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Research article

In COVID-19 outbreak, correlating the cost-based market liquidity risk to microblogging sentiment indicators

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Abstract: In the wake of the COVID-19 pandemic, this paper links the cost-based market liquidity risk to investors' sentiment analysis through microblogging content. The study performed a sentiment analysis of tweets and considered distinct measures of cost-based market liquidity. In financial market, liquidity risk and execution cost are other major concerns for both academics and those who participate in trading. The literature in asset pricing usually distinct the informed trades and uninformed trades. Due to the growth of internet and Web 2.0 phenomenon, microblogging social service providers are considerably big data sources for various purposes, including the financial market behavior modeling and prediction. The empirical results, based on the analysis of Australian Securities Exchange (ASX), found that Twitter sentiment indicators were relevant in the forecasting of market liquidity and execution cost at market level. In the COVID-19 outbreak, the investors' pessimistic perceptions about the ASX caused adverse impact on its liquidity and final cost paid by traders.

Keywords: microblogging data; textual sentiment analysis; asset pricing

JEL Codes: G41, G12, G14

1. Introduction

The cost involved in executing the transaction is important to investors, because it determines the net returns. One of the most economically meaningful estimators of execution cost is the bid-ask spread. The bid-ask spread uses transaction prices as measure of trading cost. In financial market, buyer-initiated trades are executed at ask price and seller-initiated trades are executed at bid price (Corwin and Schultz, 2012). The bid-ask spread is the range between the best lowest ask price and the best highest bid price. The bid-ask spread, and its components are also indicators of financial market liquidity. Financial market liquidity or its risk is an active area of research for both academics and those who participate in trading.

The literature in asset pricing, in general, defines the liquid market with the features, such as the low transaction cost and the immediacy of transaction execution. In other words, a market is recognized as liquid where a trade can be immediately executed with minimum effect on price. The recent breakdown in global financial markets which began in the middle of 2007 crucially suggests that the financial market liquidity is an important area for institutions to consider. Market liquidity influences the corporate financing decision-making process (Amihud and Mendelson, 2008; Norli et al., 2015), assets' returns and cost of capital (Amihud and Mendelson, 1986; Acharya and Pedersen, 2005). Market liquidity considerably matters in maintaining financial system stability and is an important issue in the literature of market microstructure.

Market microstructure is majorly concerned with details of how financial securities are traded, costs involved with facilitating transaction services, and effects of these costs on assets' prices. Market liquidity is a multidimensional concept, and defined in various ways according to the context in which it is used. In economics, market liquidity is referred to the future volatility of prices or the immediate execution of transaction (Hicks, 1962). Financial market liquidity, in general, denotes to the ease of executing a transaction with limited price effect and low execution cost. The informed trading, either executed by buyer or seller, is one of the key determinants to estimate the bid-ask spread (Glosten and Milgrom, 1985).

The community of online social media is growing globally at a rapid pace. Social media is crucial in awareness creation and covers a wide area of research fields. It facilitates the best mode of communication, where users can share their interest. Twitter is one such social media, which permits its users to share short opinionated information on any topic, including the financial analysis for investment decision making. Unlike traditional media, microblogging data is readily available at low cost, and permits the realized assessment of investors' mood (Oliveira et al., 2017). However, the sufficient knowledge is required to operate distinct statistical programming that can transform the unstructured shared information into potential sentiments' indicators.

Text mining of microblogging can be applied to construct the unstructured information into valuable opinionated contents (Feldman, 2013). These opinionated contents are crucial for behavioral analysis of financial market (Bank et al., 2019). In this context, investors are using social media to share their knowledge and intuition about the expected future value of financial assets (Oliveira et al., 2017). In financial market, market liquidity risk is one of major concerns for both academics and investors. This risk arises in which a transaction cannot be executed quickly enough to prevent or minimize a loss. Market liquidity risk, in general, is considered the center of any financial crisis and the systemic liquidity risk should closely be monitored (Saleemi, 2014).

