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Research article

COVID-19 and liquidity risk, exploring the relationship dynamics between liquidity cost and stock market returns

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Abstract: The impact on economic aspects of the COVID-19 is continuing under discussion. This study unveils effects of the pandemic on relationship dynamics between liquidity cost and stock market returns. Using the time series and machine learning techniques, the analysis is based on the Dow Jones Industrial Average (DJI) index. If the entire dataset was examined, the liquidity cost was found to be positive and significantly related to the DJI index returns. From the VAR estimation, the market returns were significantly explained by past values of the liquidity cost. The statistical Granger-causality was also observed between variables. If the relationship was analyzed during peak restrictions, the results were changed. The liquidity cost was observed to be negative and insignificantly related to the DJI index returns. The market returns were not associated with lags of the liquidity cost. In addition, the Granger-causality was not found between variables. If effects associated with easing restrictions were examined, the liquidity cost was found to be positive and significantly associated with returns on the DJI index. Meanwhile, the returns were more sensitive to the liquidity cost. However, the market returns were not explained by lags of the liquidity cost. The liquidity cost did not Granger-cause returns. The findings suggest that the liquidity cost must be priced in returns due to the pandemic-related uncertainty.

Keywords: asset pricing; liquidity cost; stock market returns; Covid-19 impact

JEL Codes: G12, G01

1. Introduction

The immense concerns about effects of the COVID-19 are raised by academic communities and those who participate in the financial markets. The global financial markets have become highly volatile due to the recent pandemic-related uncertainty and economic destruction (Zhang et al., 2020). The daily growth in the coronavirus cases and deaths are imposing adverse consequences on yields of the assets (Al-Awdahi et al., 2020). As fear grows about the pandemic-related uncertainty, the lower market liquidity and higher trading cost was significantly explained by the investors' pessimistic mood (Saleemi, 2020a). The COVID-19 is imposing immense obstacles in the global economic development (Goddell, 2020). Meanwhile, the policy makers are announcing potential financial packages to alleviate the economic uncertainty caused by the pandemic.

Since March 2020, the recent pandemic-related uncertainty and its damages on the global economic markets are continuing under discussion. On December 31, 2020, several coronavirus cases were identified in China. As the coronavirus cases were gradually shifted from China to worldwide, the World Health Organization (WHO) announced a global alert on January 30, 2020. Following the enormous cases and deaths around the globe, the coronavirus was announced as a pandemic on March 11, 2020. The various health policies with the particular focus on social distancing have been implemented. Over 1 billion people were compelled to follow severe social and economic restrictions. The patchwork of restriction causes the liquidity deterioration in the emerging stock markets and plays no vital role in the developed stock markets (Zaremba et al., 2021).

The global stock indices are noted to be greatly volatile during the COVID-19 crisis (David et al., 2021). As the coronavirus grows, the liquidity shrinks in the emerging stock markets (Haroon and Rizvi, 2020), and bond markets (Gubareva, 2020). The coronavirus cases in the US have no impact on the market liquidity (Just and Echaust, 2020). This study revisits the US stock market, and the focus lies on the relationship dynamics between liquidity cost and market returns. Since the US is one of the most severely affected countries from the coronavirus, this study investigates whether the pandemic uncertainty influences the relationship dynamics between liquidity cost and market returns.

With regard to the trading cost or liquidity risk, the coronavirus crisis is raising concerns among investors (Saleemi, 2020a). This work studies whether the liquidity cost explains the stock market returns during the recent pandemic. To the best of author's knowledge, this is the first work that investigates changes in the relationship dynamics between liquidity cost and stock market returns if caused by the pandemic-related uncertainty. Following the recent uncertainty, the findings can elucidate the response of returns towards the liquidity cost or illiquidity. The higher liquidity cost is referred to the illiquidity.

The market liquidity is one of the key variables in determining performance of the financial markets. The liquidity cost or its risk is a potential area of interest for both academics and investors, as it immediately impacts a trader's movements (Guijarro et al., 2019). The market liquidity is a priced risk factor in the financial markets (Le & Gregorious, 2020). Several studies have reported that the market liquidity shrinks during the financial uncertainty (Schnabel and Shin, 2004; Severo, 2012; Saleemi, 2014). This study examines whether the liquidity cost can be considered as a potential predictor for the stock market returns during the recent pandemic-related uncertainty.

The rest of the work is organized as follows. The literature is discussed in Section 2. Section 3 discusses the data and methods adopted in the study. Section 4 reports findings of the study. The obtained results are discussed in Section 5. Finally, the main outcomes are reported in Section 6.

2. Review of literature

The stock market direction or its estimation is an active area of research (Cervelló-Royo and Guijarro, 2020). The market liquidity drives investors' choices (Saleemi, 2020a), and traders' movements in the financial market (Guijarro et al., 2019). In the market microstructure, the market liquidity is denoted as a potential feature of the capital assets (Amihud and Mendelson, 1991). The extant literature in the asset pricing research elucidated that the market liquidity can better reflect changes in the asset returns (Amihud et al., 2015). The market liquidity influences the cost of capital (Acharya and Pedersen, 2005), assets' prices (Amihud and Mendelson, 1991), and corporate decision-making process (Norli et al., 2015).

In two main avenues, the abundant studies have examined effects on returns of the market liquidity. The first stream of studies investigated whether the liquidity as a feature influences returns of the asset. The other stream of research related returns to the systematic liquidity risk. The financial market liquidity is a risk factor in the financial markets. When accepting the illiquid financial inventory, the liquidity provider tends to be compensated by a higher yield. The securities whose yields are more sensitive to the liquidity shocks relate to the higher returns (Le & Gregorious, 2020). Amihud and Mendelson (1989) exhibited distinct yields on the assets that have identical risk factors. The market liquidity was illuminated as the major factor for dissimilarity in yields.

The cost of trading or liquidity cost drives yields on the asset (Jacoby et al., 2000). Amihud et al. (1997) documented a positive relationship between market liquidity and market returns. They further reported that the liquidity improvement is related with a positive and perpetual price appreciation. Brennan et al. (1998) elucidated that the market liquidity is negatively associated with stock returns. Aparicio and Estrada (2001) suggested that the market liquidity crucially elucidates returns across capital markets. Pástor and Stambaugh (2003) examined whether the market-wide liquidity is an important factor to explain the stock returns. They demonstrated that the expected yields on assets are associated cross-sectionally with sensitivities of returns to variations in aggregate market liquidity.

