The QS model is constructed in Equation (4)

$$QS_t = \frac{R_t}{(SHL_t)(0.5)} \tag{4}$$

where R_t denotes to the range of quoted prices on day t and SHL_t indicates the sum of quoted prices on day t.

The variables are first modelled, as per Equation (5), where the multiple linear regression unfolds the response of liquidity-associated cost against the sentiment indicators:

$$LPC_t = \alpha + \gamma_1 \sum_{t=1}^{T} PS_t + \gamma_2 \sum_{t=1}^{T} OS_t + \epsilon_t \tag{5}$$

where LPC_t elucidates the quantification of liquidity-providing cost on day t and $\sum_{t=1}^{T} PS_t$ ($\sum_{t=1}^{T} OS_t$) explicates the accumulation of pessimistic sentiments (optimistic sentiments) on same trading day.

An additional experiment was performed on the dataset using the Bayesian Theorem. This approach uncovers the relatedness of dataset considering a conditional probability. Therefore, the study understands the posterior likelihood of liquidity-providing cost against the sentiment indicators. The Bayesian model is constructed, as per Equation (6):

$$p(LPC|Sentiments) = \frac{p(LPC \cap Sentiments)}{p(Sentiments)} \tag{6}$$

where $p(LPC|Sentiments)$ illustrates the occurrence of liquidity-associated cost in response to pessimistic or optimistic sentiments, $p(Sentiments)$ suggests the likelihood of pessimistic or optimistic sentiments to being true, and $p(LPC \cap Sentiments)$ indicates the probability of all parameters being true. The term $p(LPC \cap Sentiments)$ can be depicted, as per Equation (7):

$$p(LPC \cap Sentiments) = p(Sentiments|LPC)\, p(LPC) \tag{7}$$

where $p(LPC)$ suggests the likelihood of liquidity-pricing cost and conditioning the liquidity-pricing cost to being true and $p(Sentiments|LPC)$ guides the probable occurrence of pessimistic or optimistic sentiments. The Bayesian approach for normal distribution is defined as:

$$p(LPC|Sentiments) = \frac{p(Sentiments|LPC)\, p(LPC)}{p(Sentiments)} . \tag{8}$$

Finally, the change in liquidity-pricing cost on trading day t is examined as function of its corresponding past changes, as well as the previous changes of pessimistic or optimistic sentiments. In this context, the vector error correction model (VECM) is constructed, as per Equation (9):

$$\Delta LPC_t = \beta_0 + \sum_{i=1}^{n} \vartheta_i \, \Delta LPC_{t-i} + \sum_{i=1}^{n} \delta_i \Delta\, PS_{t-i} + \sum_{i=1}^{n} \emptyset_i \Delta\, OS_{t-i} + \varphi ECT_{t-1} + \epsilon_t \tag{9}$$

where ΔLPC_t (ΔLPC_{t-i}) describes the change in liquidity-pricing cost of day t $(t-i)$, ΔPS_{t-i} demonstrates the past changes of pessimistic sentiments on day $t-i$, ΔOS_{t-i} explains the previous changes of optimistic sentiments on day $t-i$, and ECT_{t-1} exhibits the error correction term of day $t-1$. The optimal lags are selected using the schwarz criterion technique, and given as per Equations (10)–(12):

$$\Delta LPC_{t-i} = \vartheta_1 \Delta LPC_{t-1} + \vartheta_2 \Delta LPC_{t-2} \ , \tag{10}$$

$$\Delta PS_{t-i} = \delta_1 \Delta PS_{t-1} + \delta_2 \Delta PS_{t-2} \ , \tag{11}$$

$$\Delta OS_{t-i} = \emptyset_1 \Delta OS_{t-1} + \emptyset_2 \Delta OS_{t-2}. \tag{12}$$

3. Results and discussion

Table 1 exhibits a descriptive summary on a daily basis, where the dataset is positively skewed with a fat-tailed distribution. The positive skewness suggests a right-skewed distribution of the dataset. The measurement of variables is graphically visualized in Figure 1. The graphical demonstration suggests that there is no constant pattern for the corresponding variable over time. This variability raises concerns over whether the time-varying sentiment indicators have an authoritative role to estimate the liquidity-pricing cost, particularly during the political instability era.

Table 1. Descriptive summary.