The bid-ask spread is obviously important for empirical research in market microstructure, and widely used as the proxy for market liquidity and trading cost at both market and firm levels. The transactions are usually separated into the informed or uninformed trades (Kyle, 1985). This has considerably essential implications in the price formation. Trading with informed party can lead to adverse selection (Glosten and Milgrom, 1985). In this context, the literature in asset pricing argues that information, either possessed private or public, is crucial in estimating the cost-based market liquidity. Investors on financial markets can have distinct information sources. Twitter, as a microblogging social network, distributes information on professional contexts. Therefore, investors are seen to share financial related tweets (Sprenger et al., 2014).

There are various studies using Twitter sentiment indicators for the prediction of distinct areas in financial markets, but however, there is still required to cover some disciplines regarding the impact on the cost-based market liquidity of microblogging data at market and firm levels (Guijarro et al., 2019). In the coronavirus pandemic, this is the first paper that studies the impact of coronavirus outbreak on the microblogging content-based investors' behavior and as results, on the cost-based market liquidity regarding the Australian Securities Exchange (ASX). Since the end of 2019, coronavirus disease, named COVID-19, has been spreading throughout the world. On 30 January 2020, World Health Organization (WHO) announced a global alert regarding COVID-19. The coronavirus cases were gradually shifted from china to worldwide. On 11 March 2020, WHO declared COVID-19 as a pandemic. As the coronavirus cases soared and to prevent the spread of the disease, the public health policies were proposed and implemented worldwide, including travel restrictions, and curfews. Since March 2020, the impacts of COVID-19 on the global economy and the functioning of financial markets continue under debates. In coronavirus outbreak, changes in the dynamics of investments in financial and non-financial assets are relevant, and must be assessed (Sukharev, 2020). In the scenario of COVID-19 pandemic, this study uses tweeting-content based investors' sentiments to determine the cost-based market liquidity at market level.

In this context, the rest of the work is organized as follows. A brief review of the literature is presented in Section 2. A detail of the procedure for collecting the data is provided in Section 3. The obtained results are included and discussed in Section 4. The main findings of the work are concluded in Section 5.

2. Literature review

The analysis of microblogging content-based sentiments has been gained huge attention into the various fields, including to forecast stock market (Yu et al., 2013). Sentiment analysis is a field of Natural Language Processing (NLP). NLP helps in understanding and extracting distinct opinions on a given subject. Investor's sentiment is a multidimensional concept, and broadly explained into expectations about the fundamental value of financial assets (De Long et al., 1990), the future underlying assets' value (Baker and Stein, 2004), optimistic or pessimistic expectations (Baker and Wurgler, 2006, 2007), rational and irrational sentiments (Verma and Verma, 2007), and irrational preferences (Barberis and Huang, 2008). Social media is considerably active and crucial in user-generated information (Broadstock and Zhang, 2019).

Social media can be explained into multidimensional disciplines, including social networking sites, blogs, microblogs, collaborative projects, virtual game worlds, content communities, and virtual communities (Kaplan and Haenlein, 2010). The influential role of social media has been examined in the tourism (Zeng and Gerritsen, 2014), polling estimation (Ceron et al., 2015), healthcare (Adams et al., 2015), collaborative learning (Zhang et al., 2015), social participation (Boulianne, 2015), sport (Filo et al., 2015), communication (McFarland and Ployhart, 2015), recruiting decisions (Roth et al., 2016), crisis event analysis (Pope and Griffith, 2016), organizing (Leonardi and Vaast, 2017), public spending review (Agostino et al., 2017), and financial market prediction (Oliveira et al., 2017). Unlike traditional media, social media are easily available networks while eradicating geographical barriers (Guijarro et al., 2019).

Market participants can be seen to share information and opinions related to financial markets. Investors therefore can take advantage of social media to obtain a feedback on their investment decision-making. Social media is an efficient network for both active and passive marketing, while eliminating geographical barriers (Constantinides, 2014). Apart influence of social media on firms' marketing, the effects of it on firms' market performance, market value, and stocks have been studied in the literature of sentiment analysis (Luo and Zhang, 2013; Chung et al., 2015). Public opinions on social media effect the financial market's functioning (Li et al., 2017), and influence the financial assets' prices, returns, volatility, and trading volume (Oliveira et al., 2017).

