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Microblogging Perceptive and Pricing Liquidity: Exploring Asymmetric Information as a Risk Determinant of Liquidity in the Pandemic Environments

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ABSTRACT

Liquidity can be a real phenomenon for execution of the financial holding. Its risk falls in debate to impose a conditional cost on the counterparty. The time-varying liquidity is often linked to the expected fundamental value of an investment. In this work, the microblogging-based informed transaction is examined as a determinant of the liquidity-facilitating cost. Most importantly, this study investigates the economic blockade era and post-pandemic uncertainty. The sentiment indicators were found to be determinants of liquidity. These findings were consistent in the post-pandemic period. However, the investor pessimistic sentiment was a priced risk factor in liquidity during the economic blockade period. Based on the Bayesian theorem, a relativeness was reported between sentiment indicators and the liquidity-facilitating cost. The same findings were depicted in environments of the pandemic era. Nevertheless, the posterior probability indicated an occurrence of the liquidity-associated cost in response to the pessimistic sentiments during the economic blockade period. This quantification may have potential implications in terms of exploring liquidity from the microblogging perceptive.

KEYWORDS

Pandemic; Microblogging-opinionated content; Sentiment Analysis; Pricing Liquidity

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1. Introduction

Since the coronavirus has turned into a pandemic phenomenon, the global economic prospective is under debate among policymakers. This disease has not only caused exceptional fatalities, but it may have impacted the economic realities more than the earlier devastating financial crises. As the economic activities were postponed by the global regulators, the pandemic root is explored in various economic dimensions, including the economic blockade (Vidya and Prabheesh, 2020), economic development (Goodell, 2020), crypto market (Conlon & McGee, 2020), global lifestyles (Ahundjanov et al., 2021), traditional financial market (David et al., 2021; Saleemi, 2021), and commodity market (Gharib et al., 2021).

Social media has been considerably explored to find patterns of rumors with different disciplines. In the context of the information source, the role of social networking matters during the economic blockade period. This phenomenon may even more concern whether such information impacts different subjects, including the economic sciences. In this work, the microblogging data is linked to the conditional cost of facilitating liquidity in the financial market. The analysis is executed on the Karachi Stock Exchange (KSE) 100 Index, where the microblogging-based investor sentiments are examined as determinants of liquidity, particularly in the economic blockade and post-pandemic era.

The microblogging data is largely applied to estimate the pattern between sentiment-driven participants and different determinants of the financial market (Zhang et al., 2011; Yu et al., 2013; Sprenger et al., 2014; Prokofieva, 2015; Bartov et al., 2018; Bank et al., 2019; Guijarro et al., 2019). This opinionated data matters in the behavioral study (Guijarro et al., 2021), and is economically more applicable for sentiment analysis than the traditional source of information (Oliveira et al., 2017). In the financial market, the transparency of an asset's value is crucial to execute the financial transaction. The transaction execution often relates to the willingness of the liquidity supplier at a conditional liquidity-facilitating cost (Saleemi, 2020).

Market liquidity undoubtedly matters for users of financial liquidity, as it is an immediate source of transaction execution (Acharya and Pedersen, 2005; Amihud and Mendelson, 2008; Guijarro et al., 2019; Saleemi, 2022). Liquidity is illustrated in different dimensions, but easiness of the transaction execution with the lowest cost is suggested for higher liquidity. The bid-ask spread may be a meaningful estimation for almost the entire trading cost (Sarr and Lybek, 2002). The spread, as a cost of trading, is widely used to estimate market liquidity (Corwin and Schultz, 2012). The liquidity supplier tends to reduce its risk exposure against future price uncertainty, informed counterparty, and transaction processing friction (Huang and Stoll, 1997; Saleemi, 2020). In this debate, the spread is perceived as a compensation for the liquidity provider. A higher spread is suggested to illiquidity (Roll, 1984; Fong et al., 2017).

In the context of asymmetric information, a trade is illiquid (Gorton and Metrick, 2010). Therefore, this risk must be considered in the liquidity-facilitating cost (Glosten and Milgrom, 1985; Saleemi, 2022). As microblogging-based opinionated content is gaining attention for behavioral analysis, this study understands the liquidity supplier's behavior in terms of imposing a conditional cost on the counterparty against the microblogging perceptive. To the author's knowledge, there is no empirical understanding of how microblogging content impacts the liquidity-facilitating cost for the KSE 100 Index. Therefore, the study aims to be the first empirical attempt, particularly in the pandemic environments.