Variables	Median	Mean	SD	Skewness	Kurtosis
QS	0.0119	0.0139	0.0082	2.4955	13.271
ES	0.0069	0.0086	0.0076	2.4272	13.926
PS	0.0400	0.0565	0.0519	2.3504	14.053
OS	0.1200	0.1311	0.0940	0.9952	5.0655

Notes: Quoted Spread: QS; Effective Spread: ES; Pessimistic Sentiments: PS; Optimistic Sentiments: OS; Standard Deviation: SD; Significance level codes: *** < 0.001; ** < 0.01; * < 0.05.

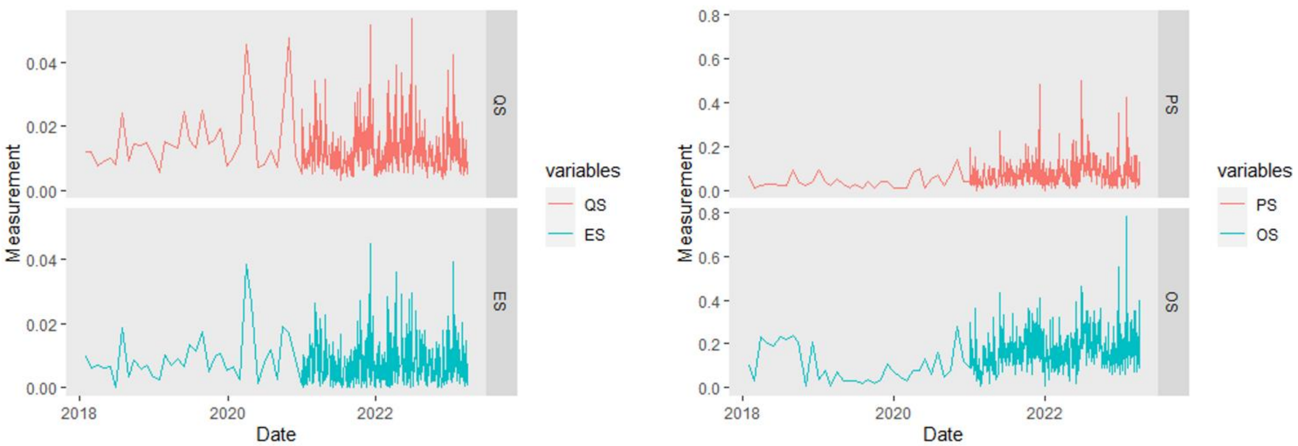

Figure 1. Time-varying graphical demonstration for variables.

The variables are first understood using a multiple linear regression, as shown in Table 2. This experiment was performed on a daily basis. During the political stability period, the liquidity-pricing cost was noted to be influenced by the sentiment indicators. The pessimistic sentiments are positive and significantly linked to the liquidity-facilitating cost. This indicates a higher size of the trading cost in response to any negative opinions. The relative size of the liquidity-associated cost compensates the liquidity providers within pessimistic market environments. Meantime, the optimistic sentiments are negative, though they are significantly associated with the liquidity-pricing cost. This implies an acknowledgment of the positive opinions by the liquidity providers, which helps to reduce the liquidity-providing cost.

The findings are reported to be influenced within political instability environments. An insignificant linkage was found between liquidity and optimistic sentiments. This provides an understanding of the risk aversion behavior, where the liquidity facilitator avoids the positive opinions during the political instability era. However, the liquidity-pricing cost is positive and is significantly explained by the pessimistic sentiments. This association guides that the cost against accepting the financial position increases in response to the negative opinions. Therefore, the market maker reduces the risk element by pricing the liquidity during the political-obsessed era.

Table 2. Regression model quantification.

Variables			Estimate	Std. Error	p-value
Political stability period					
QS	(i)	Intercept	0.0122	0.0004	0.000 ***
		Bearish	0.0761	0.0059	0.000 ***
		Bullish	−0.0137	0.0029	0.000 ***
ES	(ii)	Intercept	0.0071	0.0004	0.000 ***
		Pessimistic	0.0539	0.0057	0.000 ***
		Optimistic	−0.0079	0.0028	0.005 **
Political instability period					
QS	(iii)	Intercept	0.0084	0.0009	0.000 ***
		Bearish	0.0493	0.0090	0.000 ***
		Bullish	−0.0019	0.0065	0.763
ES	(iv)	Intercept	0.0046	0.0008	0.000 ***
		Pessimistic	0.0299	0.0085	0.000 ***
		Optimistic	0.0039	0.0061	0.522

Notes: i) Adjusted R-squared: 0.1322; F-statistic: 81.62; p-value: 0.000; (ii) Adjusted R-squared: 0.077; F-statistic: 45.17; p-value: 0.000; (iii) Adjusted R-squared: 0.1995; F-statistic: 31.15; p-value: 0.000; (iv) Adjusted R-squared: 0.1243; F-statistic: 18.17; p-value: 0.000.