Acharya and Pedersen (2005) proposed a liquidity-adjusted Capital Asset Pricing Model (CAPM). They suggested that the market liquidity is a priced element in cross section of the asset yield. Bekaert et al. (2007) noted in their research that the market liquidity is not a significant predictor for the asset return. Korajczyk and Sadka (2008) reported that the market liquidity as a feature of the financial asset is priced in cross section of the asset returns. Hasbrouck (2009) found a positive relationship between effective trading cost and asset returns. Whether the liquidity is priced in the asset returns, Lam and Tam (2011) demonstrated that the stock returns are significantly explained by the market excess return, size, book-to-market ratio, and market liquidity.

Chikore et al. (2014) suggested that changes in the market liquidity highly impact returns because the liquidity provider would price liquidity premium in the asset. They found a negative association between market liquidity and asset returns. Whether the systematic liquidity risk influences the stock returns, Vu et al. (2015) demonstrated that the liquidity risk is priced and time-varying. They empirically elucidated that the aggregate liquidity risk significantly impacts returns, especially during the market downturns. Hartian and Sitorus (2015) analyzed market liquidity and stock index returns in distinct markets. In developing markets, they observed a positive correlation between market liquidity and stock index return. Meanwhile in the developed markets, the liquidity corresponds negatively with the stock index return.

Whether illiquidity risk relates to the expected excess returns, Chiange and Zheng (2015) noted a positive association between returns and illiquidity risk. Vo and Bui (2016) found that the liquidity risk impact is small in elucidating the asset returns. Dinh (2017) found a significant impact on returns of the idiosyncratic risk and liquidity. The study suggested that the idiosyncratic risk plays a more authoritative role than the systematic risk. Leirvik et al. (2017) demonstrated that the stock market returns are not explained by the market liquidity and liquidity cost. Marozva (2019) suggested that the market liquidity is a crucial aspect in pricing the asset yields. The study revealed that the asset excess returns are positively associated with illiquidity.

The above discussion indicates that there is no unified standard to elucidate the relationship between market liquidity and asset returns. The time-varying liquidity risk is a potential area of research for both academics and traders. The market liquidity is a multidimensional concept and is elucidated in distinct context. Hicks (1962) referred the market liquidity to the future volatility of prices. Roll (1984) applied the effective trading cost to estimate the market liquidity. Glosten and Milgrom (1985) suggested that the information about fundamental value of the asset drives level of liquidity in the financial market. Lybek and Sarr (2002) described the market liquidity in the context of immediacy, cost, depth, breadth, and resiliency features. Liu (2006) argued that an asset is liquid if it is immediately traded at low cost without causing a big change in its price. Gorton and Metrick (2010) suggested that a financial transaction is illiquid in times of informed counterparty.

The financial market liquidity, in general, relates to the ease of executing the financial transaction at a low cost (Saleemi, 2020b). The abundant measures, either focusing on volume-based market liquidity or cost-based market liquidity, are proposed in the asset pricing literature (Goyenko et al., 2009). In early stages, the literature devoted attention on trading price and quantity to estimate the market liquidity. Following the bid-ask spread model introduced by Roll (1984), the literature in the cost-based market liquidity has gained a considerable amount of attention. In the financial market, the bid-ask spread is the most common method to estimate the liquidity cost.

The elucidation of bid-ask spread or its measurement is a multidimensional concept. However, two aspects are common in distinct bid-ask spread models (Degennaro and Robotti, 2007). The market frictions influence the market liquidity and the liquidity is a time-varying risk factor. The market frictions are referred to the cost at the time of trade. The trading cost is categorized into explicit cost and implicit cost. The explicit cost is tax or brokerage fees and clearly recognizable at the time of trade. Meanwhile, the implicit cost is not identifiable in advance of trading. The bid-ask spread elucidates almost the entire cost of trading (Corwin and Schultz, 2012; Saleemi, 2020b).

In the asset pricing literature, the bid-ask spread is separated into inventory immediacy cost, asymmetric information cost and order processing cost. The market makers play a vital role in functioning the financial markets by matching buy and sell orders (Demsetz, 1968). These activities inject liquidity in the market when the actual counterparty is absent or unwilling to accept the inventory position. When accepting the risk of holding financial inventory, the liquidity provider would also minimize its risk exposure against the future price dispersion. In this context, the supplier of liquidity tends to impose a cost on the seller. Ho and Stoll (1981) related the higher immediacy cost to the higher expected volatility of asset prices.

The asymmetric information cost model investigates information effects on the ease and cost of trading (Gorton and Metrick, 2010). The asymmetric information is priced in the asset pricing (Saleemi, 2020b). In case of informed trader about fundamental value of the asset, there is a risk of loss for the uninformed counterparty (Gorton and Metrick, 2010). The supplier of liquidity tends to be compensated for such potential loss. Therefore, a higher liquidity cost is imposed on the seller (Easley and O'Hara, 2004). The other stream of area includes order processing cost to framework the bid-ask spread. The higher spread compensates against the higher order processing cost.

The prices of the asset are quoted in pairs. The quoted prices are referred to the ask price and bid price. The spread, in general, is defined as the difference between ask price and bid price. The supplier of liquidity would accept a position at the best low or bid price, and redeem it later at the best high or ask price. This ability of the liquidity provider generates yields at the asset redemption. The size of the spread is crucially relevant in the context of market liquidity (Corwin and Schultz, 2012; Saleemi, 2020b). The liquidity provider tends to be protected against uncertainty of the future price dispersion. The higher spread elucidates unwillingness of the liquidity supplier to accept the financial inventory without imposing a cost on the counterparty. In this context, a higher spread is referred to the illiquidity or higher liquidity cost.