2. Materials and Methods

The work performs the analysis in the domain of behavioral finance, where the microblogging-based opinionated content is linked to liquidity risk. This phenomenon is particularly investigated in response to the pandemic uncertainty. As the measurement of liquidity is a multidimensional debate, a combination of different liquidity measures is included to find more comprehensive results.

Among the liquidity proxies, the Quoted Spread (QS) is a simple computational model of the liquidity-providing cost. The QS model is estimated through Equation (1).

$$QS_t = \frac{Range_t}{(h_t + l_t)\left(\frac{1}{2}\right)} \tag{1}$$

where $Range_t$ depicts the difference between high quote, h_t, and low quote, l_t, of day t. Modeling the risk of asymmetric information in the trading, another version of the realized spread is developed by Saleemi (2022). This methodology may provide a comprehensive estimation of the spread in the context of the informed counterparty. The Informed Realized Spread (IRS) is estimated per Equation (2).

$$IRS_t = \frac{2|[E(QM_{t+1})] - closing_t|}{(h_t + l_t)\left(\frac{1}{2}\right)} \tag{2}$$

where $E(QM_{t+1})$ illustrates the possibility of an informed trading, and it is estimated through Equation (3).

$$E(QM_{t+1}) = \frac{EA_{t+1} + EB_{t+1}}{2} \tag{3}$$

where EA_{t+1} indicates the expected highest price for the next trading day, and it takes into conditional as per Equation (4).

$$EA_{t+1} = (h_{t+1})p + \left[(QSUM_{t+1})\left(\frac{1}{2}\right)\right]p \tag{4}$$

where p suggests the presence of the optimistic buyer; h_{t+1} shows the highest quoted price of the next trading day, and $QSUM_{t+1}$ defines the sum of the quoted prices on the following session. Realizing the presence of the pessimistic seller, EB_{t+1} explains the expected lowest bid price of day $t+1$. EB_{t+1} takes into conditional as per Equation (5).

$$EB_{t+1} = (l_{t+1})\delta + \left[(QSUM_{t+1})\left(\frac{1}{2}\right)\right]\delta \tag{5}$$

where δ guides the probability of the pessimistic seller, and l_{t+1} is the lowest quoted price for the next trading session.

For constructing the behavioral indicators, the unstructured text is transformed into a valuable content. This process is executed using the Natural Language Processing (NLP) and Text Mining (tm) libraries in the R programming language. The Syuzhet library is applied to quantify the structured data in either a pessimistic or optimistic sentiment. The sentiment indicators are linked to different cost-based liquidity models for the period January 01, 2018 – January 06, 2023, where the root of the pandemic is investigated from March 11, 2020.

A linear combination of the variables is first checked by means of the Multiple Linear Regression technique, and it is structured as per Equation (6).

$$CBL_t = \alpha + \gamma_1 \sum_{t=1}^{T} Pessimistic_t + \gamma_2 \sum_{t=1}^{T} Optimistic_t + \epsilon_t \tag{6}$$

where CBL_t indicates the measurement of the cost-based liquidity on day t; T shows the pessimistic or optimistic emotions of day t; $\sum_{t=1}^{T} Pessimistic_t$ denotes the sum of the bearish values in the same trading session; and $\sum_{t=1}^{T} Optimistic_t$ depicts an accumulation of the bullish values on day t.

The dataset is further analyzed using the Gaussian distribution. In this context, the Bayesian model for a normal distribution is derived as:

$$p(CBL|S) = \frac{p(CBL \cap S)}{p(S)} \tag{7}$$

where S refers to the pessimistic or optimistic sentiments; $p(CBL|S)$, also known as the posterior likelihood, depicts the occurrence of liquidity-providing cost in response to the investor sentiments; $p(S)$ explains the probability of the investor sentiments being true; and $p(CBL \cap S)$ is the likelihood of all the variables being true. The term, $p(CBL \cap S)$, can be rewritten as:

$$p(CBL \cap S) = p(S|CBL)\, p(CBL) \tag{8}$$

The Bayesian Theorem is defined as:

$$p(CBL|S) = \frac{p(S|CBL)\, p(CBM)}{p(S)} \tag{9}$$

where $p(CBL)$ shows the probability of the liquidity-facilitating cost; and $p(S|CBL)$ is the probable occurrence of the investor sentiments, conditioning the liquidity-providing cost being true.

3. Analysis and Discussion

The dataset is quantified in Table 1, where the variables are reported to be positively skewed with a fat-tailed numerical distribution. The liquidity proxies are checked in terms of relationship to measure the liquidity-providing cost. Table 2 depicts that the liquidity measures are positive and significantly correlated. The measurement of the liquidity-facilitating cost and investor emotions are plotted in Figure 1. It is clearly noted that the variables are not constant. This variability matters to be investigated.

