

Crypto Market and Liquidity Risk in Environments due to Pandemic Uncertainty

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Abstract: *The recent pandemic is still under debate and is raising concerns about future economic perspectives. This work investigates whether liquidity is priced in various cryptocurrencies' returns, and if the relationship has been affected during the COVID-19 period. In a particular trading session analyzed before the pandemic uncertainty, liquidity was priced in returns on Bitcoin, Cardano, and XRP. However, the findings have changed due to the pandemic crisis. During the pandemic uncertainty, liquidity was found to be priced in Cardano returns during the same trading session. In addition, the liquidity cost imposed against accepting the position of Tether on day $t-1$ was noted to be priced in its returns for day t .*

Keywords: *Crypto market, Pandemic uncertainty, Asset pricing, Market liquidity, Returns.*

JEL Classification: *G12, G01.*

1. Introduction

The recent pandemic uncertainty, or its risk on distinct aspects of the global economy, is still being investigated. The financial crisis of 2007–2009 spread due to the global financial and economic relationship (Saleemi, 2014). However, traveling was a major cause of the Covid-19 pandemic (Wójcik & Ioannou, 2020). The global pandemic has not only caused an exceptional number of fatalities, but it has undoubtedly affected global financial markets (Zhang, Hu, & Ji, 2020), economic development (Goodell, 2020), returns on investment (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020), and market liquidity (Saleemi, 2021).

In early 2020, the pandemic suddenly halted global economic activity (Gerlagh, Heijmans, & Rosendahl, 2020). A sudden halt in global economic activity undoubtedly changed economic realities more than the financial crisis of 2007–2009. It was also a turning point in the reforms of the global economy. Researchers are raising concerns about whether the pandemic will have long-lasting effects on distinct aspects of the financial markets, as well as on the behavior of investors.

Liquidity providers imposed higher costs on counterparties during the pandemic uncertainty (Saleemi, 2021). The pandemic uncertainty has not only caused a change in the business model of some industries, but has also affected their income and cost structures (Gregurec, Tomičić Furjan, & Tomičić-Pupek, 2021). It is unclear how long the COVID-19 crisis will last, so it is difficult to estimate the overall costs and consequences for the global economy.

While several commodities and financial assets have lost their value during the recent crisis, the pandemic has had a positive impact on the crypto market efficiency (Mnif, Jarboui, & Mouakhar, 2020). The market for cryptocurrencies is often reported to a safe haven (Klein, Thu, & Walther, 2018). However, the crypto market has no hedging or safe haven capabilities during the pandemic crisis (Jana & Das, 2020). The crypto market is well-known for its co-explosivity (Bouri, Shahzad, & Roubaud, 2019), price jumps (Fakhfekh & Jeribi, 2020), and higher bubbles (Liu & Serletis, 2019).

Cryptocurrency is mainly held for speculative purposes, and leads to extreme volatilities and bubbles in the crypto market (Goodell & Goutte, 2021). More recently, it has been noted that yields on traditional assets are very sensitive to the liquidity cost in environments of pandemic uncertainty (Saleemi, 2021). It is a matter of interest to

look at how returns on distinct cryptocurrencies respond to the cost of liquidity, especially during the pandemic period.

Market liquidity is defined as the immediacy of a transaction execution at the lowest cost. Liquidity cost is characterized by a conditional cost that the liquidity provider imposes on the counterparty in environments of price uncertainty (Saleemi, 2020). The liquidity cost determines the execution of a financial transaction (Guijarro, Moya-Clemente, & Saleemi, 2021), a trader's movements (Guijarro, Moya-Clemente, & Saleemi, 2019), and compensates the liquidity suppliers in terms of higher returns on traditional assets (Saleemi, 2021).

To the author's knowledge, this is the first paper to study whether market liquidity is priced in various cryptocurrencies' returns in pre- and post-pandemic times. As there is no previous study on how the liquidity cost affects yields on distinct cryptocurrencies, especially in times of pandemic uncertainty, this research aims to be the first empirical approach to this problem. This research fills a gap in the crypto market literature and helps us to understand the impact of liquidity on cost cryptocurrency returns in a broader sense.

The rest of the paper is organized as follows: A brief survey of the literature is elucidated in Section 2; the procedure adopted to build the benchmark model is discussed in Section 3; the findings of the research are reported in Section 4; and finally, the conclusions are highlighted in Section 5.

2. Review of Literature

The pandemic and its associated effects are highly researched in the discipline of economic sciences. The research based on COVID-19 has disclosed potential implications in banking (Li, Xie, & Lin, 2021), insurance (Richter & Wilson, 2020), exchange rates (Umar & Gubareva, 2020), financial systems (Zhang et al., 2020), and market liquidity risk (Saleemi, 2021). The liquidity risk matters to investors, and it immediately affects a trader's movements in the financial market (Guijarro et al., 2019). The impact of the pandemic on the crypto market is also gaining attention in the field of finance.

The crypto market is a potential asset class for speculative purposes (Cheah & Fry, 2015) and is well-known due to its price spikes (Fakhfekh & Jeribi, 2020). The crypto market is reported as a safe haven for several reasons. It is unregulated from monetary policy, it is a store of value, and it has a limited relationship with traditional assets (Klein et al., 2018). As the recent crisis developed, the crypto market has not acted as a safe haven (Conlon & McGee, 2020). The crypto market suffered from financial contagion early in the pandemic crisis, but it promptly rebounded (Caferra & Vidal-Tomás, 2021).