3. Materials and method

In the asset pricing literature, several measures have been proposed to estimate the liquidity cost. A few shortcomings are identified in various liquidity cost models (Goyenko et al., 2009; Saleemi, 2020b). Most recently, an alternative model of the cost-based market liquidity (CBML) was developed by Saleemi (2020b). In this study, the CBML model is applied with primary focus on the low-frequency data. The liquidity proxies are separated into the high-frequency and low-frequency measures. The high-frequency proxies are used to analyze the intraday transactions. Conversely, the low-frequency measures entirely focus on daily features of an asset. The CBML measure is based on daily features of the DJI index, namely the high prices, low prices, and closing prices. The construction of the CBML model is given as below:

$$CBML_t = \sqrt{[(S_{t-1}) - (v_t^S)]^2} \tag{1}$$

where, S_{t-1} defines a ratio of the stock range to its closing price on day $t-1$.

$$S_{t-1} = \frac{(High_{t-1} - Low_{t-1})}{Close_{t-1}} \tag{2}$$

where, $High_{t-1}$ is the ask price of day $t-1$; and Low_{t-1} refers to the bid price of day $t-1$. The model demonstrates asymmetric information impact for the following trading session. In this context, v_t^S is the ratio of the informed stock range to its closing price on day t.

$$v_t^S = \frac{(v_t^{ask} - v_t^{bid})}{Close_t} \tag{3}$$

By considering risk neutrality for the future trading session, the stock is valued at:

$$\eta_t = \frac{(High_t + Low_t)}{2} \tag{4}$$

Assuming equal probability of the informed market participant, the estimated ask value for which the inventory holder tends to redeem its position is expected conditional at:

$$v_t^{ask} = (High_t \pi) + (\eta_t \pi) \tag{5}$$

Meanwhile, the future bid value is conditional on a trade at:

$$v_t^{bid} = (Low_t \pi) + \ (\eta_t \pi) \tag{6}$$

v_t^{bid} is the expected lowest price of the stock that a buyer would pay in the following trading session. To examine effects on returns of the liquidity cost, the stock market yield is estimated from the following analytical expression.

$$R_t = \left(\frac{p_t}{p_{t-1}}\right) - 1 \tag{7}$$

where, R_t refers to the stock market return of day t; p_t is the closing price of day t; and p_{t-1} denotes to the closing price of day $t-1$. The dataset was considered from January 01, 2001 to December 10, 2020. The analysis is performed on R programming software.

The study examines whether the pandemic-related uncertainty influences the relationship dynamics between liquidity cost and stock market returns. The following linear regression model is structured to estimate effects on returns of the liquidity cost.

$$R_t = \alpha + \beta CBML_t + \epsilon_t \tag{8}$$

In the adopted regression model, R_t refers to the stock market yield of day t; $CBML_t$ denotes to the cost-based market liquidity or liquidity cost of day t; and ϵ_t is the error term. Meanwhile, the study does not include control variable.

The study also investigates linear interdependence among the multiple time series of variables. The multivariate forecasting algorithm strategy, namely the Vector Autoregression (VAR), is applied to unveil the impact of lags on variables. For estimation of lags' effects, the VAR model is constructed as follows:

$$SMR_t = \ \alpha_{SMR} + \beta_{11} SMR_{t-1} + \ \beta_{12} SMR_{t-2} + \ \gamma_{11} LC_{t-1} + \gamma_{12} LC_{t-2} \ + \epsilon_{SMR,t} \tag{9}$$

where, SMR_t indicates the stock market yield of day t; SMR_{t-1} refers to the lag value of the market return on day $t-1$; SMR_{t-2} denotes to the lag value of the return on day $t-2$; and $\epsilon_{SMR,t}$ is the white-noise variable.

$$LC_t = \ \alpha_{LC} + \ \beta_{21} SMR_{t-1} + \ \beta_{22} SMR_{t-2} + \ \gamma_{21} LC_{t-1} + \gamma_{22} LC_{t-2} \ + \epsilon_{LC,t} \tag{10}$$

where, LC_t denotes to the liquidity cost of day t; LC_{t-1} indicates the lag value of the liquidity cost on day $t-1$; LC_{t-2} refers to the lag value of the liquidity cost on day $t-2$; and $\epsilon_{LC,t}$ is the white-noise variables.

In the VAR model, SMR_t and LC_t are structured as linear combinations of their own lags and each other lags. The VAR model is reviewed in a matrix notation as:

$$\begin{bmatrix} SMR_t \\ LC_t \end{bmatrix} = \begin{bmatrix} \alpha_{SMR} \\ \alpha_{LC} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} SMR_{t-1} \\ SMR_{t-2} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} LC_{t-1} \\ LC_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{SMR,t} \\ \epsilon_{LC,t} \end{bmatrix} \tag{11}$$

Equation (11) can be further elucidated as:

$$RL_t = \begin{bmatrix} SMR_t \\ LC_t \end{bmatrix} \tag{12}$$

$$\alpha = \begin{bmatrix} \alpha_{SMR} \\ \alpha_{LC} \end{bmatrix} \tag{13}$$

$$\beta = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \tag{14}$$

$$SMR_t = \begin{bmatrix} SMR_{t-1} \\ SMR_{t-2} \end{bmatrix} \tag{15}$$

$$\gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \tag{16}$$

$$LC_t = \begin{bmatrix} LC_{t-1} \\ LC_{t-2} \end{bmatrix} \tag{17}$$

$$\epsilon_t = \begin{bmatrix} \epsilon_{SMR,t} \\ \epsilon_{LC,t} \end{bmatrix} \tag{18}$$

Equations (12)–(18) are structured as:

$$RL_t = \alpha + \beta SMR_t + \gamma LC_t + \epsilon_t \tag{19}$$

4. Results

The descriptive statistics of the variables are reported in Table 1. The numerical values are estimated from the daily financial data. The stock market returns and the liquidity cost are graphed in Figure 1. The study vividly observed that the variables are not constant and change over time. It is worth to investigating whether there is a relationship between liquidity cost and stock market returns. The relationship is found to be statistically significant in the executed experiments if the p-value corresponds to the following conditions: *** < 0.001; ** < 0.01; * < 0.05.

Table 1. Descriptive statistics for the dataset.