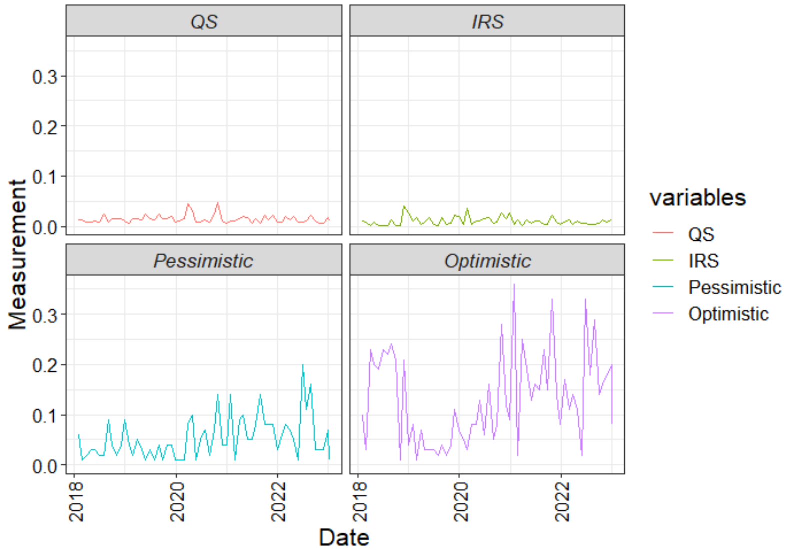


Figure 1. Time-varying measurement of the variables (Monthly basis).

Table 1. Descriptive quantification (daily basis).

Variables	Median	Mean	Standard Deviation	Skewness	Kurtosis
QS	0.0119	0.0140	0.0084	2.5036	13.2685
IRS	0.0076	0.0099	0.0093	2.1717	10.5175
Pessimistic	0.0400	0.0549	0.0506	2.3338	14.1394
Optimistic	0.1100	0.1277	0.0919	0.8412	3.6913

*Notes: Quoted Spread: QS; Informed Realized Spread: IRS. Significance level codes: *** < 0.001; ** < 0.01; * < 0.05.*

Table 2. Association between liquidity proxies (daily basis).

Variables	Correlation	p-value
(QS, IRS)	0.34	0.000 ***

Table 3. Regression Analysis (daily basis).

Variables		Estimate	p-value
Entire Dataset Analysis			
QS (a)	Intercept	0.0123	0.000 ***
	Pessimistic	0.0663	0.000 ***
	Optimistic	-0.0151	0.000 ***
IRS (b)	Intercept	0.0103	0.000 ***
	Pessimistic	0.0262	0.000 ***
	Optimistic	-0.0136	0.000 ***
Post-Pandemic Analysis			
QS (c)	Intercept	0.0109	0.000 ***
	Pessimistic	0.0801	0.000 ***

	Optimistic	-0.0206	0.000 ***
IRS (d)	Intercept	0.0095	0.000 ***
	Pessimistic	0.0365	0.000 ***
	Optimistic	-0.0178	0.001 **
Economic Blockade Analysis			
QS (e)	Intercept	0.01241	0.000 ***
	Pessimistic	0.22856	0.000 ***
	Optimistic	0.02613	0.515
IRS (f)	Intercept	0.010920	0.00163 **
	Pessimistic	0.260564	0.000 ***
	Optimistic	-0.053325	0.25082

Notes: (a) Adjusted R-squared: 0.1215; F-statistic: 86.92; p-value: 0.000; (b) Adjusted R-squared: 0.0179; F-statistic: 12.33; p-value: 0.000; (c) Adjusted R-squared: 0.1374; F-statistic: 56.82; p-value: 0.000; (d) Adjusted R-squared: 0.0209; F-statistic: 8.486; p-value: 0.000; (e) Adjusted R-squared: 0.5184; F-statistic: 28.45; p-value: 0.000; (f) Adjusted R-squared: 0.3715; F-statistic: 16.08; p-value: 0.000.

A linear combination of the variables is first examined in Table 3 by means of the Multiple Linear Regression technique. The investigation of the entire dataset reports that the investor sentiments are linked with the liquidity-providing cost. The pessimistic sentiments are positive and significantly associated with the liquidity measures. This implies–that the cost against trading of the KSE 100 Index inclines in the bearish periods. Therefore, the liquidity supplier tends to be compensated in environments of uncertainty and imposes a higher cost for accepting the position of the KSE 100 Index. Meantime, the liquidity-providing cost is negative and significantly explained by the investor optimistic sentiments. The positive association indicates-that the cost of trading of the KSE 100 Index declines in the bullish market periods.

