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Liquidity spillover in cryptocurrency markets

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Abstract: This study will investigate the liquidity spillover effects of five cryptocurrencies: Bitcoin, Ether, Binance-coin, Ripple, and Tether. Firstly, the researcher utilizes the Amihud illiquidity ratio to quantify the liquidity performance of the five currencies, which we treat as weekly for the purposes of our study due to data collecting constraints. Secondly, to quantify the liquidity spillover effect in the cryptocurrency market over the period of 2017-2022, the researcher employs Diebold and Yilmaz's spillover index. The results identify the senders and receivers of liquidity spillovers on an individual and pairwise basis for the five major currencies and demonstrate the presence of time variation. Additionally, this paper evaluates the news report-based cryptocurrency uncertainty index (UCRY). This includes the price of cryptocurrencies (UCRY price) and the uncertainty surrounding cryptocurrency policy (UCRY policy). Considering the constructed index follows the same path as the largest cryptocurrency, Bitcoin, it is therefore recommended that the Bitcoin price can be used to forecast the cryptocurrency uncertainty index. Overall, this study has filled a gap in the literature by conducting research on liquidity spillovers in cryptocurrency markets, and it presents some preliminary conclusions. However, in order to verify the validity of our findings and to provide more meaningful results, additional research is required over a longer time horizon and with additional cryptocurrency types.

1. Introduction

For two decades, analog and electronic technology has been rapidly transformed into digital technology. This enormous technological revolution occurred in the millennial era, and consequently, a new form of money called cryptocurrency emerged in daily economic life. It represents a digital version of money and an investment function that offers the convenience of production, storage and consumption using digital cryptography [1]. In 2008, the financial crisis struck the world with the force of a mountainous economic tsunami. On the 1st of November 2008, the mysterious Satoshi Nakamoto published "Bitcoin: A Peer-to-Peer Electronic Cash System" on the P2P Foundation website, outlining his idea for a digital currency. Satoshi Nakamoto produced the first block of Bitcoin, the Genesis Block, by hand in 2009 on a modest server in Helsinki, Finland. Bitcoin began as a toy in the hands of programmers. It was not until the 22nd of May 2010, when a Florida programmer named Laszlo Hanyecz paid 10,000 bitcoins for two pizzas, that bitcoin truly became viable, and Bitcoin Pizza Day was born. Consequently, cryptocurrency has gained attention since 2008 and has also received increasing attention in recent years. Cryptocurrencies are set to become the currency of future as the world is entering an increasingly digital era, which makes the study of the cryptocurrency market vital.

In the last five years, bitcoin and other virtual currencies have grown in popularity significantly, causing a change in attitudes towards this market among people of all backgrounds. The research on cryptocurrencies has increased significantly, and the literature on the topic is growing quickly. For instance, Chuen set out to educate readers about cryptocurrencies and to examine their risk and return characteristics via the lens of the Cryptocurrency Index (CRIX). Additionally, Hileman provides a systematic and comprehensive overview of a fast-expanding business, by demonstrating how cryptocurrencies are used, stored, transacted, and mined [2]. Moreover, Wang provides a deep observation from a dynamic perspective by including 973 different types of cryptocurrencies and 30 foreign indices. Price prediction is accomplished using two machine learning techniques, namely linear regression (LR) and support vector machine (SVM), with a time series of daily ether cryptocurrency closing prices. Yarovaya applies a variety of quantitative methodologies to calculate hourly prices for the four most actively traded cryptocurrency markets - USD, EUR, JPY, and KRW - for the period 1 January 2019 to 13 March 2020[3]. The primary contribution of Mnif was to conduct a multifractal analysis to determine the level of cryptocurrency efficiency prior to and following the coronavirus pandemic [4].