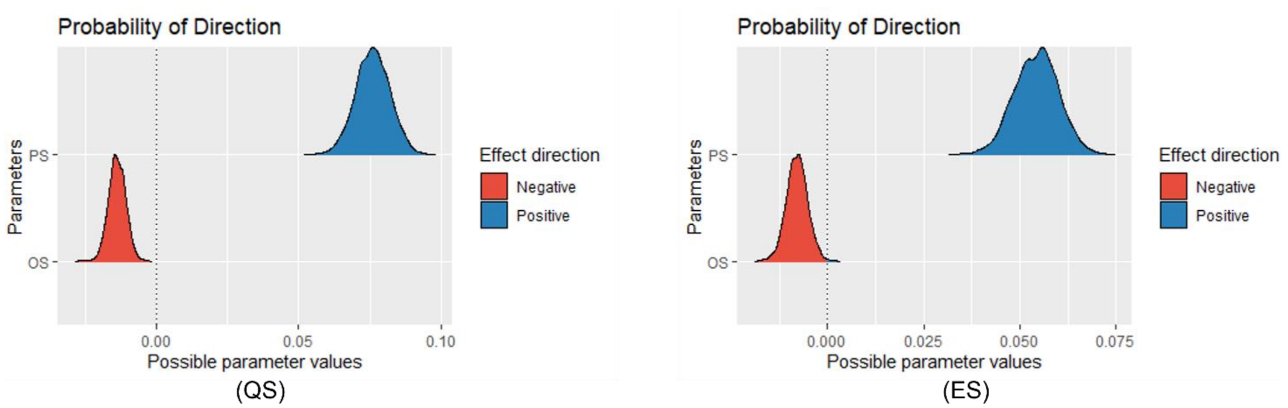

Figure 2. Probability of Direction for parameters in political stability environments.

On a daily basis, the dataset is further quantified through the Bayesian Theorem, as shown in Table 3. During the political stability period, the posterior probability suggests an occurrence of the liquidity-pricing cost against the sentiment indicators. The Bayesian Theorem reports a 100% positive relativeness between pessimistic opinions and liquidity-occurring cost. This measurement identifies a higher likelihood for the occurrence of the liquidity-facilitating cost against the pessimistic sentiments. Meantime, the posterior likelihood guides a 100% negative linkage between optimistic opinions and the quoted spread. Similarly, there is a 99.9% negative relativeness between the effective spread and positive opinions. In this sense, there is a higher probability of occurrence for liquidity-pricing cost in response to the optimistic sentiments.

These quantifications are further supported by Figure 2, where the probability of direction for the parameters is visually presented on a daily basis. This graphical demonstration suggests an increased positive relatedness between liquidity proxies and pessimistic sentiments. Therefore, the posterior probability is higher for the occurrence of the liquidity-facilitating cost in response to pessimistic opinions. Similarly, an increased, but negative relation is observed between liquidity measures and optimistic sentiments. In this debate, the liquidity-providing cost is more probable to occur against any optimistic opinions.

Table 3. Summary of Posterior Distribution.

Variables	Parameters	Median	PD	% in ROPE	ESS
Political stability period					
QS	Intercept	0.01	100%	0%	2419
	PS	0.08	100%	0%	1686
	OS	-0.01	100%	0%	1775
ES	Intercept	0.0071	100%	0%	3225
	PS	0.05	100%	0%	2009
	OS	-0.0079	99.9%	0%	2040
Political instability period					
QS	Intercept	0.0083	100%	0%	3059
	PS	0.05	100%	0%	1689
	OS	-0.0021	63%	8.03%	1686
ES	Intercept	0.0046	100%	0%	2539
	PS	0.03	100%	0%	1321
	OS	0.0041	75%	6.61%	1369