Variables	Min	Median	Mean	Max	SD	Skewness	Kurtosis
R	−0.1292655	0.000505	0.0002789	0.1136504	0.01202	−0.1008	16.4759
CBML	0.00000107	0.004776	0.006843	0.07974	0.00720	3.0346	18.5838

Note: Standard deviation: SD.

Table 2. The regression analysis is executed on a daily basis for the entire dataset.

Variable		Estimate	p-value
R	Intercept	−0.0002376	0.30973
	CBML	0.0754838	0.00135**

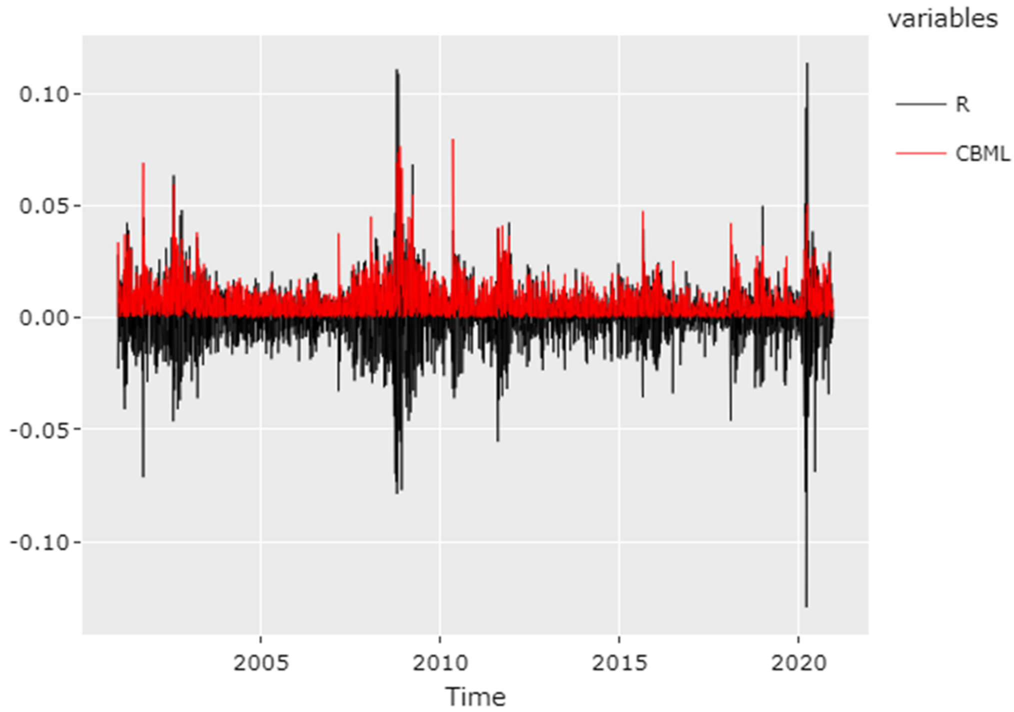

Figure 1. The time-varying liquidity cost and stock market returns.

Table 3. Linking lags to the future market return. The VAR analysis represents the entire dataset.

Variable		Estimate	p-value
SMR	$\beta_{11,SMR}$	−0.777	0.000***
	$\gamma_{11,LC}$	0.09664	0.000388***
	$\beta_{12,SMR}$	−0.3788	0.000***
	$\gamma_{12,LC}$	0.08079	0.002933**
	α_{SMR}	0.000002707	0.988911

Note: ARCH test: 0.000; JB test: 0.000.

Table 4. Linking lags to the future liquidity cost. The VAR analysis is based on the entire dataset.

Variables		Estimate	p-value
LC	$\beta_{21,SMR}$	0.03003	0.000***
	$\gamma_{21,LC}$	−0.8528	0.000***
	$\beta_{22,SMR}$	0.01031	0.103
	$\gamma_{22,LC}$	−0.3944	0.000***
	α_{LC}	−0.00000319	0.973

Note: ARCH test: 0.000; JB test: 0.000.

Table 5. Granger-causality estimation for the entire dataset.

Pairwise Granger-causality: (SMR, LC); (LC, SMR).	F-test	p-value
SMR does Granger-cause LC	12.123	0.00000551***
LC does Granger-cause SMR	6.8109	0.001107**

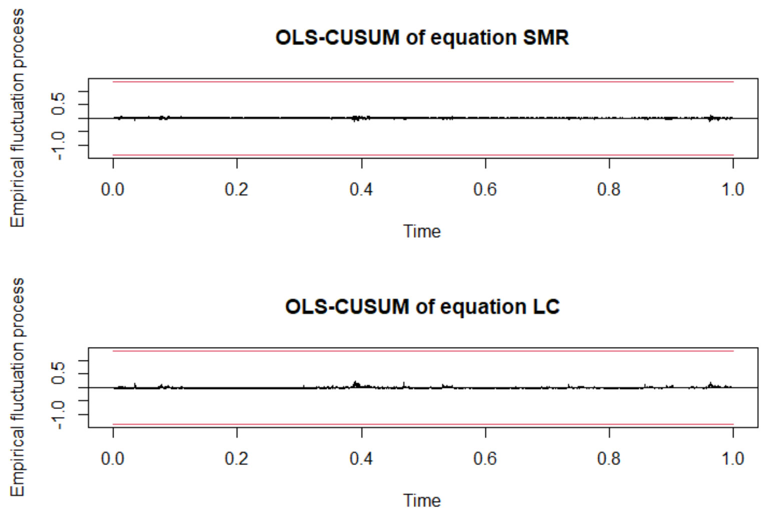

Figure 2. CUSUM test is based on the entire dataset.