Overall, whether viewed from the perspective of investors, regulators, or academics, the cryptocurrency market is indeed gaining more attention. However, to date, no previous articles have examined and quantified the spillover effect of cryptocurrency liquidity. Therefore, this article will calculate the amihud illiquidity ratio to quantify the liquidity of five cryptocurrencies using the opening price, closing price, and daily trading volume of the top five cryptocurrencies as listed on coinmarketcap.com. Diebold and Yilmaz's variance decomposition approach have been applied to investigate the liquidity spillover effect in the cryptocurrency market. The researcher’s contribution to the literature is threefold. First, this is the first article (to the researcher’s knowledge) that will examine the liquidity spillover effects in major cryptocurrency markets. Second, the researcher will identify the senders and receivers involved in the process of liquidity propagation in various currencies, as well as the pairwise direction of liquidity propagation. Finally, the researcher understands that the price of bitcoin has the same index trend as the cryptocurrency uncertainty index provided by Lucey[5]. As a result, the researcher proposes that this study will roughly estimate the uncertainty index using the intraday price of bitcoin and confirm that they are affected appropriately in the case of a financial crisis.

The purpose of this paper is to examine liquidity spillovers in the cryptocurrency market by using Diebold and Yilmaz Spillover Index. It will also determine whether regulatory policy is a determinant of liquidity spillover in the cryptocurrency market by analysing Cryptocurrency Uncertainty Index.

This article mainly studies the following Research Question:

(1) How to measure liquidity spillovers in the cryptocurrency market?

(2) Who are the receivers and senders of liquidity spillovers?

(3) Do the policies imposed by regulators on cryptocurrencies and major events in the cryptocurrency market have an impact on the uncertainty index?

2. Literature Review

2.1 Background

In recent years, literature on the cryptocurrency market has become more prevalent. Bitcoin and other cryptocurrencies are currently deeply ingrained within the economic system, they are now changing into a broadly accepted form of online payment. In 2020, the Economist Intelligence Unit (EIU) conducted a survey measuring the relative acceptance of digital currencies and other digital payment methods. The findings revealed a strong global trend toward cashless consumers. Meanwhile various governments are increasing planning or piloting central bank digital currencies (CBDC) and companies are experimenting with accepting open-source digital currencies for financial or portfolio distribution (e.g., Bitcoin). According to the previous year's study, the trend toward cash-lessness was already strong, but in 2021, the epidemic prompted more people to abandon cash payments. In 2020, roughly 72% of respondents believed that their country was likely to become a cashless society; this year that percentage grew to more than 81%. A new survey conducted by The Economist Intelligence Unit in February and March 2021, aims to measure how people's sentiment has changed over the past year. Results from this year indicate a rise in the popularity of digital trading and cryptocurrency. In the past 12 months, 27% of survey respondents said they always (as close to 100% of purchases as possible) used digital payments instead of physical bills, coins, or credit cards, compared to 22% in the previous year's study. Looking at this metric from the opposite perspective, the percentage of respondents who rarely use digital payment options fell from 14% to 12%, indicating a decline in adherent users of physical cash.

2.2 Liquidity in the Economic System

Liquidity is the lifeblood of financial markets. When it disappears, markets no longer operate efficiently. One aspect of the literature focuses on liquidity in the economic system and describes and tests different methods of measuring liquidity. In this paper the researcher will choose a suitable method in these articles to study the liquidity of cryptocurrencies. For example, Guo illustrate that the central bank's sincere desire to encourage economic growth through surplus liquidity, feeds real estate prices and exacerbates the inflation bias [6]. Additionally, Evans argue that liquidity is responsible for the within-month activity cycle [7]. The model is analysed using numerical simulations and systemic risk modeling, in which the model captures and analyses the local interaction of units through the bilateral provision of liquidity among units [8]. Smimou examines the dynamic macro-liquidity link in terms of consumer attitudes/sentiments [9]. Also, Zheng contend that, while giving moderate liquidity is an efficient tool for stabilizing the economy within a well-studied macroeconomic ABM that permits enterprises to diversify their economic performance, excessive liquidity can result in abnormal wealth dispersion and consequent severe endogenous crises [10]. These articles confirm that liquidity is an important concept in economics and that many policy issues, including central banking, are closely related to it.