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

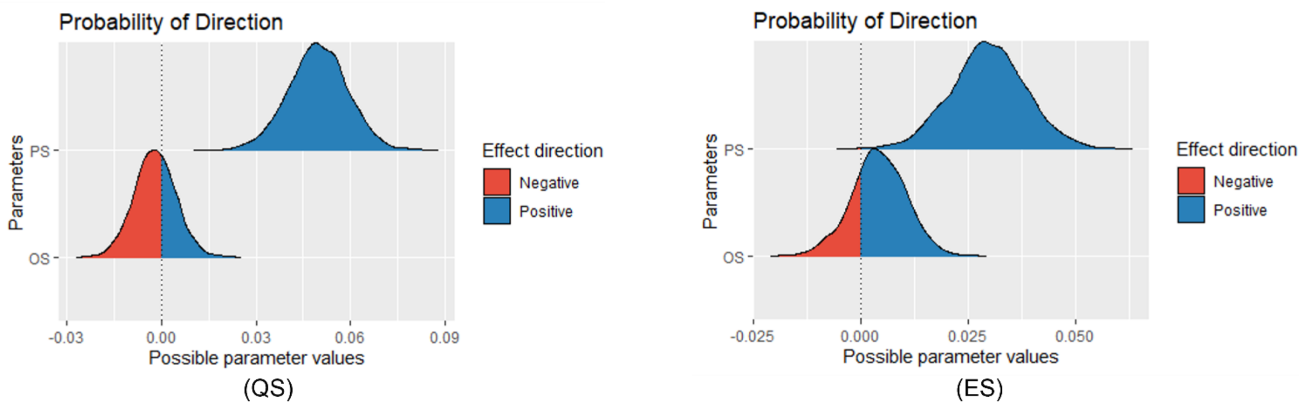

Figure 3. Probability of Direction for parameters in political instability environment.

The measurement of the Bayesian model is reported to be influenced by the political instability environments. The probability of direction guides a 100% positive relativeness between pessimistic sentiments and liquidity-occurring cost. Therefore, there is a higher probability for occurrence of liquidity-facilitating cost in response to the pessimistic opinions. However, the Bayesian Theorem notes a 63% posterior probability of occurrence for the quoted spread in response to any optimistic opinions. Conversely, the probability of direction identifies a 75% relativeness between the effective spread and optimistic opinions. In this case, there is a decreased likelihood of occurrence for liquidity-pricing cost in response to the optimistic sentiments.

These findings are endorsed by Figure 3, where the probability of direction for sentiment parameters is visually demonstrated on a daily basis. This graphical presentation suggests an increased positive linkage between liquidity proxies and pessimistic-opinionated content. Therefore, the liquidity-providing cost is more probable to occur in response to the pessimistic sentiments. However, a decreased negative relatedness is observed between liquidity measurements and optimistic-opinionated content. In this case, the liquidity-facilitating cost is less likely to occur against the optimistic sentiments.

Table 4. Unit root test using Augmented Dickey-Fuller approach.

Variables	ADF Statistics	p-value	1 PCV	5 PCV	10 PCV
Political stability period					
QS	−5.102	0.000	−2.58	−1.95	−1.62
ES	−7.916	0.000	−2.58	−1.95	−1.62
PS	−8.5425	0.000	−2.58	−1.95	−1.62
OS	−5.0907	0.000	−2.58	−1.95	−1.62
Political instability period					
QS	−3.129	0.000	−2.58	−1.95	−1.62
ES	−4.499	0.000	−2.58	−1.95	−1.62
PS	−3.4068	0.000	−2.58	−1.95	−1.62
OS	−2.373	0.000	−2.58	−1.95	−1.62

Notes: Percent Critical Value: PCV.

Before examining the relationship dynamics using the VECM technique, the dataset is checked for stationarity in Table 4. The Augmented Dickey-Fuller (ADF) test guides that there is no unit root in the time series. Therefore, the dataset is featured with stationarity. The measurement of the VECM approach is quantified in Table 5, where the change in liquidity-associated cost is investigated as a function of its corresponding past changes, as well as the previous changes of pessimistic or optimistic opinions.

Within the political stability environment, the term ΔLPC_t is not significantly explained by changes in the past time series of sentiment indicators. This implies that a change associated with the liquidity-occurring cost on day t is not linked to changes in the previous time series of pessimistic and optimistic opinions. However, a change in the cost against providing the liquidity on day t is significantly explained by its corresponding lags.