Cryptocurrencies are efficient in certain periods (Kristoufek & Vosvrda, 2019), exposed to systematic risk (Corbet, Lucey, Urquhart, & Yarovaya, 2019), sensitive to certain events (Tran & Leirvik, 2020), and correlated with regard to volatility spillovers (Omane-Adjepong & Alagidede, 2019). The ease of trading, known as market liquidity, varies for distinct cryptocurrencies (Phillip, Chan, & Peiris, 2018). The limited liquidity cost is referred to as higher liquidity (Saleemi, 2020).

The crypto market is significantly efficient in times of higher liquidity (Brauneis & Mestel, 2018). Liquidity is a crucial element to determine the efficiency and yields in the crypto market (Wei, 2018). In a progressively regulated global economy, the crypto market is vague with regard to regulations and policies. The unregulated crypto market causes surges in its trading volume, price, and volatility (Corbet, Lucey, & Yarovaya, 2018). Cryptocurrency is held for several reasons, including electronic cash and speculation.

The future cryptocurrency value is a preliminary concern for investors (Cheah & Fry, 2015), and it is sensitive to price bubbles (Corbet et al., 2018). Speculators accept a financial position due to earning incentives. The provider of liquidity tends to be compensated in environments of future price uncertainty, and therefore imposes a cost on the counterparty (Saleemi, 2020). Market liquidity is a multidimensional area of study, and it is characterized by the market attributes of transaction speed, cost, depth, breadth, and resilience (Lybek & Sarr, 2002).

Market liquidity affects the price of assets (Liu, 2006), cost of capital (Acharya & Pedersen, 2005), returns on investments (Amihud, Hameed, Kang, & Zhang, 2015), and a trader's movements (Guijarro et al., 2019). In general, it is the ease of trading with limited cost. In the early stages of market microstructure literature, the liquidity of assets is reported to be estimated by the volume-based liquidity method (Goyenko, Holden, & Trzcinka, 2009). Trading price and quantity are the main elements of the volume-based liquidity models. Since the inception of Roll's bid-ask spread model (Roll, 1984), the literature on cost-based market liquidity has progressively expanded with theoretical and empirical implications.

Bid-ask spread, known as liquidity cost, has gained considerable attention and is used to estimate the transaction speed and cost in financial markets (Corwin & Schultz, 2012; Guijarro et al., 2021). Although the spread models are based on distinct theoretical and empirical assumptions, the two aspects are common. The

market friction impacts the liquidity, and its effects are time-varying in financial markets (Degennaro & Robotti, 2007). The liquidity cost is estimated under three main aspects, namely the transaction immediacy cost, informed trading cost, and order processing cost (Huang & Stoll, 1997).

The inventory immediacy cost model suggests that the spread compensates the inventory holders against accepting the financial position in environments of price uncertainty (Amihud & Mendelson, 1986). The informed trading cost model protects the liquidity providers against the risk of trading with the informed counterparty (Gorton & Metrick, 2010). The inventory holders are also compensated for the order processing cost, that is, for the administration expenses and taxes.

The spread is the range between the quoted prices of an asset, the known as ask price, and the bid price (Corwin & Schultz, 2012; Glosten & Milgrom, 1985; Roll, 1984). The maximum price that a buyer intends to pay for an asset is referred to as the bid price. The minimum price that an inventory holder is willing to receive on the investment redemption is the ask price. In the financial market, the liquidity provider undoubtedly accepts the financial position at the lowest bid price and redeems its position at the highest ask price. This activity ensures that the liquidity supplier can generate yields on the investment.

3. Materials and Methods

This paper provides an insight into the authoritative role of liquidity cost on distinct cryptocurrencies' returns, especially during the pandemic crisis. Most recently, Saleemi (2020) developed a new measure of the bid-ask spread, known as Cost-Based Market Liquidity (CBML). In this study, the CBML measure is adopted to estimate the liquidity cost in the crypto market. The CBML estimator is developed from low-frequency data, which contains high, low, and closing prices. The low-frequency data is referred to an asset's attributes, including the daily opening price, high price, low price, closing price, and trading quantity. The analytical expression of the CBML model is as follows:

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

where, S_{t-1} is characterized as a ratio of the asset range to its closing price on the past trading session, and $E(v_t^S)$ is the expected ratio of an informed asset range to its closing price for the following trading session.

$$S_{t-1} = \frac{(h_{t-1} - l_{t-1})}{c_{t-1}} \quad (2)$$

where, h_{t-1} is the highest price on day $t - 1$; l_{t-1} denotes the lowest price on day $t - 1$; and c_{t-1} refers to the closing price of the past trading session. $E(v_t^S)$ estimates the asymmetric information effects on the prices, and it is computed as:

$$E(v_t^S) = \frac{(v_t^{ask} - v_t^{bid})}{c_t} \quad (3)$$

In the next trading session, the asset is valued with the risk neutrality as:

$$\eta_t = (h_t + l_t) * \left(\frac{1}{2}\right) \quad (4)$$

where, h_t denotes the highest price of day t ; l_t refers to the lowest price of day t ; and η_t is a mean value for the next trading session. If we assume equal probability of an informed seller, the expected ask value for which the inventory holder redeems his position is assumed to be conditional on a trade, such as:

$$v_t^{ask} = (h_t)(\pi) + (\eta_t)(\pi) \quad (5)$$

where, π indicates the probability of an informed trader in the market. Assuming equal probability of an informed buyer, the estimated bid value for which the liquidity provider accepts the inventory position is assumed to be conditional on a trade, such as:

$$v_t^{bid} = (l_t)(\pi) + (\eta_t)(\pi) \quad (6)$$

The experiments are performed on four cryptocurrencies – Bitcoin (BTC), Tether (USDT), Cardano (ADA), and XRP. Although the examined cryptocurrencies were developed at different times, the study covers the period from January 01, 2017, to September 25, 2021. The low-frequency data of the corresponding cryptocurrency is obtained by applying a package ``crypto`` in the statistical software R. The analysis is executed pre- and post-pandemic crisis. The pre-pandemic study covers the period from January 01, 2017, to March 10, 2020, and the

post-pandemic analysis covers the period from March 11, 2020, to September 25, 2021. It is undoubtedly worth investigating whether the recent pandemic has impacted the relationship between cryptocurrencies' spreads and their yields. The cryptocurrencies' returns are estimated on a daily basis, and they are computed as:

$$YC_t = \left(\frac{c_t}{c_{t-1}} \right) - 1 \quad (7)$$

where, YC_t is the cryptocurrency return of day t ; c_t refers to the closing price of day t ; and c_{t-1} denotes the closing price of the past trading session. Using the time series and multivariate statistical techniques in the R software, the benchmark models are developed as:

$$YC_t = \alpha + \beta SC_t + \epsilon_t \quad (8)$$

where, YC_t indicates the yield on the corresponding cryptocurrency of day t ; SC_t refers to the liquidity cost associated with the corresponding cryptocurrency of day t ; and ϵ_t is the error term.

The research is further expanded to investigate whether there is any linear combination of a variable's own past time series and the lags of other variables. In this case, the vector autoregression (VAR) approach is applied to study the relationship between multivariate time series. The VAR method is the multivariate forecasting algorithm strategy, which provides insight into the authoritative role of past time series on the variable more broadly. To unveil effects of the past time series, the multivariate forecasting algorithm model is constructed using Equations 9 and 10:

$$Y_t = \alpha_Y + \beta_{11}Y_{t-1} + \gamma_{11}S_{t-1} + \epsilon_{Y,t} \quad (9)$$

$$S_t = \alpha_S + \beta_{21}Y_{t-1} + \gamma_{21}S_{t-1} + \epsilon_{S,t} \quad (10)$$

where, Y_t indicates the return of the corresponding cryptocurrency on day t ; Y_{t-1} denotes the lag value of the corresponding cryptocurrency yield on day $t - 1$; S_{t-1} is the liquidity cost associated with the corresponding cryptocurrency on day $t - 1$; $\epsilon_{Y,t}$ refers to the white noise variable; S_t indicates the liquidity cost of the corresponding cryptocurrency on day t ; and $\epsilon_{S,t}$ is another white noise variable.

The matrix notation of the VAR model is elucidated as:

$$\begin{bmatrix} Y_t \\ S_t \end{bmatrix} = \begin{bmatrix} \alpha_Y \\ \alpha_S \end{bmatrix} + \begin{bmatrix} \beta_{11} \\ \beta_{21} \end{bmatrix} [Y_{t-1}] + \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \end{bmatrix} [S_{t-1}] + \begin{bmatrix} \epsilon_{Y,t} \\ \epsilon_{S,t} \end{bmatrix} \quad (11)$$

Equation 11 is further elaborated in the following manner:

$$YS_t = \begin{bmatrix} Y_t \\ S_t \end{bmatrix}, A_t = \begin{bmatrix} \alpha_Y \\ \alpha_S \end{bmatrix}, \beta_t = \begin{bmatrix} \beta_{11} \\ \beta_{21} \end{bmatrix}, Y_t = [Y_{t-1}], \gamma_t = \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \end{bmatrix}, S_t = [S_{t-1}], \epsilon_t = \begin{bmatrix} \epsilon_{Y,t} \\ \epsilon_{S,t} \end{bmatrix} \quad (12)$$

Finally, the VAR model is restructured as Equation 13:

$$YS_t = A_t + \beta_t Y_t + \gamma_t S_t + \epsilon_t \quad (13)$$

4. Results and Discussion

The descriptive statistics of the dataset are estimated on a daily basis and are demonstrated in Table 1. The liquidity cost imposed against accepting the position of the corresponding cryptocurrency is positively skewed with a fat-tailed distribution. The positive skewness of the cryptocurrencies' spreads specifies a right-skewed distribution with values to the right of the mean. The Bitcoin returns are negatively skewed with a fat-tailed distribution. The negative skewness of the corresponding data sample indicates a left-skewed distribution with most values to the left of the mean. Meanwhile, the Tether returns, Cardano returns, and XRP returns are noted to be positively skewed with fat-tailed numerical distributions. The positive skewness of the corresponding returns indicates a right-skewed distribution with most values to the right of the mean. The cryptocurrencies' spreads and their returns are depicted in Figure 1, where it is noted that the variables are not constant and change over time. The study performs the augmented Dickey–Fuller (ADF) test to check the stationarity of the time series sample. It is observed that the p-value is less than the significance level. In addition, the test statistic is noted to be lower than the critical values. Therefore, the time series is stationary for the dataset. These findings are consistent for both pre- and post-pandemic uncertainty periods. In the crypto market, it is worthwhile investigating whether liquidity is priced in returns over time.