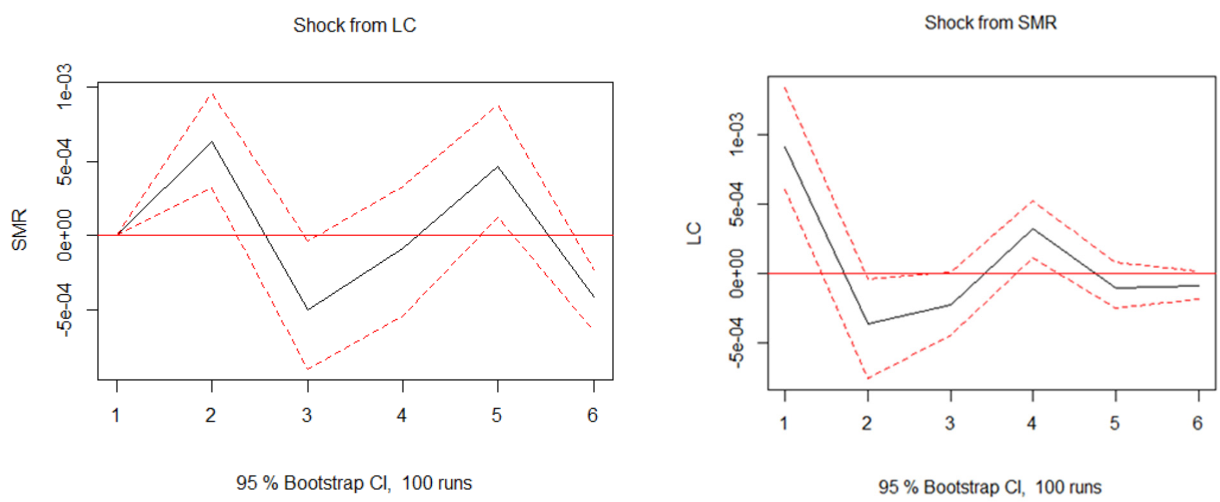

Figure 3. The Impulse Response analysis for the entire dataset.

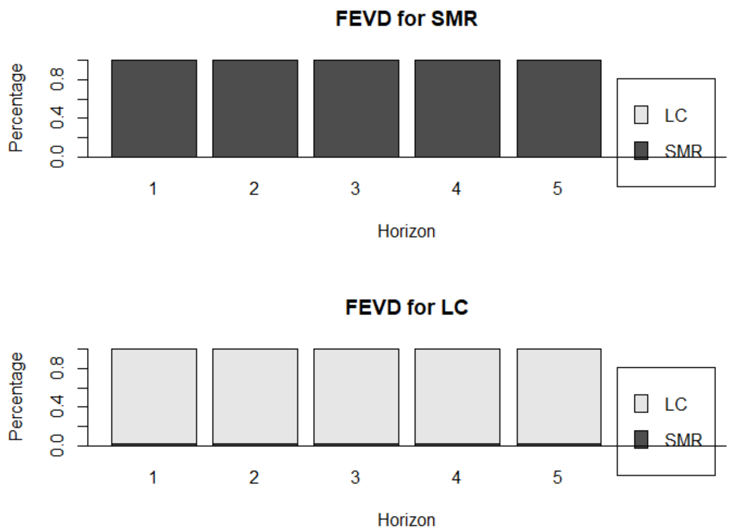

Figure 4. The variance decomposition analysis for the entire dataset.

Table 6. The regression analysis is performed during the period March 11, 2020–May 29, 2020.

Variable		Estimate	p-value
R	Intercept	0.003046	0.731
	CBML	−0.121834	0.776

Table 7. During the period March 11, 2020–May 29, 2020, linking lags to the future market return.

Variable		Estimate	p-value
SMR	$\beta_{11,SMR}$	−0.9433038	0.000 ***
	$\gamma_{11,LC}$	0.0619682	0.9059
	$\beta_{12,SMR}$	−0.2592523	0.0355*
	$\gamma_{12,LC}$	0.0163513	0.9745
	α_{SMR}	0.0002978	0.9527

Note: ARCH test: 0.3217; JB test: 0.000.

Table 8. For the period March 11, 2020–May 29, 2020, linking lags to the future liquidity cost.

Variables		Estimate	p-value
LC	$\beta_{21,SMR}$	0.0127112	0.6699
	$\gamma_{21,LC}$	−0.6932733	0.000***
	$\beta_{22,SMR}$	0.0472270	0.1227
	$\gamma_{22,LC}$	−0.2848358	0.0306*
	α_{LC}	−0.0008158	0.5178

Note: ARCH test: 0.3217; JB test: 0.000.

Table 9. Granger-causality estimation during the period March 11, 2020–May 29, 2020.

Pairwise Granger-causality: (SMR, LC); (LC, SMR).	F-test	p-value
SMR does not Granger-cause LC	2.0111	0.1394
LC does not Granger-cause SMR	0.0081649	0.9919

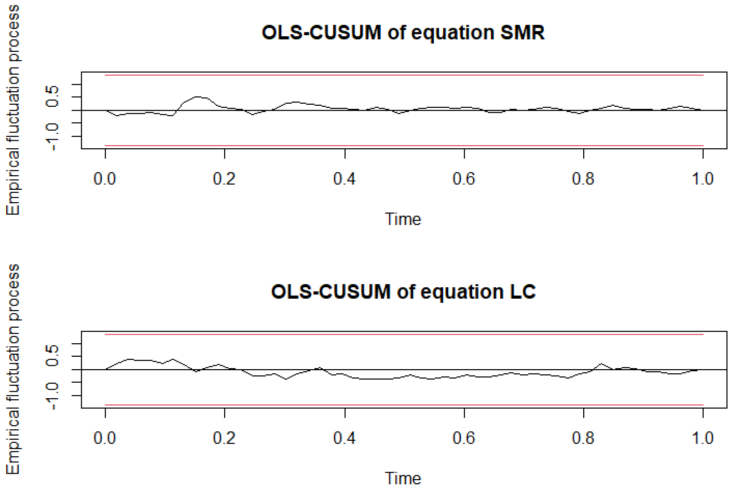

Figure 5. CUSUM test is based on the period March 11, 2020–May 29, 2020.