3. Data and Methodology

3.1 Data

This paper collected data from the daily open and close prices and the trading volume of the top eight cryptocurrencies in terms of market capitalisation. This was for the period between 1st Jan 2017 to 1st Jan 2022. Over this period, the researcher continuously used MATLAB to freely access the public API of one of the largest cryptocurrency websites, coinmarketcap.com. After that, the researcher discovered that not every cryptocurrency had valid data available in January 2017, especially Terra, Solana and Usd-coin which started very late. Therefore, the researcher decided to remove those three rows, and chose to start from the date in which data was available (2nd Oct 2017) for the remaining five currencies: Bitcoin, Ethereum, Tether, Binance coin and Ripple.

The sample selected for this research consists of 1,553 observations for each currency and the opening and closing prices, and trading volume are listed in US dollars. This empirical study begins by calculating summary statistics for the cryptocurrencies price returns and volume ratios. The Augmented Dickey-Fuller (ADF) test is also employed to determine the existence of unit roots in the ratio. Moreover, this research followed the cryptocurrency uncertainty index constructed by Lucey which was based on 726.9 million news articles from the LexisNexis database [5]. This database provides data for the UCRY Policy Index and UCRY Price Index from 30th Dec 2013 to 3rd Oct 2021.

3.2 Measure of Liquidity

Amihud's (2002) illiquidity measure is one of the most extensively used liquidity proxies in finance literature. Over one hundred studies published in the Journal of Finance, the Journal of Financial Economics and the Review of Financial Studies between 2009 and 2013 used the Amihud (2002) measure for their empirical analysis. This formula compares the absolute value of the daily return for the previous N trading days to the current day's turnover, before the arithmetic average is calculated using the above ratio for the next N trading days. This measure depicts market liquidity in terms of volume, and also the degree of price change, which is more consistent with our earlier definition of liquidity. The greater the value of this component, the more easily the currency's price can be manipulated through trading activity, implying that liquidity is poor. Conversely, if the value of this factor is minimal, liquidity is excellent. Indeed, this concept has been employed by numerous scholars in the past; for example, individuals used to describe liquidity using the ratio of price movements to the number of orders.

The Amihud illiquidity ratio calculated for each subinterval is the absolute return (measured from the opening price to the closing price of the subinterval) divided by the dollar trading volume in the subinterval:

$$Amihud_t = \frac{1}{t}\sum_i \frac{|C_{t,i}/Q_{t,i} - 1|}{\$Vol_{t,i}}$$

where $C_{t,i}$ and $Q_{t,i}$ denote the opening and closing prices in the subinterval i, respectively. The unweighted average of the ratios for the subintervals in is the illiquidity ratio for interval, but 5-minutes of high-frequency data was not collected. The data was transformed into a weekly format for analysis. In theory, the illiquidity ratio is a measure of price effect. However, in empirical applications, it is frequently employed as a proxy for overall liquidity. After collecting the results, the researcher performed The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to examine the existence of unit roots.

3.3 Measuring Liquidity Spillover

DY Spillover Index: Following Diebold and Yilmaz, the liquidity spillover effect for cryptocurrency i is quantified by the proportion of its liquidity forecast error variance that is caused by shocks to cryptocurrency j's liquidity, for all i. In a VAR(p) system, denote y_t as an n-dimensional vector:

$$y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t$$

where y_t is a *K*-dimensional vector of endogenous variables; A_p is a *K-by-K* matrix. The VAR (*p*) can be casted in the companion VAR (1) form as follows

$$Y_t = v + AY_{t-1} + U_t$$

$$Y_t = \begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{pmatrix}, \quad A = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_K & 0 & \cdots & 0 & 0 \\ 0 & I_K & 0 & 0 & 0 \\ \vdots & \vdots & I_K & \vdots & \vdots \\ 0 & 0 & \cdots & I_K & 0 \end{bmatrix}, U_t = \begin{pmatrix} U_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