Twitter is seen one such social network that can be applied for the stock market prediction (Zhao et al., 2016). There are around 313 million active users of Twitter who can share their opinions with tweets in more than 40 languages. The influential role of Twitter microblogging service has been investigated in various disciplines, such as election results and political debates (Larsson and Moe, 2012; Hong and Kim, 2016), academic communications (Holmberg and Thelwall, 2014), brand reputations (Vidya et al., 2015), stock market behavioral modeling (Bollen et al., 2011; Yu et al., 2013; Sprenger et al., 2014; Nasseri et al., 2015; Zhao et al., 2016; Oliveira et al., 2017; Bartov et al., 2018; Bank et al., 2019), and liquidity risk (Guijarro et al., 2019). Microblogging social network is a cost-effective source for analyzing the infinite audience and larger information, which as results, permits a deeper understanding of the relationship between users' mood and stock market. Several studies adopted tweeting content-based sentiment indicators for the financial analysis, at both market and firm levels. These studies quantified tweeting content, either into binary sentiment values (bullish vs bearish) or multi-level sentiment results.

Over the past years, there has been growing interest in issues related to the execution of financial transaction. In financial market, a trader is much interested in predicting and minimizing the execution cost at the time of trade (Almgren and Chriss, 2001; Almgren, 2003; Alfonsi et al., 2010; Predoiu et al., 2011; Gatheral and Schied, 2011). The bid-ask spread is relevant in this context, and a cost faced by investors. The bid-ask spread captures the cost of asymmetry information, immediacy cost, and order processing cost. In the literature of asset pricing, these costs are considered major components in the construction of distinct bid-ask spread models (Huang and Stoll, 1997).

The asymmetric information cost is referred to trading with the better-informed buyer or seller, which is one of the determinants of bid-ask spread. An informed buyer or seller is present with equal probability in the market (Glosten and Milgrom, 1985). An informed investor with optimistic sentiments would buy an asset at a higher ask price, and a pessimistic trader with bad news would sell an asset at a lower bid price. In case of informed trading, a financial market is perceived as illiquid and trading may cause of loss (Gorton and Metrick, 2010).

The transaction reflects inventory holding cost, in other words, the immediacy cost that liquidity providers demand against the provision of price fluctuations in the meantime and would be compensated for this risk by imposing cost on the seller (Amihud and Mendelson, 1980). The spread also compensates the liquidity providers for the order processing cost. The order processing cost is stable in the short-term (Saleemi, 2014). Spread anticipation is also relevant in the context of market liquidity risk, which considerably matters for both investors and portfolio managers (Guijarro et al., 2019). Liquidity risk is time-varying, as it is often assumed in standard asset pricing studies (Hasbrouck and Seppi, 2001).

Liquidity is a multidimensional concept, and separated into market liquidity and funding liquidity. The change in one can influence the other (Brunnermeier and Pedersen, 2009). Funding liquidity is the ease to obtain funds in the purchase of financial securities, while market liquidity refers to the immediacy of transaction execution in financial market. As market liquidity has immediate impact on traders' movements, the risk of market liquidity is an active area of research for both academics and those who participate in trading (Guijarro et al., 2019). The ease in trading a financial asset with limited price effect and low execution cost is seen to higher liquidity. The bid-ask spread is a useful measure of transaction costs faced by investors at the time of trade, and thus, a meaningful proxy for market liquidity (Roll, 1984; Glosten and Milgrom, 1985; Amihud and Mendelson, 1986; Corwin and Schultz, 2012). Liquidity providers would buy an asset at the best bid (low) price, P_{Bid}, and sell it later at the best ask (high) price, P_{Ask}. This ability ensures that liquidity providers gain yield on the transaction.

In general, the difference between P_{Ask} and P_{Bid} is the bid-ask spread, that indicates the profit claimed by liquidity providers at the time of trade. The time-varying transparency of information about assets' value, the number of liquidity providers, and the provision of liquidity uncertainty have impacts on the market liquidity (Saleemi, 2014). Market liquidity tends to be highly volatile, which implies that it can shrink within minutes and even cause a systemic risk (Guijarro et al., 2019). This risk is time-varying and increased in situations in which financial transactions cannot be executed quickly enough to prevent or minimize a loss. The forward-looking investors would protect themselves against the provision of higher illiquidity and impose cost on the seller, i.e., a higher spread. This declines the financial assets' prices. A higher spread is seen as illiquidity.