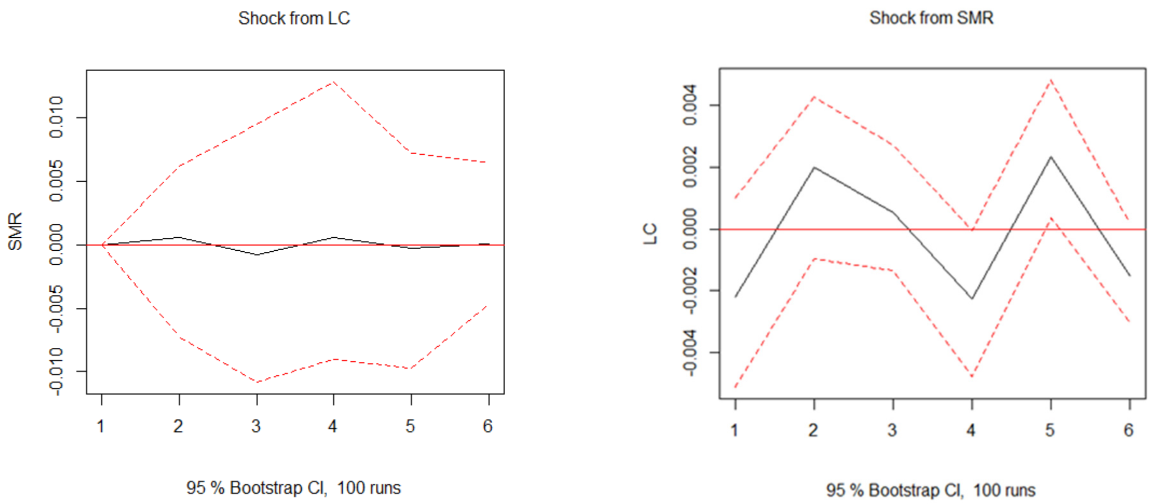

Figure 6. The Impulse Response analysis for the period March 11, 2020–May 29, 2020.

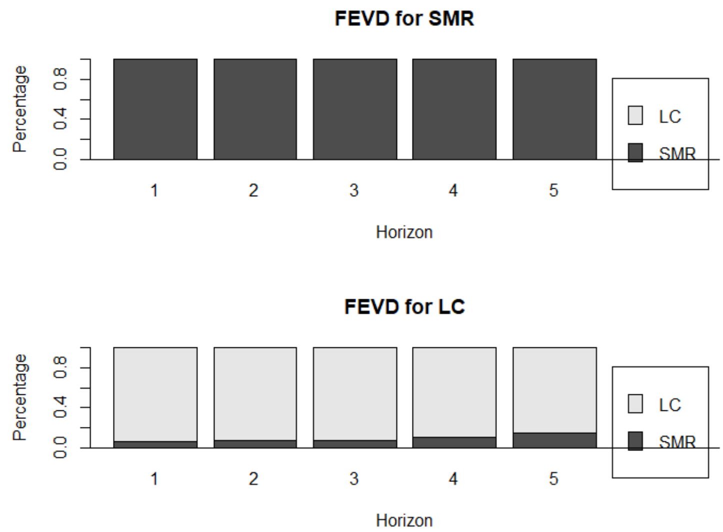

Figure 7. The Variance Decomposition analysis for the period March 11, 202–May 29, 2020.

Table 10. The regression estimates represent the period June 01, 2020–December 10, 2020.

Variable		Estimate	p-value
R	Intercept	−0.002191	0.2250
	CBML	0.445936	0.0144*

Table 11. For the period June 01, 2020–December 10, 2020, linking lags to the future return.

Variable		Estimate	p-value
SMR	$\beta_{11,SMR}$	−0.7035629	0.000***
	$\gamma_{11,LC}$	−0.1241180	0.5208
	$\beta_{12,SMR}$	−0.2014567	0.0274 *
	$\gamma_{12,LC}$	0.1761773	0.3574
	α_{SMR}	−0.0002391	0.8552

Note: ARCH test: 0.000238; JB test: 0.000.

Table 12. Following the same subset, linking lags to the future liquidity cost.

Variables		Estimate	p-value
LC	$\beta_{21,SMR}$	−0.09874	0.0106*
	$\gamma_{21,LC}$	−0.6627	0.000***
	$\beta_{22,SMR}$	−0.001959	0.9594
	$\gamma_{22,LC}$	−0.4266	0.000***
	α_{LC}	0.00001032	0.9852

Note: ARCH test: 0.0002381; JB test: 0.000.

Table 13. Granger-causality is examined during the period June 01, 2020–December 10, 2020.

Pairwise Granger-causality: (SMR, LC); (LC, SMR)	F-test	p-value
SMR does Granger-cause LC	4.6944	0.00994**
LC does not Granger-cause SMR	1.1047	0.3329

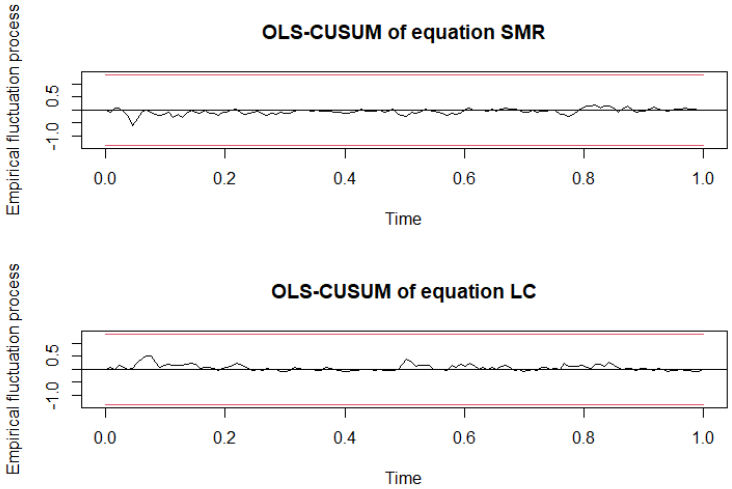

Figure 8. CUSUM test is based on the period June 01, 2020–December 10, 2020.