Similar results are found during the political instability era. The term ΔLPC_t is not significantly associated with changes in the previous time series of sentiment indicators. In this case, a change in the liquidity-facilitating cost for the following trading session is not linked to the past series changes of pessimistic and optimistic sentiments. Meantime, a change associated with the quoted spread on the next trading session is significantly explained by its own lags. Conversely, a change in the effective spread on trading day t is not significantly linked to its corresponding lags.

Table 5. Measurement of the vector error correction model.

$\Delta ILC_{QS,t}$	Estimates	$\Delta ILC_{ES,t}$	Estimates
	Political stability period		
ECT	−0.0021(0.0090)	ECT	−0.0452(0.0158)**
Intercept	−0.000053(0.0003)	Intercept	−0.0006(0.0003)
$\Delta LPC_{QS,t-1}$	−0.6188(0.0317)***	$\Delta LPC_{ES,t-1}$	−0.6798(0.0312)***
ΔPS_{t-1}	0.0029(0.0075)	ΔPS_{t-1}	−0.0144(0.0078)
ΔOS_{t-1}	0.0023(0.0039)	ΔOS_{t-1}	0.0030(0.0041)
$\Delta LPC_{QS,t-2}$	−0.2929(0.0313)***	$\Delta LPC_{ES,t-2}$	−0.3334(0.0299)***
ΔPS_{t-2}	0.0007(0.0063)	ΔPS_{t-2}	−0.0070(0.0065)
ΔOS_{t-2}	−0.0002(0.0039)	ΔOS_{t-2}	−0.0019(0.0041)
	Political instability environment		
ECT	−0.0328(0.0371)	ECT	−0.7491(0.1115)***
Intercept	0.0009(0.0012)	Intercept	0.0034(0.0006)***
$\Delta LPC_{QS,t-1}$	−0.5607(0.0724)***	$\Delta LPC_{ES,t-1}$	−0.0793(0.0928)
ΔPS_{t-1}	−0.0101(0.0140)	ΔPS_{t-1}	−0.0136(0.0085)
ΔOS_{t-1}	0.0068(0.0097)	ΔOS_{t-1}	−0.0015(0.0058)
$\Delta LPC_{QS,t-2}$	−0.2877(0.0693)***	$\Delta LPC_{ES,t-2}$	−0.0849(0.0694)
ΔPS_{t-2}	−0.0044(0.0110)	ΔPS_{t-2}	−0.0017(0.0083)
ΔOS_{t-2}	−0.0003(0.0076)	ΔOS_{t-2}	−0.0042(0.0058)

4. Conclusions

The cost against facilitating liquidity is modelled as a behavioral phenomenon from a political perceptive. In this context, the KSE 100 Index was examined in environments of political stability , as well as during the political uncertainty period. Before the political instability took place in Pakistan, the liquidity-occurring cost was significantly explained by microblogging sentiment indicators. During the political instability era, optimistic sentiments were not considered by the facilitator of liquidity. However, the liquidity facilitator was reported to price the liquidity in political instability environments using microblogging pessimistic opinions.

Based on a gaussian distribution, the Bayesian Theorem was utilized in the analysis. In political stability environments, a higher posterior probability was noted for the occurrence of liquidity-facilitating cost against the microblogging sentiment indicators. In the political uncertainty environments, there was a decreased likelihood of occurrence for liquidity-facilitating cost against the optimistic sentiments. Meantime, a higher posterior probability was reported for the occurrence of liquidity-providing cost in response to the microblogging pessimistic sentiments.

The VECM technique was applied to broadly uncover the relationship dynamics of the time series. The change in the liquidity-occurring cost for the following trading session was not significantly explained by the past time series changes of optimistic and pessimistic sentiments. These results were consistent during the political stability period, as well as the political uncertainty environments.

In the asset behavioral studies, the findings may have significant implications in terms of pricing the liquidity from a political perceptive. This debate may raise important concerns regarding Pakistan's economy, where the political crisis has turned into a full-blown financial uncertainty. Based on the investors' behavioral perspective, the study of other economic dimensions may provide deeper insights into the political-obsessed environments.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

Anonymous reviewers are appreciated for their valuable remarks and suggestions.

Conflict of interest

There are no conflicts of interest in this manuscript.