3. Data sampling and method

The literature in asset pricing has been proposed various bid-ask spread models, either focused on high-frequency data or low-frequency data. The length of examined time interval is different between high-frequency data and low-frequency data. In financial markets, the bid-ask prices of a security are quoted in seconds daily once a day, and the analysis of such dataset can be referred to the high-frequency data. However, the information of bid-ask prices quoted in seconds once a day are materially limited or not available at all related to many financial markets (Goyenko et al., 2009). Unlike the high-frequency data, the low-frequency data is easily accessible over a long history. The low-frequency data can be explained into daily features of a stock, named opening price, closing price, low price, high price, and trading volume. A wide number of services have been providing daily information of the low-frequency data. The data used in this research contains daily information of high price, low price, and closing price. This paper is considering distinct spread proxies.

3.1. Bid-ask spread proxies

In this study, the choice of spread proxies is emphasized on simple computational models because some users of liquidity (i.e., new investors) can rarely understand and utilize sophisticated models. Among the execution cost measures, these spread proxies are used most and also indicators of market liquidity.

$$Percent\ Quoted\ Spread_t = \frac{Ask_t - Bid_t}{\eta_t} \tag{1}$$

$$\eta_t = \frac{(Ask_t + Bid_t)}{2} \tag{2}$$

Quoted spread captures the pre-trade cost, which may not define the real cost that is finally paid by buyers. This issue can be resolved in the effective spread.

$$Percent\ Effective\ Spread_t = \frac{2|C_t - \eta_t|}{\eta_t} \tag{3}$$

where η_t is the mean of Ask_t and Bid_t, and C_t refers to close price of the asset on day t. A realized spread is one of the meaningful measures of cost-based market liquidity that uses the future value of bid and ask prices. It captures the immediacy cost that liquidity providers impose on seller at the time of trade. Liquidity providers take into consideration the risk of price variations in the meantime and would be compensated for this risk. The time delay in selecting the future prices depends on different markets that facilitate the information of buy and sell orders. Following an ad hoc manner, the previous studies selected different waiting periods for the future bid and ask prices, such as 5 minutes (Berkman et al., 2005), 30 minutes (Bacidore and Sofanos, 2003), 24 hours (Bessembinder and Kaufman, 1997), or daily ask and bid prices (Beebower, 1989).

$$Percent\ Realized\ Spread_t = \frac{2|\eta_{t+1} - C_t|}{\eta_t} \tag{4}$$

$$\eta_{t+1} = \frac{(Ask_{t+1} + Bid_{t+1})}{2} \tag{5}$$

where η_{t+1} is the waiting period and referred to the average of the following trading-day bid and ask prices.

3.2. Data processing

To link tweeting content-based sentiments with measures of cost-based market liquidity, this study analyzed 216,051 tweets related to the ASX during the period October 01, 2019–June 03, 2020. Figure 1 reflects the procedure adopted to create Twitter sentiment indicators. The analysis was executed on R programming software. The machine learning tools were applied to investigate the various aspects involved in this area. The Corpus function in R was used to arrange the unstructured texts into valuable contents by removing punctuations, eliminating stop words, striping leading or trailing spaces, converting words into lower case, and for privacy reasons, setting all users' identification into "@user".

In the second stage, the sentiment analysis tool on R was used to extract the structured information into distinct emotional results, denoted as bearish sentiments, bullish sentiments, or neutral sentiments. However, this paper studies the impact of bearish sentiments and bullish sentiments on the time-varying cost-based market liquidity. As the data was contained in a large number of tweets, thereby all statistics of the corresponding sentiments for each observed day were aggregated to execute analysis.