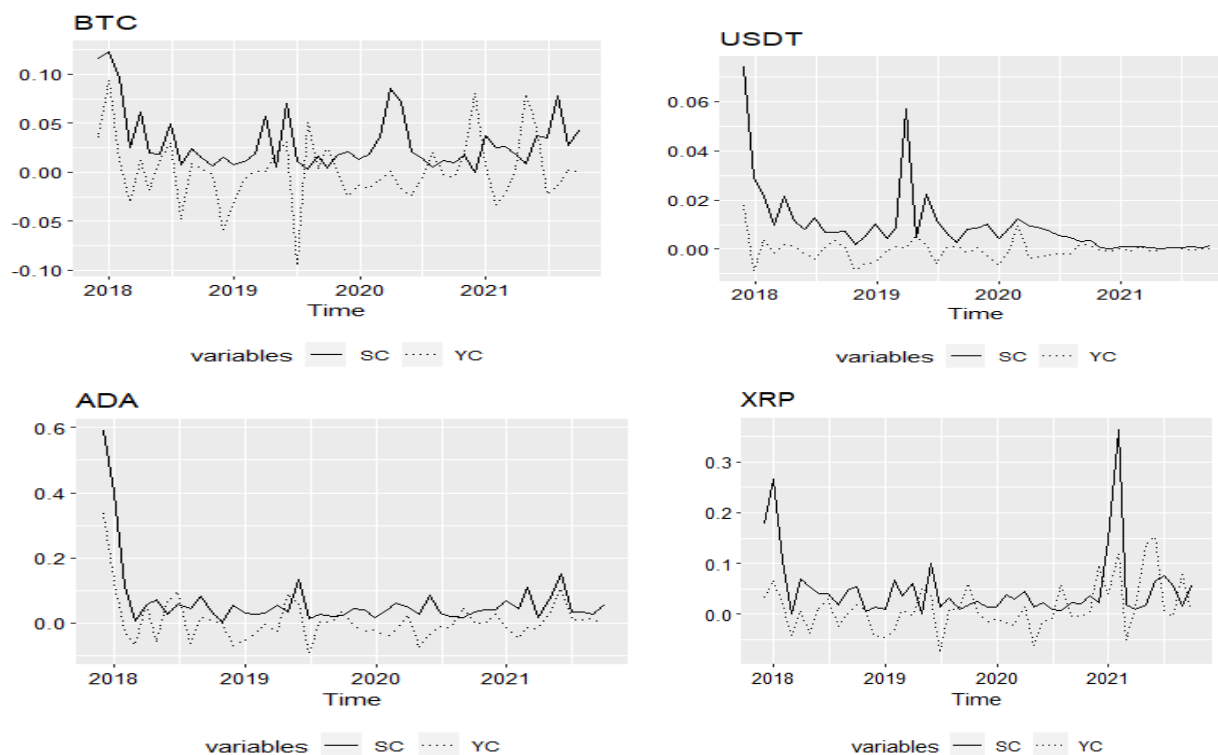


Figure 1.
Time-varying liquidity costs and returns.

Table 1.
Descriptive statistics.

Variable	Min.	Median	Mean	Max.	SD	Skewness	Kurtosis
BTC_{SC}	0.0000058	0.02049	0.03027	0.46178	0.0335	3.5637	29.7032
BTC_{YC}	-0.371695	0.00172	0.00213	0.25247	0.0418	-0.1597	10.2756
$USDT_{SC}$	0.0000013	0.00511	0.00788	0.1735	0.0106	5.0631	55.5929
$USDT_{YC}$	-0.05121	-0.00002	0.00001	0.05824	0.0052	0.8929	37.4909
ADA_{SC}	0.0000349	0.03573	0.05035	0.59054	0.0537	3.4381	22.9193
ADA_{YC}	-0.395672	0.00127	0.00592	1.36681	0.0819	5.1262	73.0178
XRP_{SC}	0.0000353	0.02905	0.04686	0.95273	0.0636	5.1760	49.8149
XRP_{YC}	-0.4233401	-0.00089	0.00353	0.83470	0.0727	2.6128	27.2878

Note: BTC_{SC} = Bitcoin liquidity cost; BTC_{YC} = Bitcoin return; $USDT_{SC}$ = Tether liquidity cost; $USDT_{YC}$ = Tether return; ADA_{SC} = Cardano liquidity cost; ADA_{YC} = Cardano return; XRP_{SC} = XRP liquidity cost; XRP_{YC} = XRP return; SD = Standard Deviation. Significance level: *** < 0.001; ** < 0.01; * < 0.05.

Table 2 presents the regression results pre-pandemic crisis, where the liquidity cost imposed on each cryptocurrency is the independent variable, and the corresponding cryptocurrency yield acts as the dependent variable. On a daily basis, it is noted that the liquidity cost is positive and is significantly associated with returns on cryptocurrencies, including Bitcoin, Cardano, and XRP. This implies that a higher cost is imposed by liquidity providers against accepting the position of BTC, ADA, and XRP. In this context, a higher liquidity cost helps the inventory holders to earn higher returns on the resale of the corresponding cryptocurrency. Meanwhile, it is

observed that liquidity cost is not associated with Tether returns. Before the pandemic uncertainty, liquidity was not priced in returns on the USDT.