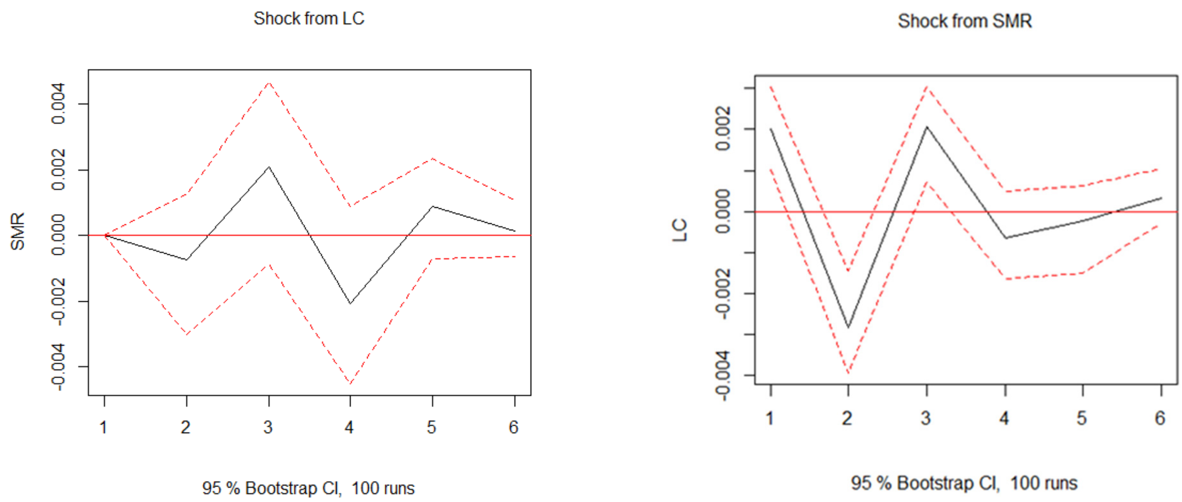

Figure 9. The Impulse Response analysis for the period June 01, 2020–December 10, 2020.

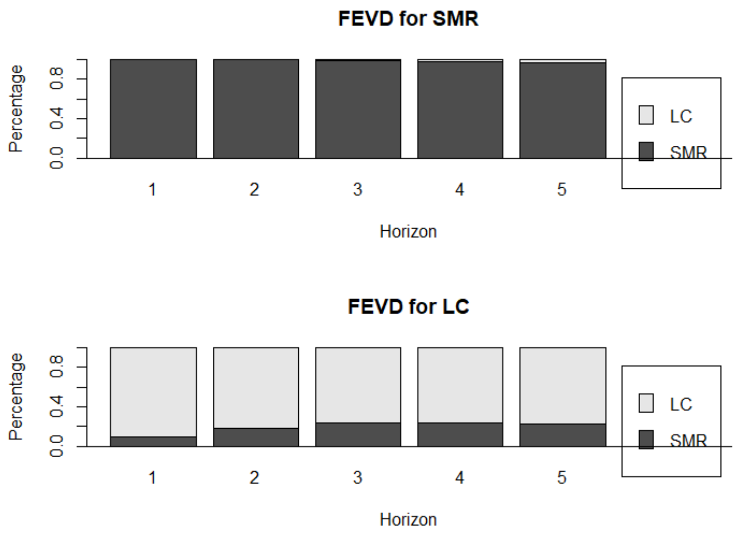

Figure 10. The Variance Decomposition analysis for the period June 01, 2020–December 10, 2020.

5. Discussion

Table 1 reports that the stock market return is negatively skewed with fat-tailed distribution. The negative skewness for the market return indicates left-skewed distributions with most values to the left of mean value. The fat-tailed distribution or higher kurtosis value for the market return denotes extreme values in its dataset. Meanwhile, the liquidity cost is positively skewed with fat−tailed distribution. The positive skewness for the CBML measure elucidates the right-skewed distributions with most values to the right of its mean. The fat-tailed distribution for the liquidity cost indicates extreme values in its data sample.

The empirical analysis is based on the time series and machine learning techniques. The experiments are separated in distinct avenues: the analysis of the entire dataset; analyzing the relationship in times of peak restrictions; and exploring later effects of lifting lockdown. On a daily basis, the linear relationship is quantified in Table 2. In the regression model, the stock market return is considered as a response variable and the liquidity cost acts as an explanatory variable. Table 2 reports outcomes for the entire dataset.

It is noted that the liquidity cost is positively correlated with the stock market returns and their relationship is significant. This implies that the liquidity providers are imposing a higher cost against the trading of DJI index during the market illiquidity. The higher liquidity cost compensates the liquidity providers with higher yields on resale of the DJI index. Whether the variable is associated as a linear combination of its own lags and other variable lags, the study adopts the multivariate forecasting algorithm approach. For the entire dataset, Table 3 links the future yield to its own past values and lags of the liquidity cost.

From the VAR estimation, it is observed that the DJI index yield is positively significant correlated with lags of the liquidity cost. This seems that the future yield is based on the previous cost associated with the trading of DJI index. The DJI index, in general, seems an uncertain investment for the liquidity providers. Thereby, the liquidity providers are not accepting the DJI index without imposing a higher cost on seller. This activity ensures to earn a higher yield on future trading of the DJI index. Meanwhile, the stock market return is significantly explained by its own lags.

Table 4 reports whether lags help to estimate the future liquidity cost for the entire dataset. It is noticed that changes in the liquidity cost are significantly explained by its past values. In addition, the liquidity cost is positively explained by lag_{t-1} of the yield and their relationship is significant. However, an insignificant relationship is observed between liquidity cost and lag_{t-2} of the stock market return. The Granger−causality is also checked for the entire dataset. The Granger−causality test is executed on a bivariate frame with two lags of SMR variable and LC variable. It is observed that there is statistical Granger−causality between variables.

In the VAR model, the study investigates the distribution of residuals, heteroscedasticity effects, structural stability, Impulse Response (IR) and Forecast Error Variance Decomposition (FEVD). The Jarque−Bera (JB) test reports that residuals are not normally distributed. The autoregressive conditional heteroscedastic (ARCH) test elucidates that there is ARCH impact on variables. The Cumulative Sum (CUSUM) test discloses in Figure 2 that there are no structural breaks in residuals. The IR function explains whether one standard deviation shock to the variable causes increase or decrease in the other variable.

From the Figure 3, the left graph reports the impulse response of returns to the LC shocks. The LC shock significantly explains the changes in the stock market returns. The market return fluctuates around the line zero at each responsive period. The right graph in the Figure 3 is referred to the impulse response of liquidity cost to the SMR shocks. The shock in the market returns effects the value of the liquidity cost. The FEVD experiment in Figure 4 explains that the exogenous shocks in the liquidity cost influence its own value. Conversely, the stock market return is lagged by its own variance.