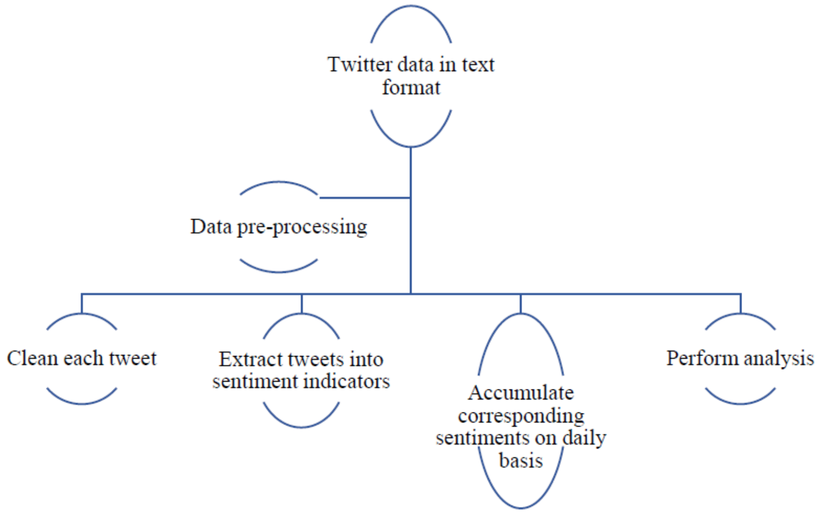

Figure 1. The procedure for extracting the microblogging data.

3.3. Benchmark model

This study constructed three regression models, that used the daily aggregated sentiments (bullish vs bearish) as the independent variables and the abovementioned cost-based market liquidity measures as the response variables.

$$Spread_t = \alpha + \beta_1 \sum_{t=1}^{T} bearish_t + \beta_2 \sum_{t=1}^{T} bullish_t + \epsilon_t \tag{6}$$

where T reflects the number of tweets related to the ASX, $bearish_t$ refers to the aggregated negative sentiments on day t, and $bullish_t$ denotes to the accumulated positive sentiments on day t. The $Spread_t$ corresponds to each cost-based market liquidity measure on day t. The ϵ_t is the error term, and no control variables were considered in the analysis.

4. Results and discussion

The descriptive statistics of the variables are shown in Table 1 and computed on daily basis. The variables are positively skewed for the data sample, which shows the right-skewed distributions with values to the right of their mean. The higher kurtosis for variables is indicating the possibility of extreme values in the data sample. The measurements of cost-based market liquidity and sentiments are presented in Figures 2 and 3, respectively. The time-series plot, presented in Figure 2, vividly identifies differences between the measures of cost-based market liquidity. The applied spread proxies capture the execution cost and the market liquidity under some specific conditions. Despite differences, the coefficients between spread measures, presented in Table 2, are highly correlated. This indicates that these proxies significantly respond to the variability of cost-based market liquidity over time.

Table 1. Descriptive statistics of variables are computed from daily observations.

Variables	Min	Mean	Median	Max	Std. Dev.	Skewness	Kurtosis
Bearish Sentiments	6.0	376.7	348.0	2357	279.19	3.31	20.74
Bullish Sentiments	10.0	643.1	661.0	2169	327.88	0.55	4.76
Quoted Spread	0.6528	2.50	1.76	13.30	2.04	2.65	11.12
Effective Spread	0.0129	1.53	1.09	12.75	1.79	3.47	18.93
Realized Spread	0.0493	1.93	1.21	12.63	2.08	2.45	10.32

Table 2. Correlation values among spread measures.

Pair	Correlation	p-value
(QS, ES)	0.8166	0.000***
(QS, RS)	0.5797	0.000***
(ES, RS)	0.5690	0.000***

Note: Quoted Spread: QS; Effective Spread: ES; Realized Spread: RS.

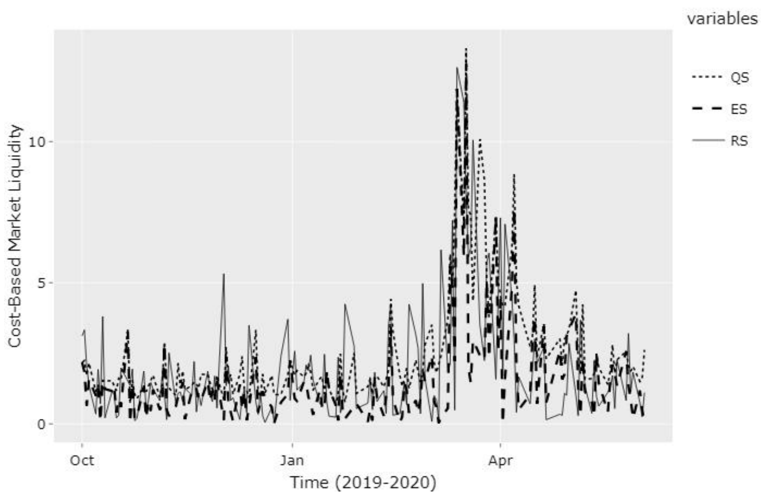

Figure 2. Time-varying cost-based market liquidity.