Table 2.
Pre-pandemic uncertainty, regression analysis results.

Variable		Estimate	P-value
BTC_{YC} (a)	Intercept	-0.001729	0.378
	BTC_{SC}	0.095569	0.042 *
$USDT_{YC}$ (b)	Intercept	-0.000085	0.751
	$USDT_{SC}$	0.009874	0.594
ADA_{YC} (c)	Intercept	-0.002526	0.541
	ADA_{SC}	0.131101	0.022 *
XRP_{YC} (d)	Intercept	-0.003164	0.291
	XRP_{SC}	0.128280	0.004 **

Note: a) Adjusted R-squared = 0.003; F-statistic = 4.134; P-value = 0.042; (b) Adjusted R-squared = -0.0008; F-statistic = 0.284; P-value = 0.593; (c) Adjusted R-squared = 0.004; F-statistic = 5.229; P-value = 0.022; (d) Adjusted R-squared = 0.0084; F-statistic = 8.315; P-value = 0.004. Significance level: *** < 0.001; ** < 0.01; * < 0.05.

The post-pandemic effects are quantified in Table 3, where the cryptocurrency yield is linked as a linear combination of its liquidity cost during the trading session. On a daily basis, the liquidity cost is found to be positive and significantly associated with the Cardano (ADA) returns. This illustrates an unwillingness of liquidity providers to accept the position of ADA without imposing a higher cost on the counterparty. In this context, a higher liquidity cost compensates the inventory holders in terms of higher returns on the redemption of Cardano. Conversely, it is noted that the liquidity cost is not significantly linked to the Bitcoin, Tether, or XRP returns. In the post-pandemic uncertainty period, liquidity is not priced in returns for BTC, USDT, and XRP. Tables 4 and 5 indicate the pre- and post-pandemic unit root test results.

Table 3.
Post-pandemic uncertainty, regression analysis results.

Variable		Estimate	P-value
BTC_{YC} (a)	Intercept	0.004183	0.075
	BTC_{SC}	-0.011128	0.813
$USDT_{YC}$ (b)	Intercept	-0.000093	0.643
	$USDT_{SC}$	0.0248	0.182
ADA_{YC} (c)	Intercept	0.002595	0.516
	ADA_{SC}	0.122501	0.020 *
XRP_{YC} (d)	Intercept	0.002733	0.499
	XRP_{SC}	0.052085	0.225

Note: a) Adjusted R-squared = -0.001; F-statistic = 0.055; P-value = 0.813; (b) Adjusted R-squared = 0.001; F-statistic = 1.782; P-value = 0.182; (c) Adjusted R-squared = 0.007; F-statistic = 5.39; P-value = 0.02; (d) Adjusted R-squared = 0.0008; F-statistic = 1.472; P-value = 0.225. Significance level: * < 0.05

Table 4.
Pre-pandemic uncertainty, augmented Dickey-Fuller (ADF) test for unit roots.

Variable	Test statistic	P-value	1% Critical value	5% Critical value	10% Critical value
BTC_{SC}	-14.9207	0.000	-3.43	-2.86	-2.57
BTC_{YC}	-19.9961	0.000	-3.43	-2.86	-2.57
$USDT_{SC}$	-17.7905	0.000	-3.43	-2.86	-2.57
$USDT_{YC}$	-29.6148	0.000	-3.43	-2.86	-2.57
ADA_{SC}	-15.8055	0.000	-3.43	-2.86	-2.57
ADA_{YC}	-16.2253	0.000	-3.43	-2.86	-2.57
XRP_{SC}	-14.8324	0.000	-3.43	-2.86	-2.57
XRP_{YC}	-17.4468	0.000	-3.43	-2.86	-2.57

Table 5.
Post-pandemic uncertainty, augmented Dickey–Fuller (ADF) test for unit roots.

Variable	Test statistic	P-value	1% Critical value	5% Critical value	10% Critical value
BTC_{SC}	-12.7115	0.000	-3.43	-2.86	-2.57
BTC_{YC}	-18.2274	0.000	-3.43	-2.86	-2.57
$USDT_{SC}$	-11.357	0.000	-3.43	-2.86	-2.57
$USDT_{YC}$	-33.9873	0.000	-3.43	-2.86	-2.57
ADA_{SC}	-12.2878	0.000	-3.43	-2.86	-2.57
ADA_{YC}	-17.0619	0.000	-3.43	-2.86	-2.57
XRP_{SC}	-11.5206	0.000	-3.43	-2.86	-2.57
XRP_{YC}	-17.3212	0.000	-3.43	-2.86	-2.57

Table 6.
Pre-pandemic crisis, estimation of cryptocurrencies' returns from the past time series.

Variable		Estimate	P-value
BTC_Y (a)	$\beta_{11,Y}$	-0.5072	0.000 ***
	$\gamma_{11,S}$	0.0185	0.693
	α_Y	-0.000065	0.970
$USDT_Y$ (b)	$\beta_{11,Y}$	-0.6075	0.000 ***
	$\gamma_{11,S}$	0.0330	0.077
	α_Y	-0.0000103	0.967
ADA_Y (c)	$\beta_{11,Y}$	-0.5878	0.000 ***
	$\gamma_{11,S}$	-0.0023	0.967
	α_Y	-0.0000505	0.988
XRP_Y (d)	$\beta_{11,Y}$	-0.5325	0.000 ***
	$\gamma_{11,S}$	0.0706	0.115
	α_Y	-0.0000342	0.990

Note: a) ARCH test = 0.000; JB test = 0.000; (b) ARCH test = 0.000; JB test = 0.000; (c) ARCH test = 0.000; JB test = 0.000; (d) ARCH test = 0.000; JB test = 0.000. Significance level: *** < 0.001.