References

Acharya VV, Pedersen LH (2005) Asset pricing with liquidity risk. *J Financ Econ* 77: 375–410. https://doi.org/10.1016/j.jfineco.2004.06.007

Amihud Y, Mendelson H (2008) Liquidity, the value of the firm, and corporate finance. *J Applied Corp Financ* 20: 32–45. https://doi.org/10.1111/j.1745-6622.2008.00179.x

Amihud Y, Hameed A, Kang W, Zhang H (2015) The Illiquidity Premium: International Evidence. *J Financ Econ* 117: 350–368. https://doi.org/10.1016/j.jfineco.2015.04.005

Bank S, Yazar EE, Sivri U (2019) Can social media marketing lead to abnormal portfolio returns? *Europ Research Manag Bus Econ* 25: 54–62. https://doi.org/10.1016/j.iedeen.2019.04.006

Bartov E, Faurel L, Mohanram P (2018) Can Twitter help predict firm-level earnings and stock returns? *Accounting Rev* 93: 25–27. https://doi.org/10.2308/accr-51865

Broadstock D, Zhang D (2019) Social-media and intraday stock returns: The pricing power of sentiment. *Financ Res Lett* 30: 116–123. https://doi.org/10.1016/j.frl.2019.03.030

Cervelló-Royo R, Guijarro F (2020) Forecasting stock market trend: a comparison of machine learning algorithms. *Financ Mark Valuation* 6: 37–49. https://doi.org/10.46503/NLUF8557

Corwin SA, Schultz P (2012) A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. *J Finance* 67: 719–760. https://doi.org/10.1111/j.1540-6261.2012.01729.x

Guijarro F, Moya-Clemente I, Saleemi J (2019) Liquidity Risk and Investors' Mood: Linking the Financial Market Liquidity to Sentiment Analysis through Twitter in the S&P500 Index. *Sustainability* 11: 7048.

Guijarro F, Moya-Clemente I, Saleemi J (2021) Market Liquidity and Its Dimensions: Linking the Liquidity Dimensions to Sentiment Analysis through Microblogging Data. *J Risk Financ Manag* 14: 394. https://doi.org/10.3390/jrfm14090394

Huang RD, Stoll HR (1997) The Components of the Bid-Ask Spread: A General Approach. *Rev Financ Studies* 10: 995–1034. https://doi.org/10.1093/rfs/10.4.995

Mazboudi M, Khalil S (2017) The attenuation effect of social media: Evidence from acquisitions by large firms. *J Financ Stability* 28: 115–124. https://doi.org/10.1016/j.jfs.2016.11.010

Oliveira N, Cortez P, Areal N (2013) On the predictability of stock market behavior using stocktwits sentiment and posting volume. *Prog artific intellig. Lect notes comput science* 8154: 355–365. https://doi.org/10.1007/978-3-642-40669-0_31

Oliveira N, Cortez P, Areal N (2017) The impact of microblogging data for stock market prediction: using twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Syst Applications* 73: 125–144. https://doi.org/10.1016/j.eswa.2016.12.036

Prokofieva M (2015) Twitter-based dissemination of corporate disclosure and the intervening effects of firms' visibility: Evidence from Australian-listed companies. *J Inform Systems* 29: 107–136. https://doi.org/10.2308/isys-50994

Roll R (1984) A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *J Finance* 39: 1127–1139. https://doi.org/10.1111/j.1540-6261.1984.tb03897.x

Saleemi J (2020) An estimation of cost-based market liquidity from daily high, low and close prices. *Financ Mark Valuation* 6: 1–11. https://doi.org/10.46503/VUTL1758

Saleemi J (2022) Asymmetric information modelling in the realized spread: A new simple estimation of the informed realized spread. *Financ Mark Valuation* 8: 1–12. https://doi.org/10.46503/JQYH3943

Sarr A, Lybek T (2002) Measuring liquidity in financial markets. *Intern Monet Fund* 2: 1–64.

Smailović J, Grčar M, Lavrač N, Žnidaršič M (2013) Predictive sentiment analysis of Tweets: a stock market application. *Human-Comput Interac Know Dis Comp, Unstructured, Big Data*, 77–88. https://doi.org/10.1007/978-3-642-39146-0_8

Sprenger TO, Tumasjan A, Sandner PG, Welpe IM (2014) Tweets and trades: the information content of stock microblogs. *Europ Financ Manag* 20: 926–957. https://doi.org/10.1111/j.1468-036X.2013.12007.x

Yu Y, Duan W, Cao Q (2013) The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Dec Support Systems* 55: 919–926. https://doi.org/10.1016/j.dss.2012.12.028