The moving average (**MA**) representation is

$$y_t = u + \sum\nolimits_{j=1}^{\infty} \phi_i \, u_{t-i}$$

To compute variance decompositions, orthogonal innovations are required, although our VAR innovations are typically contemporaneously coupled. While Cholesky's factorisation identification approaches achieve orthogonality, the variance decompositions become dependent on the variable ordering. This study has attempted to overcome this limitation by utilising the extended VAR framework developed by Koop, Pesaran, and Potter; Pesaran and Shin (KPPS), which generates variance decompositions that are ordering invariant. Rather than attempting to orthogonalise shocks, the generalised method permits correlated shocks but correctly adjusts for them using the historically known distribution of mistakes. Due to the non-orthogonal nature of the shocks to each variable, the total of the contributions to the variance of the prediction error (that is, the row sum of the variance decomposition table items) is not always equal to 1.

Denoting the KPPS H-step-ahead forecast error variance decompositions by

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_i)}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)}$$

where $\sum$ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term in the jth data, and e_i is the selection vector, with one as the ith member and zeros elsewhere. As shown previously, the total of the items in each row of the variance decomposition table does not equal 1: $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$.

To make use of the information included in the variance decomposition matrix while calculating the spillover index, each row sum item is normalised in the variance decomposition matrix as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$$

By construction, $\sum_{j=1}^{N} \theta_{ij}^{g}(H)$=1 and $\sum_{i,j=1}^{N} \theta_{ij}^{g}(H) = N$

Built on the H-step-ahead forecast error variance decompositions (FEVD) the total spillover index is defined:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \theta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \theta_{ij}^{g}(H)}{N} \times 100$$

Measuring the directional spillovers received by cryptocurrency i from all other cryptocurrency j as:

$$S_{i*}^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \theta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \theta_{ij}^{g}(H)}{N} \times 100$$

Also, the directional spillovers transmitted by cryptocurrency i to all other cryptocurrency j are measured the same way:

$$S_{*i}^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \theta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \theta_{ij}^{g}(H)}{N} \times 100$$

Obtaining the net liquidity spillover from cryptocurrency i to all other cryptocurrency j as

$$S_{i}^{g}(H) = S_{*i}^{g}(H) - S_{i*}^{g}(H)$$

The net liquidity spillover is the difference between the gross liquidity shocks transmitted to and those received from all other cryptocurrencies (Table 1).

Table 1: Diebold–Yilmaz Connectedness (FEVD)

$k\downarrow$ $j\rightarrow$	**Currency 1**	**Currency 2**	$\cdots$	**Currency N**	**FROM Others**
Currency 1	$S_{11}^{g}(H)$	$S_{12}^{g}(H)$	$\cdots$	$S_{1N}^{g}(H)$	$\sum_{j=\{1\ldots N\}\backslash 1} S_{1j}^{g}(H)$
Currency 2	$S_{21}^{g}(H)$	$S_{22}^{g}(H)$	$\cdots$	$S_{2N}^{g}(H)$	$\sum_{j=\{1\ldots N\}\backslash 2} S_{2j}^{g}(H)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Currency N	$S_{N1}^{g}(H)$	$S_{N2}^{g}(H)$	$\cdots$	$S_{NN}^{g}(H)$	$\sum_{j=\{1\ldots N\}\backslash N} S_{N1}^{g}(H)$
TO Other	$\sum_{k=\{1\ldots N\}\backslash 1} S_{k1}^{g}(H)$	$\sum_{k=\{1\ldots N\}\backslash 2} S_{k1}^{g}(H)$	$\cdots$	$\sum_{k=\{1\ldots N\}\backslash N} S_{kN}^{g}(H)$	$\frac{1}{\mathrm{N}} \sum_{k,j=\{1\ldots N\},i\neq j} S_{ij}^{g}(H)$