The following experiments were conducted to study whether the variable is linked to the past time series. Table 6 presents the VAR coefficients before the pandemic crisis, where the returns are linked to their own lags and the past time series of the corresponding liquidity costs. The cryptocurrencies' returns are not significantly explained by the past time series of the liquidity costs. Meanwhile, the returns are reported to be significantly correlated with their own corresponding past time series.

Table 7 reports the VAR coefficients before the pandemic crisis, where the cryptocurrencies' spreads are linked to their own lags and the past time series of the corresponding yields. The XRP liquidity cost is negative and is significantly explained by the past time series of its returns. This implies that the previous day's lower return leads to a higher liquidity cost against accepting the position of XRP in the next trading session. Conversely, the liquidity cost associated with Bitcoin, Tether, and Cardano are not significantly explained by the past time series of their own returns. The cryptocurrencies' spreads are found to be significantly linked to their corresponding past time series.

Table 7.
Pre-pandemic crisis, estimation of cryptocurrencies' spreads from the past time series.

Variable		Estimate	P-value
BTC_S (a)	$\beta_{21,Y}$	-0.0332	0.080
	$\gamma_{21,S}$	-0.4851	0.000 ***
	α_S	0.0000129	0.990
$USDT_S$ (c)	$\beta_{21,Y}$	-0.0501	0.257
	$\gamma_{21,S}$	-0.4526	0.000 ***
	α_S	-0.0000242	0.952
ADA_S (d)	$\beta_{21,Y}$	-0.0043	0.783
	$\gamma_{21,S}$	-0.3920	0.000 ***
	α_S	-0.0001965	0.919
XRP_S (f)	$\beta_{21,Y}$	-0.0443	0.027 *
	$\gamma_{21,S}$	-0.4163	0.000 ***
	α_S	-0.0000065	0.997

Note: a) ARCH test = 0.000; JB test = 0.000; (b) ARCH test = 0.000; JB test = 0.000; (c) ARCH test = 0.000; JB test = 0.000; (d) ARCH test = 0.000; JB test = 0.000. Significance level: *** < 0.001; * < 0.05

The following analysis covers the post-pandemic effects on the relationship dynamics between cryptocurrencies' spreads and their corresponding returns through the VAR approach. Table 8 demonstrates the post-pandemic effects, where the cryptocurrencies' returns are linked to their own past time series and lags of the corresponding liquidity costs. The Tether returns are found to be positive and are significantly explained by the past time series of their liquidity costs. This relationship indicates that a higher cost imposed against accepting the position of USDT on day $t - 1$ compensates the liquidity providers in terms of higher returns for the following trading session. However, the yields on other cryptocurrencies are not significantly associated with the past time series of the corresponding liquidity costs. A significant association is observed between cryptocurrencies' yields and their own corresponding lags.

Table 8.
Post-pandemic uncertainty, linking the past time series to the cryptocurrencies' yields.

Variable		Estimate	P-value
BTC_Y (a)	$\beta_{11,Y}$	-0.5755	0.000 ***
	$\gamma_{11,S}$	0.0467	0.330
	α_Y	0.0006416	0.759
$USDT_Y$ (b)	$\beta_{11,Y}$	-0.6682	0.000 ***
	$\gamma_{11,S}$	0.0856	0.000 ***
	α_Y	-0.0000931	0.673
ADA_Y (c)	$\beta_{11,Y}$	-0.5690	0.000 ***
	$\gamma_{11,S}$	-0.0433	0.415
	α_Y	0.0007186	0.834
XRP_Y (d)	$\beta_{11,Y}$	-0.4996	0.000 ***
	$\gamma_{11,S}$	0.0040	0.929
	α_Y	0.0006012	0.882

Note: a) ARCH test = 0.000; JB test = 0.000; (b) ARCH test = 0.000; JB test = 0.000; (c) ARCH test = 0.000; JB test = 0.000; (d) ARCH test = 0.000; JB test = 0.000. Significance level: *** < 0.001.

Table 9 presents the VAR coefficients for the post-pandemic uncertainty period, where the cryptocurrencies' spreads are linked to their own lags and the past time series of the corresponding returns. The liquidity cost is negative and is significantly explained by the past time series of the Bitcoin, Tether, and XRP returns. This relationship shows that the lower return of day $t - 1$ leads to a higher liquidity cost on day t against accepting the positions of BTC, USDT, and XRP. Nonetheless, the Cardano liquidity cost of day t is not significantly explained by the past time series of its yields. It is noted that the cryptocurrencies' spreads are significantly linked to their own corresponding lags.

A few experiments were further conducted to study the distribution of residuals, and heteroscedasticity. In this context, the Jarque–Bera (JB) test is applied to unveil the distribution of residuals, and the autoregressive conditional heteroscedastic (ARCH) test is adopted to investigate the heteroscedasticity. It is observed that the residuals are not normally distributed. Meanwhile, the ARCH effects are reported in the VAR models.

Table 9.
Post-pandemic uncertainty, linking the past time series to the cryptocurrencies' spreads.