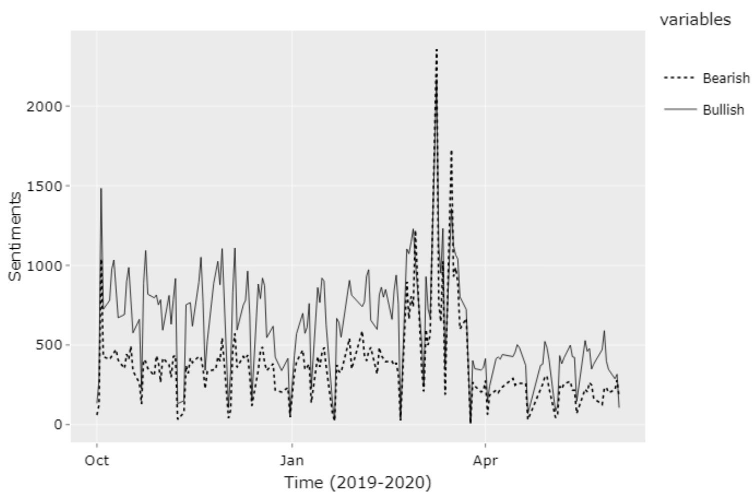

Figure 3. Time-varying Twitter sentiment indicators.

Table 3. The findings are based on daily observations, and reflect the analysis for the entire dataset.

Variables		Estimate	p-value
QS (A)	Intercept	2.9211	0.000***
	Bearish	0.0540	0.000***
	Bullish	−0.0381	0.000***
ES (B)	Intercept	1.7634	0.000***
	Bearish	0.0236	0.0113*
	Bullish	−0.0175	0.0270*
RS (C)	Intercept	2.2997	0.000***
	Bearish	0.0512	0.000***
	Bullish	−0.0357	0.000***

Note: A) Adjusted R-squared: 0.1473; F-statistic: 15; p-value: 0.000; (B) Adjusted R-squared: 0.0275; F-statistic: 3.291; p-value: 0.0397; (C) Adjusted R-squared: 0.126; F-statistic: 12.68; p-value: 0.000; Significance codes: *** < 0.001; ** < 0.01; * < 0.05.

Following the COVID-19 outbreak, the upward trend in the bid-ask spreads can be clearly seen in Figure 2. Figure 3 shows the time-varying Twitter sentiment indicators regarding the ASX. It has been seen that bullish sentiment indicator and bearish sentiment indicator are not constant. This study analyzed the relationship between cost-based market liquidity and investors' sentiments by means of a regression analysis. In Table 3, the relationship of Twitter sentiment indicators with distinct cost-based market liquidity measures is quantified for the entire dataset.

Table 3 shows the coefficients values where sentiment indicators (bearish vs bullish) are considered as the independent variables and each spread proxy is the dependent variable. The obtained results identified that the bearish sentiments are positively significant correlated with each spread measure. This seems, that an incline in negative sentiments increases the execution cost, and as results, shrinks the market liquidity over time. The statistical numbers of R-Squared, p-values, and F-statistics, shown in Table 3, further clearly indicate that a much larger proportion of the investors' pessimistic mood affect the time-varying cost-based market liquidity for each dataset. The findings illuminate that the investors' negative expectations about the ASX impose adverse impacts on its liquidity and cost of trading.