Additionally, it is worthwhile to investigate net pairwise liquidity spillovers, which is defined as:

$$S_{ij}^{g}(H) = \left(\frac{\theta_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \theta_{ik}^{g}(H)} - \frac{\theta_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \theta_{jk}^{g}(H)}\right) \times 100 = \left(\frac{\theta_{ji}^{g}(H) - \theta_{ij}^{g}(H)}{N}\right) \times 100$$

The difference between the gross liquidity shocks transferred from cryptocurrencies i to market j, and those transmitted from j to i, is the net pairwise liquidity spillover between cryptocurrencies i and j.

3.4 Construction of UCRY index

Following Lucey, the uncertainty index of policy (UCRY Policy) is defined as:

$$UCRY\ Policy_t = \left(\frac{N_{1_t} - \mu_1}{\sigma_1}\right) + 100$$

The uncertainty index of price (UCRY Price) is defined as:

$$UCRY\ Police_t = \left(\frac{N_{2_t} - \mu_2}{\sigma_2}\right) + 100$$

where $UCRY\ Policy_t$ is the value of the Cryptocurrency Policy (Price) Uncertainty Index throughout the period December 2013 to February 2021. N_{1_t} (N_{2_t}) denotes the weekly observed value of news items on LexisNexis business on the uncertainties, μ_1 (μ_2) denotes the mean of these same articles, and σ_1 (σ_1) denotes their standard deviation.

4. Empirical Results and Findings

The Amihud indicator determines how sensitive the price is to trading volume by calculating the ratio of cryptocurrency returns to trading volume over time. If variations in the volume of the currency's transactions cause severe fluctuations in the share price, the larger the Amihud indicator and the less liquid the currency is. Conversely, if changes in the number of transactions have less impact on price changes, the currency is more liquid. Figure 1 displays the illiquidity ratio of the five chosen cryptocurrencies in this paper. In this bar graph it is evident that Tether's indicator is dramatically higher than the other four currencies. This indicates that his trading volume fluctuations can seriously affect its price, meaning that it is the least liquid. Secondly, Ripple's illiquidity is also slightly higher than the other three cryptocurrencies, ranking as the second least liquid currency in our study. Finally, Bitcoin, Ethereum and Binance coin appear to have better liquidity, especially Bitcoin, whose trading volume changes have little impact on the price, and it is the most liquid cryptocurrency.

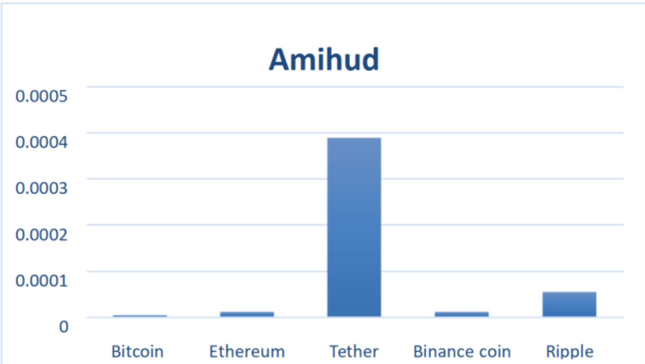

Figure 1: Results of Amihud illiquidity ratio

The daily illiquidity ratio of cryptocurrency i, yi,t are defined as:

$$yi,t = \frac{Ai,t - Ai,t-1}{Ai,t-1}$$

where Ai,t is the $\frac{|C_{t,i}/Q_{t,i}-1|}{\$Vol_{t,i}}$ of cryptocurrency i on day t.

Table 2 summarises the results of unit root tests. At the 1% level of significance, the Augmented Dickey-Fuller (ADF) test produces substantial negative values refuting the null hypothesis of a unit root, indicating that the weekly ratios of all five cryptocurrencies are stationary.