On March 11, 2020, the COVID-19 was declared as a pandemic. A patchwork of restrictions was introduced across the globe. The grievous restrictions were imposed in the late March and early April 2020. Meanwhile, the common challenge for governments was to determine the right time for easing restrictions. The easing lockdown and its associated consequences were major concerns for health officials. However, the governments were gradually seen to ease various restrictions. The worldwide lockdown, in general, was temporarily lifted in May 2020, but time varies to each country.

During the period March 11, 2020–May 29, 2020, the study examines the impact of the pandemic on relationship dynamics between stock market return and liquidity cost. In this context, Table 6 reports regression analysis where the liquidity cost is considered as an explanatory variable and the yield on the DJI index is the response variable. It is worth to noting that the liquidity cost negatively relates to yields on the DJI index. However, there is no statistically significant relationship between variables. For the same dataset, lags are also examined to estimate the DJI index return and the liquidity cost.

Table 7 links lags to the DJI index return. It is noted that the DJI index return is not significantly explained by past values of the liquidity cost. Meanwhile, the DJI index return is significantly associated with its own lags. Table 8 reports the relationship between lags and future liquidity cost. It is identified that the liquidity cost is not significant explained by past values of the DJI index return. However, there is significant association between liquidity cost and its past values. For the corresponding period, the Granger-causality test is also performed. Table 9 elucidates that there is no statistical Granger-causality between variables.

In the corresponding VAR model, the distribution of residuals, heteroscedasticity, structural stability, IR and FEVD are checked. It is noted that residuals are not normally distributed. However, variables do not suffer from the ARCH effects. The CUSUM test for structural stability unveils in Figure 5 that there are no structural breaks in residuals. From the Figure 6, the left graph indicates the impulse response of returns to the LC shocks. It is observed that the standard deviation shocks in the liquidity cost are not highly effective to impact the market returns during the peak restrictions. The right graph in the Figure 6 reports the impulse response of liquidity cost to the SMR shocks. It is noted that the liquidity cost fluctuates around the line zero at each responsive period. This implies, that the standard deviation shock in the market return effects the liquidity cost. The FEVD experiment in Figure 7 reports that the stock market return is relatively influenced by its own variance shocks during the peak restrictions. The value of the liquidity cost is found to be highly influenced by its own variance.

As the lockdown was lifted in May 2020, the study investigates later effects on relationship dynamics between variables. The following experiment is based on the period June 01, 2020–December 10, 2020. Table 10 reports the DJI index return as a dependent variable and its liquidity cost as a predictor variable. On a daily basis, the liquidity cost is positively associated with the DJI index return. The relationship is statistically significant. This seems that the cost demanded by the liquidity providers against the trading of DJI index is positively linked to later yields. The higher liquidity cost is a compensation due to the uncertainty and the liquidity providers are generating higher yields on resale of the DJI index. In addition, the regression coefficient, β, further indicates that returns on the DJI index have become sensitive to the illiquidity or liquidity cost.

Following the same period, Table 11 reports that the DJI index return is not significantly explained by lags of the liquidity cost. Meanwhile, there is significant association between yield on the DJI index and its own lags. Table 12 elucidates that there is significant correlation between liquidity cost of the DJI index and its past values. In addition, the liquidity cost is significantly explained by lag_{t-1} of the DJI index return. Meanwhile, the insignificant association is observed between liquidity cost and lag_{t-2} of the stock market return. For the corresponding period, Table 13 reports that the DJI index return does Granger−cause the liquidity cost. Meanwhile, the liquidity cost does not Granger−cause stock market return.

The JB test unveils that residuals are not normally distributed. In addition, there are ARCH effects in the VAR model. Meanwhile, there are no structural breaks in residuals. From the Figure 9, the left graph elucidates the impulse response of returns to the LC shocks. It is vividly seen that the standard deviation shocks in the liquidity cost are effective to influence the market returns. The market returns are found to be fluctuated around the line zero at each responsive period. The right graph in the Figure 9 explains the impulse response of liquidity cost to the SMR shocks. The standard deviation shock in the market return influences the liquidity cost, and the liquidity cost fluctuates over time. The FEVD experiment in Figure 10 demonstrates that the stock market return and liquidity cost are highly influenced by their corresponding variance shocks. In addition, some effects of the SMR variance shocks are also observed on the liquidity cost.

6. Conclusions

This study examines the effects of the resent pandemic-related uncertainty on relationship dynamics between stock market returns and liquidity cost. When examining the entire dataset, the liquidity cost was positively correlated with yields on the DJI index. The statistically significant correlation elucidated that suppliers of liquidity would not accept the DJI index without imposing a higher cost on seller. This activity helps the liquidity providers to gain higher yield on resale of the DJI index. From the VAR estimation, the yields on the DJI index were significantly explained by past values of the liquidity cost. The statistical Granger-causality was also reported between variables.

If the period is analyzed during the pandemic-related restrictions, the results were changed. The liquidity cost was found to be negatively related with yields on the DJI index. However, the relationship was not statistically significant. For the same period, the VAR analysis was also executed. The DJI index returns were not significantly explained by lags of the liquidity cost. In addition, there was no statistical Granger-causality between variables.

If the period is examined related to the lifted lockdown or easing restrictions, the relationship between variables was vividly changed. The liquidity cost was found to be positive and significantly correlated with yields on the DJI index. The yields on the DJI index were found to be sensitive to the liquidity cost. For the same period, the DJI index return was not significantly explained by lags of the liquidity cost. In addition, the liquidity cost did not Granger-cause market returns.

The study has revealed that the liquidity cost is priced in returns of the DJI index. Additionally, the DJI index yields have become sensitive to the liquidity cost. The work provides potential financial policy implications in response to the pandemic-related uncertainty. The findings can facilitate market participants in the liquidity risk management. In spite of potential contribution in the asset pricing literature, the geographical area of research is a limitation in the study. Certainly, the coronavirus is still active. The experts are concerned about spikes of the coronavirus. The future work can include new financial assets. In other financial markets, it is worth to unveiling effects of the pandemic-related uncertainty.

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Conflict of interest

The author declares no conflicts of interest in this paper.

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