The regression analysis is executed between March 11, 2020 - January 06, 2023, i.e., the post-pandemic. In environments of the pandemic uncertainty, the investor sentiment indicators are found to be determinants of the liquidity-providing cost. The liquidity-facilitating cost is positive and significantly explained by the pessimistic sentiments. This indicates that negative sentiment increases the cost of accepting the position of the KSE 100 Index during the pandemic era. Thereby, the liquidity supplier would be compensated against trading of the KSE 100 Index in environments of the pandemic uncertainty and imposes a higher cost on the counterparty. The optimistic sentiments are negative and significantly associated with the liquidity proxies. This implies that the bullish period decreases the trading cost of the KSE 100 Index during the pandemic era.

The analysis of the economic blockade covers the period March 11, 2020 - May 29, 2020. This phenomenon relates to a sudden halt in global economic activities against the patchwork of social and economic restrictions. In the period of the economic blockade, the liquidity-facilitating cost is reported to be positive and significantly associated with the investor pessimistic sentiments. This implies that the trading cost of the KSE 100 Index increases in response to the bearish sentiments. Therefore, the liquidity supplier perceives the KSE 100 Index as a risker investment in the economic blockade era and imposes a higher conditional cost on the counterparty. However, the liquidity-facilitating cost is not significantly explained by the investor optimistic sentiments in the period of the economic blockade.

Table 4. Bayesian Analysis (daily basis).

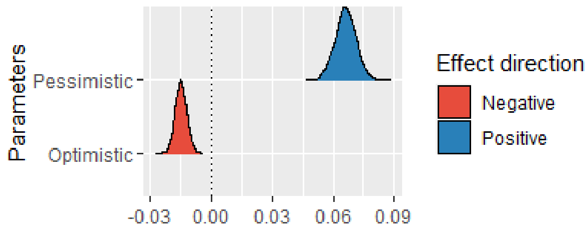
Variables	Parameters	Median	PD	% in ROPE	ESS
Entire Dataset Analysis					
QS	Intercept	0.01	100%	0%	3133
	Pessimistic	0.07	100%	0%	1866
	Optimistic	-0.01	100%	0%	1819
IRS	Intercept	0.01	100%	0%	3208
	Pessimistic	0.03	100%	0%	1503
	Optimistic	-0.01	100%	0%	1391
Post-Pandemic Analysis					
QS	Intercept	0.01	100%	0%	3044
	Pessimistic	0.08	100%	0%	1609
	Optimistic	-0.02	100%	0%	1599

IRS	Intercept	0.009	100%	0%	2970
	Pessimistic	0.04	100%	0%	1600
	Optimistic	-0.02	99.88%	0%	1686
Economic Blockade Analysis					
QS	Intercept	0.01	100%	0%	5157
	Pessimistic	0.23	100%	0%	1866
	Optimistic	0.03	74.52%	2.92%	1904
IRS	Intercept	0.01	99.95%	0%	5850
	Pessimistic	0.26	100%	0%	1679
	Optimistic	-0.05	86.83%	2%	1629

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

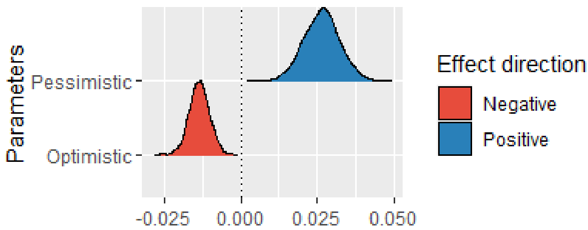
Based on the Bayesian theorem, the dataset is further quantified in Table 4 using the Gaussian distribution. If the entire dataset is examined, the posterior probability demonstrates the occurrence of the cost in accepting the KSE 100 Index in response to the investor sentiments. The probability of direction suggests a 100% positive linkage of the pessimistic sentiments with the liquidity-facilitating cost. This relationship illustrates a 100% occurrence of the cost in facilitating liquidity for the KSE 100 Index in response to the bearish periods. Meanwhile, the probability of distribution reports a 100% negative link between the optimistic sentiments and the liquidity measures. This indicates the occurrence of the liquidity-facilitating cost in response to the bullish periods. The graphical demonstration for the probability of direction is plotted in Figure 2.