Variable		Estimate	P-value
<i>BTC</i> ₅ (a)	$\beta_{21,Y}$	-0.0642	0.014 *
	$\gamma_{21,S}$	-0.3878	0.000 ***
	α_5	-0.0003922	0.811
<i>USDT</i> ₅ (b)	$\beta_{21,Y}$	-0.8751	0.000 ***
	$\gamma_{21,S}$	-0.3603	0.000 ***
	α_5	-0.0000712	0.836
<i>ADA</i> ₅ (c)	$\beta_{21,Y}$	0.0039	0.874
	$\gamma_{21,S}$	-0.4485	0.000 ***
	α_5	-0.0002797	0.909
<i>XRP</i> ₅ (d)	$\beta_{21,Y}$	-0.1145	0.000 ***
	$\gamma_{21,S}$	-0.4419	0.000 ***
	α_5	-0.0002262	0.946

Note: a) ARCH test = 0.000; JB test = 0.000; (b) ARCH test = 0.000; JB test = 0.000; (c) ARCH test = 0.000; JB test = 0.000; (d) ARCH test = 0.000; JB test = 0.000. Significance level: *** < 0.001; * < 0.05

5. Conclusions

Liquidity is often noted to be priced in returns on traditional assets because the liquidity provider is likely compensated against the provision of illiquidity. In this context, this study investigates whether liquidity is priced in returns on various cryptocurrencies, including Bitcoin, Tether, Cardano, and XRP. Using the time series and multivariate statistical techniques, the analysis is executed for pre- and post-pandemic uncertainty periods.

If the same trading session is studied before the pandemic uncertainty, the liquidity cost was found to be positive and significantly correlated with returns for Bitcoin, Cardano, and XRP. This relationship illustrates that a higher liquidity cost against accepting the position of the corresponding cryptocurrency compensates the liquidity providers in terms of higher returns. For the post-pandemic uncertainty period, the findings had changed for the same trading session. Only the Cardano returns were noted to be positive and significantly explained by their liquidity costs. This implies that a higher liquidity cost compensates in terms of higher yields on the resale of Cardano.

The VAR approach was adopted to investigate whether a variable is linked to its past time series. In the pre-pandemic period, the cryptocurrencies' returns were not significantly correlated with the past time series of the corresponding liquidity costs. In the post-pandemic period, the Tether returns were noted to be positive and are significantly explained by the past time series of their liquidity costs. This implies that a higher cost associated with the trading of USDT on day $t - 1$ compensates the liquidity providers in terms of higher returns for the next trading session.

The study has important implications in terms of quantifying the impact on various cryptocurrencies' yields of the liquidity cost, especially in environments of pandemic uncertainty. Participants may apply these findings to liquidity risk management and portfolio construction in the crypto market. Although the research fills a gap in the crypto market literature, the data sample is a limiting factor of the analysis. As the pandemic and its associated effects are ongoing, the study encourages other researchers to unveil whether liquidity is priced in other cryptocurrencies' yields. This may provide insight into the authoritative role of liquidity cost on the cryptocurrency returns more broadly.

References

- Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2), 375-410.
- Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & Alhammadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, 27, 100326. Available at: <https://doi.org/10.1016/j.jbef.2020.100326>.
- Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2), 223-249. Available at: [https://doi.org/10.1016/0304-405x\(86\)90065-6](https://doi.org/10.1016/0304-405x(86)90065-6).
- Amihud, Y., Hameed, A., Kang, W., & Zhang, H. (2015). The illiquidity premium: International evidence. *Journal of Financial Economics*, 117(2), 350-368.
- Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, 29, 178-183. Available at: <https://doi.org/10.1016/j.frl.2018.07.005>.
- Brauneis, A., & Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters*, 165, 58-61. Available at: <https://doi.org/10.4324/9781315211909-9>.
- Caferra, R., & Vidal-Tomás, D. (2021). Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. *Finance Research Letters*, 43, 101954-101954. Available at: <https://doi.org/10.1016/j.frl.2021.101954>.
- Cheah, E.-T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, 130, 32-36. Available at: <https://doi.org/10.1016/j.econlet.2015.02.029>.
- Conlon, A., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Finance Research Letters*, 35, 101607. Available at: <https://doi.org/10.1016/j.frl.2020.101607>.
- Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the bitcoin and Ethereum bubbles. *Finance Research Letters*, 26, 81-88. Available at: <https://doi.org/10.1016/j.frl.2017.12.006>.
- Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182-199. Available at: <https://doi.org/10.1016/j.irfa.2018.09.003>.
- Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, 67(2), 719-760. Available at: <https://doi.org/10.1111/j.1540-6261.2012.01729.x>.
- Degennaro, R. P., & Robotti, C. (2007). Financial market frictions. *Economic Review*, 92(Q3), 1-16.
- Fakhfekh, M., & Jeribi, A. (2020). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, 51, 101075. Available at: <https://doi.org/10.1016/j.ribaf.2019.101075>.
- Gerlagh, R., Heijmans, R. J., & Rosendahl, K. E. (2020). COVID-19 tests the market stability reserve. *Environmental and Resource Economics*, 76(4), 855-865. Available at: <https://doi.org/10.1007/s10640-020-00441-0>.
- Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1), 71-100. Available at: [https://doi.org/10.1016/0304-405x\(85\)90044-3](https://doi.org/10.1016/0304-405x(85)90044-3).
- Goodell, J. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 35, 101512. Available at: <https://doi.org/10.1016/j.frl.2020.101512>.
- Goodell, J. W., & Goutte, S. (2021). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters*, 38, 101625. Available at: <https://doi.org/10.1016/j.frl.2020.101625>.
- Gorton, G., & Metrick, A. (2010). Haircuts. *Federal Reserve Bank St Louis Review*, 92(6), 507-520.
- Goyenko, R. Y., Holden, C. W., & Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics*, 92(2), 153-181. Available at: <https://doi.org/10.1016/j.jfineco.2008.06.002>.
- Gregurec, I., Tomičić Furjan, M., & Tomičić-Pupek, K. (2021). The impact of COVID-19 on sustainable business models in SMEs. *Sustainability*, 13(3), 1-24. Available at: <https://doi.org/10.3390/su13031098>.
- Guijarro, F., Moya-Clemente, I., & Saleemi, J. (2019). Liquidity risk and investors' mood: Linking the financial market liquidity to sentiment analysis through twitter in the S&P500 index. *Sustainability*, 11(24), 1-13. Available at: <https://doi.org/10.3390/su11247048>.
- Guijarro, F., Moya-Clemente, I., & Saleemi, J. (2021). Market liquidity and its dimensions: linking the liquidity dimensions to sentiment analysis through microblogging data. *Journal of Risk and Financial Management*, 14(9), 1-12. Available at: <https://doi.org/10.3390/jrfm14090394>.
- Huang, R. D., & Stoll, H. R. (1997). The components of the bid-ask spread: A general approach. *The Review of Financial Studies*, 10(4), 995-1034. Available at: <https://doi.org/10.1093/rfs/10.4.995>.