Table 2: Units root tests

\	Bitcoin	Ethereum	Tether	Binance coin	Ripple
ADF	-38.78747***	-	-	-	-
		39.93666***	39.93663***	39.93676***	40.44478***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Note: *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.					

Table 3 shows the descriptive statistics of return/volume ratio for the five cryptocurrencies investigated in this research. The average return/volume for all five cryptocurrencies is positive, ranging from 0.00% (Tether) to 0.4% (Binance coin). Furthermore, Ripple is the most volatile cryptocurrency, assessed with a standard deviation of 7.07%, while Bitcoin has the least volatility (4.47%). It can also be seen that all price returns are polarised, with Tether having the highest excess normal distribution. Additionally, both Bitcoin and Ether have negatively skewed return volume ratios, indicating that both cryptocurrencies have a long left-tail. In contrast, the return volume ratio for Binance coin, Ripple, and Tether exhibit the opposite outcome; they are positively skewed, showing that huge positive price returns are more prevalent than large negative returns. The statistics for the Ljung-Box Q(10) and Q2(10) are used to test the null hypothesis that autocorrelations are equal to zero in residuals and squared residuals, for all lags up to lag 10. The Jarque-Bera (JB) test results beliefs based the variation from normalcy for all five ratios series, and it rejects the null of the normal distribution for all five series hypotheses. Therefore, we could proceed to model the liquidity of cryptocurrency.

Table 3: Descriptive statistics

\	**Bitcoin**	**Ethereum**	**Binance.coin**	**Ripple**	**Tether**
Mean	0.002	0.002	0.004	0.001	0
Variance	0.002	0.003	0.004	0.005	0
Skewness	-0.813***	-0.904***	0.382***	0.784***	0.380***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	11.606***	10.445***	13.122***	14.162***	20.159***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	8875.801***	7260.948***	11165.444***	13120.024***	26299.576***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-16.191***	-11.425***	-2.025**	-8.566***	-26.241***
	(0.000)	(0.000)	(0.043)	(0.000)	(0.000)
Q(10)	10.624*	21.272***	11.877**	9.910*	258.040***
	(0.052)	(0.000)	(0.028)	(0.073)	(0.000)
Q2(10)	18.053***	27.162***	159.076***	106.963***	378.791***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4: Dynamic Connectedness

\	**Bitcoin**	**Ethereum**	**Binance.coin**	**Ripple**	**Tether**	**FROM others**
Bitcoin	37.56	25.61	17.07	15.40	4.36	62.44
Ethereum	24.21	36.39	17.69	18.02	3.69	63.61
Binance.coin	19.23	20.48	42.64	14.29	3.36	57.36
Ripple	16.75	21.26	13.99	44.47	3.52	55.53
Tether	7.49	7.40	6.30	6.50	72.31	27.69
TO others	67.69	74.75	55.04	54.22	14.94	266.63
Inc.own	105.24	111.14	97.69	98.69	87.24	TCI
NET	5.24	11.14	-2.31	-1.31	-12.76	53.33
NPDC	1.00	0.00	3.00	2.00	4.00	FROM others

Table 4 shows the evidence of cryptocurrency market liquidity spillover during the saple period and summarises the liquidity spillover effects, as evaluated by the Amihud illiquidity ratio. We follow Diebold and Yilmaz (2014) and decompose the 100-step ahead forecast error (as determined by the Akaike information criterion) in the VAR (2) system using a generalised variance decomposition. Each row in a 5x5 matrix of spillover effects has a value stated in percentage units that adds up to 100 percent. It is estimated that the VAR (2) model will also use the Akaike Information Criterion for the lag length (AIC). Figure 2 summarises the liquidity spillover effects in the cryptocurrency market with a prediction horizon of h = 100 days. The (5x5) spillover matrix's (i,j)th element represents the contribution of shocks to other cryptocurrency j to the variance of the prediction error for cryptocurrency i. The diagonal element (i=j) reflects its own contribution, whereas the off-diagonal element represents liquidity spillovers between cryptocurrency i and j.