It can be seen in Table 3, that the bullish sentiments are negatively significant correlated with each spread proxy. This seems that an incline in positive sentiments leads to the lower transaction cost, and thus, facilitates the market liquidity. The corresponding R-Squared, p-values, and F-statistics further vividly explain that a much larger proportion of the investors' optimistic mood affect the market liquidity and the final cost paid by traders. The results indicate that the investors' perceptions about the bullish market have positive impacts on the cost-based market liquidity related to the ASX. On 11 March 2020, WHO declared COVID-19 as a global epidemic. The following experiment was constructed during the period March 11, 2019–June 03, 2020: the study observed whether microblogging sentiment indicators are also meaningful to explain the cost-based market liquidity for the sub-period. Table 4 reflects the regression estimates for each dataset. The results indicate that the bearish sentiments are positively significant correlated with the cost-based market liquidity, estimated by Quoted Spread and Realized Spread. This relationship clearly identifies, that an incline in pessimistic mood due to the COVID-19 increases the final cost paid by traders, and as results, shrinks the market liquidity. In the wake of the COVID-19 pandemic, the investors' pessimistic expectations about the ASX cause adverse effects on its market liquidity and cost of trading.

The experiment executed between bearish sentiment indicator and Effective Spread illuminates, that the investors' pessimistic mood is also positively correlated with the cost-based market liquidity, but nevertheless, this relationship is not seen significant. This might be caused by theoretical assumptions that are used to construct the Effective Spread. As discussed earlier, that the applied measures of cost-based market liquidity are based on distinct theoretical conditions. Despite differences behind the construction of each spread proxy, these proxies are standard in the asset pricing studies and provide meaningful information of buy or sell orders. However, the regression estimates between spread proxies and bullish sentiment indicator are again negative in each dataset, but their relationship is not significant. This implies, that the investors' optimistic expectations about the ASX are not efficacious to influence the size of its bid-ask spread in the wake of the COVID-19.

Table 4. The findings are based on daily observations during the period March 11, 2019–June 03, 2020.

Variables		Estimate	p-value
QS (A)	Intercept	4.017902	0.000***
	Bearish	0.0457	0.0275*
	Bullish	−0.0352	0.1014
ES (B)	Intercept	2.4391	0.000***
	Bearish	0.0164	0.4126
	Bullish	−0.0133	0.5261
RS (C)	Intercept	2.6876	0.000***
	Bearish	0.0473	0.0329*
	Bullish	−0.0317	0.1671

Note: A) Adjusted R-squared: 0.061; F-statistic: 3.164; p-value: 0.0488; (B) Adjusted R-squared: −0.0184; F-statistic: 0.394; p-value: 0.676; (C) Adjusted R-squared: 0.0743; F-statistic: 3.689; p-value: 0.030; Significance codes: *** < 0.001; ** < 0.01; * < 0.05.

5. Conclusion

In this study, the work proposed a robust methodology that observed whether the changes in the microblogging content-based investors' sentiments are occurred due to the COVID-19 pandemic and relevant for the prediction of the cost-based market liquidity regarding the ASX. This paper analyzed the effects of Twitter sentiment indicators on the cost-based market liquidity, estimated by distinct bid-ask spread proxies. First, the study executed analysis on a daily basis for the entire dataset, and found, that Twitter sentiment indicators were significantly seen to influence the market liquidity and the execution cost for ASX. The study identified that the time-varying cost-based market liquidity was positively correlated with the investors' pessimistic mood on Twitter. This relationship significantly indicates that the time-varying bearish sentiments on Twitter increased the execution cost, and thereby, declined the market liquidity. The investors' expectations about the bullish market were negatively correlated with the cost-based market liquidity. This relationship significantly shows that the time-varying investors' optimistic sentiments on Twitter declined the execution cost, and as results, facilitated the higher market liquidity for ASX.

If the sub-period was constructed to investigate the difference of the relationship between cost-based market liquidity and investors' sentiments due to the COVID-19 outbreak, the investors' pessimistic mood causes adverse impacts on the size of the bid-ask spread for ASX. This implies, that as fear grows about the impact of the COVID-19 pandemic, the market liquidity shrinks, and the cost of trading increases. This is an indicator of illiquid market and liquidity risk in the Australian financial market.

The obtained results found, that microblogging sentiment indicators, as source of information, are significantly relevant in the prediction of the cost-based market liquidity at market level. However, the present study only analyzed the ASX, which is limited to concluding in a broader sense whether the investors are pessimistic throughout the world due to the COVID-19 pandemic and caused illiquid markets. Understanding the systemic changes in investors' mood caused by the economic shock of coronavirus, the results encourage to investigate the effects on the global liquidity risk of the popular Twitter microblogging service.

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Conflict of interest

The author declares no conflicts of interest in this paper.

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