- Jana, R. K., & Das, D. (2020). Did Bitcoin act as an antidote to the Chinese equity market and booster to Altcoins during the Novel Coronavirus outbreak? *SSRN*, 1-28. Available at: <https://doi.org/10.2139/ssrn.3544794>.
- Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold—A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59, 105-116. Available at: <https://doi.org/10.1016/j.irfa.2018.07.010>.
- Kristoufek, L., & Vosvrda, M. (2019). Cryptocurrencies market efficiency ranking: Not so straightforward. *Physica A: Statistical Mechanics and its Applications*, 531, 120853. Available at: <https://doi.org/10.1016/j.physa.2019.04.089>.
- Li, X., Xie, Y., & Lin, J.-H. (2021). COVID-19 outbreak, government capital injections, and shadow banking efficiency. *Applied Economics*, 53(4), 495-505. Available at: <https://doi.org/10.1080/00036846.2020.1808183>.
- Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economic Review*, 30(4), 779-811. Available at: <https://doi.org/10.1007/s11079-019-09547-5>.
- Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of financial Economics*, 82(3), 631-671. Available at: <https://doi.org/10.1016/j.jfineco.2005.10.001>.
- Lybek, T., & Sarr, A. (2002). Measuring liquidity in financial markets. *International Monetary Fund*, 2(232), 1-64.
- Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance Research Letters*, 36, 101647. Available at: <https://doi.org/10.1016/j.frl.2020.101647>.
- Omane-Adjepong, M., & Alagidede, I. P. (2019). Multiresolution analysis and spillovers of major cryptocurrency markets. *Research in International Business and Finance*, 49, 191-206. Available at: <https://doi.org/10.1016/j.ribaf.2019.03.003>.
- Phillip, A., Chan, J. S., & Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, 163, 6-9. Available at: <https://doi.org/10.1016/j.econlet.2017.11.020>.
- Richter, A., & Wilson, T. C. (2020). Covid-19: implications for insurer risk management and the insurability of pandemic risk. *The Geneva risk and Insurance Review*, 45(2), 171-199. Available at: <https://doi.org/10.1057/s10713-020-00054-z>.
- Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance*, 39(4), 1127-1139. Available at: <https://doi.org/10.1111/j.1540-6261.1984.tb03897.x>.
- Saleemi, J. (2014). *Saleemi, J. (2014). An empirical analysis of cost-based market liquidity measures for US & Norwegian banks*. Master's Thesis, University of Nordland.
- Saleemi, J. (2020). A cost-based estimate of market liquidity from the high, low, and closing prices. *Finance, Markets and Valuation*, 6(2), 1-11. Available at: <https://doi.org/10.46503/vutl1758>.
- Saleemi, J. (2021). COVID-19 and liquidity risk, exploring the relationship dynamics between liquidity cost and stock market returns. *National Accounting Review*, 3(2), 218-236. Available at: <https://doi.org/10.3934/nar.2021011>.
- Tran, L. V., & Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. *Finance Research Letters*, 35(C), 1-8. Available at: <https://doi.org/10.1016/j.frl.2019.101382>.
- Umar, Z., & Gubareva, M. (2020). A time-frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. *Journal of Behavioral and Experimental Finance*, 28, 100404. Available at: <https://doi.org/10.1016/j.jbef.2020.100404>.
- Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. *Economics Letters*, 168, 21-24. Available at: <https://doi.org/10.1016/j.econlet.2018.04.003>.
- Wójcik, D., & Ioannou, S. (2020). COVID-19 and finance: market developments so far and potential impacts on the financial sector and centres. *Journal of Economic and Human Geography*, 111(3), 387-400. Available at: <https://doi.org/10.1111/tesg.12434>.
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36(C), 1-6. Available at: <https://doi.org/10.1016/j.frl.2020.101528>.