Additionally, the table indicates that other cryptocurrencies j account for 53.33% in predicted errors in liquidity during the sample period. The penultimate row of Table 4 lists the net spillover effects of cryptocurrency i on other cryptocurrencies j. Positive net spillovers occur in the Bitcoin and Ethereum markets during the sample period, with Ethereum (11.14) having the biggest net spillover effect due to the liquidity conveyed to other currency.

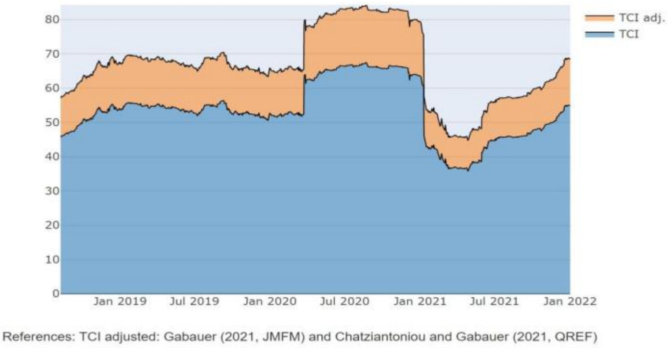

Figure 2: Dynamic Total Connectedness

To make the linkage of cryptocurrency market liquidity time-varying, we employ a rolling window sample to estimate the VAR and develop a conditional spillover indicator. Following Diebold and Yilmaz (2015), we utilise a rolling window of 100 days. Figure 3 also illustrates that the overall spillover index changes substantially over time, with the liquidity spillover peaking in the first quarter of 2020 at around 80 percent. Then again in the second and third quarters of the year at over 80% and continuing into early 2021. It then declines significantly in the first quarter of 2021, but afterwards rises again in June and lasts until early 2022.