During the Post-pandemic, the posterior probability certainly reports the occurrence of the liquidity-facilitating cost in response to the sentiment indicators. The probability of distribution depicts a 100% positive relativeness between pessimistic sentiments and liquidity measures. This quantification suggests a 100% occurrence of the cost in accepting the position of the KSE 100 Index in response to the bearish market periods. Meantime, the probability of direction finds a 100% negative linkage of the optimistic investor sentiments with the quoted spread. However, the probability of distribution illustrates a 99.88% negative relativeness of the bullish periods with the informed realized spread. This is obviously an indication for the occurrence of the liquidity-facilitating cost in response to the bullish market periods. The graphical representation for the probability of direction during the post-pandemic period is plotted in Figure 3.

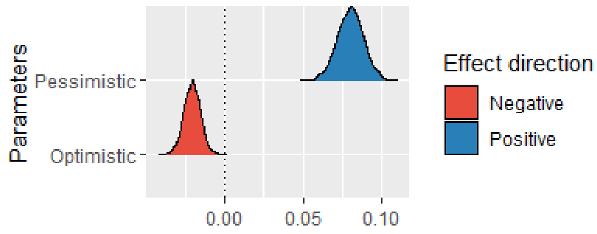


(QS)

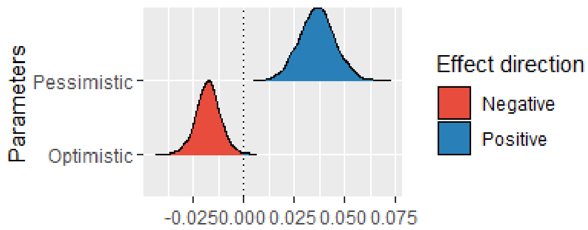
Figure 2. The graphical demonstration of the probability of direction through the entire dataset.



(IRS)



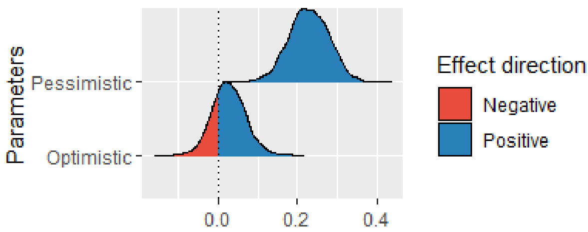
(QS)



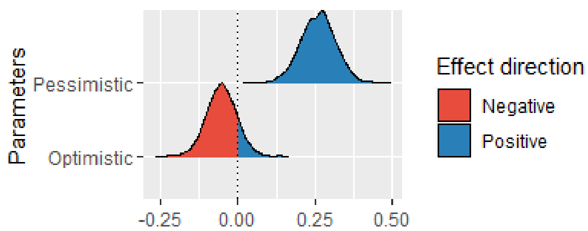
(IRS)

Figure 3. The graphical demonstration of the probability of direction during the post-pandemic period.

In the period of the economic blockade, the probability of distribution depicts a 100% positive relativeness of the bearish sentiments with the spread measures. This quantification reports a 100% occurrence of the cost in facilitating the liquidity for the KSE 100 Index in response to the investor pessimistic sentiments. Conversely, the posterior likelihood is 74.52% between bullish marker periods and the quoted spread. Meantime, the probability of direction indicates 86.83% negative relativeness of the optimistic sentiments with the informed realized spread. This implies that there is less probability for the occurrence of the liquidity-providing cost in response to the bullish market periods. In the economic blockade era, the graphical demonstration of the probability of direction is depicted in Figure 4.



(QS)



(IRS)

Figure 4. The graphical demonstration for the probability of direction in the economic blockade era.

4. Conclusion

In this study, the microblogging perceptive was applied as an opinionated source to estimate the liquidity-facilitating cost for the KSE 100 Index. This phenomenon was particularly related to the period of economic blockade and post-pandemic uncertainty. A linear combination was found between sentiment indicators and liquidity. These results were unchanged in the post-pandemic period. Importantly, the bearish sentiments were found to be priced in liquidity during the economic blockade era. From the Bayesian theorem, the occurrence of the liquidity-associated cost was noticed in response to the bearish and bullish periods. The same findings were reported in the pandemic environments. In the economic blockade era, the posterior probability identified an occurrence of the liquidity-facilitating cost during the bearish market period.

This quantification may be more applicable to managing the liquidity risk from the microblogging perceptive. The findings may have potential implications in the market microstructure, where the supplier of liquidity can reduce its risk exposure against the informed counterparty. Therefore, the transparency of an asset's value should be determined by the microblogging-opinionated content. In the context of geographical factor, the results may not be generalizable to the systematic liquidity risk. As the pandemic is still under discussion, a broader analysis may better reflect the authoritative role of microblogging-based rumors on systematic liquidity.

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Conflict of interest

The author of this manuscript declares no conflict of interest.

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