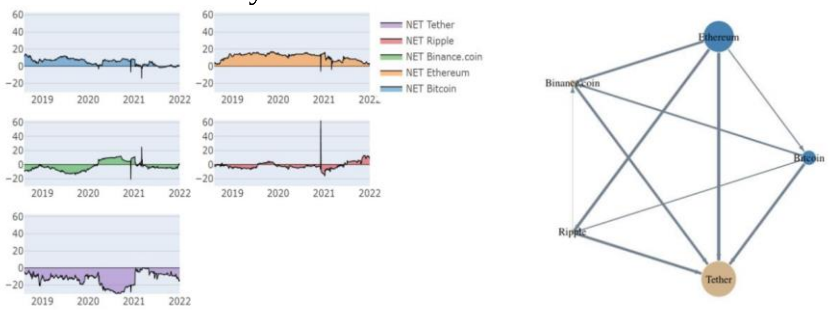

Figure 3: Net Total Directional Connectedness and Network Plot

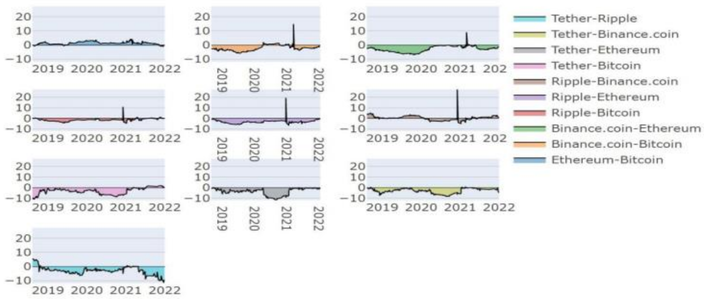

Figure 4: Net Pairwise Directional Connectedness

Figure 4 depicts the net directional spillover index for the five cryptocurrency pairs. This is defined as the difference between the amount of liquidity transferred from one currency to another, and the amount of liquidity gained by individual currencies from other currencies (Figure 3). Blue (yellow) nodes in the plot illustrate the net transmitters (receivers) of shocks. The weight of the nodes is determined by the average net pairwise directional connectivity. The size of the node represents the weighted average total directional connectivity. This means that bitcoin and Ethereum are mainly liquidity senders, while Binance coin, Tether and Ripple are liquidity receivers. The researcher utilises a rolling window of 300 days with the forecast horizon set to h = 100 trading days to get a series of spillovers for the period 2 October 2017 to 1 January 2022. On the vertical axis, the liquidity spillover index is expressed in percentages. A positive net index implies that the market for the corresponding currency pair is a net recipient of illiquidity, while the negative net index shows that the market for the corresponding currency pair is a net source of illiquidity.

As can be seen in Figure 4, Ethereum-Bitcoin is operating as a liquidity transmitter throughout the time period, whereas Tether-Bitcoin, Tether-Ethereum and Tether-Binance coin all act as receivers. In contrast, Binance Coin-Bitcoin, Binance Coin-Ethereum, Ripple-Bitcoin and Ripple-Ethereum all operated as receivers in the early phases, but started to generate strong fluctuations around December 2020. It momentarily attained a positive net index and then immediately reverted to its original level. This point in time coincided with the epidemic outbreak, but only these four cryptocurrency pairs reacted. It is not certain if they are caused by the outbreak.

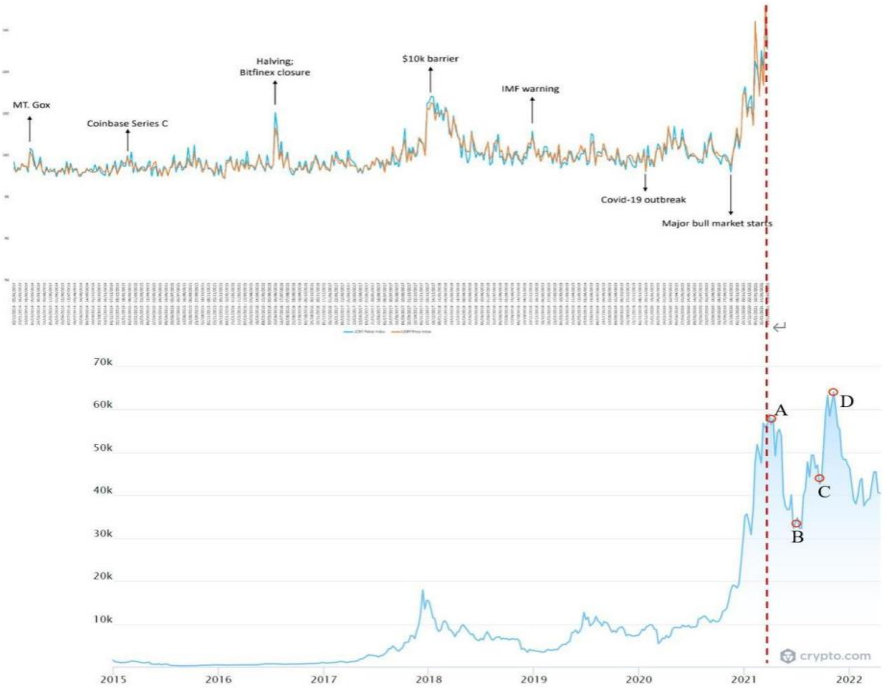

Figure 5: Bitcoin Price vs. Cryptocurrency Uncertainty Index

The graph cited in the article by Lucey illustrates weekly policy and price indices, highlighting the significant changes that coincide with developments in cryptocurrency and related economic sectors. This article considers the daily price graph of Bitcoin (Figure 5) to compare with the index, and it appears that the policy and price uncertainty indexes have the same pattern as the price of Bitcoin, which confirms that they are highly correlated. So, it could be argued that the price of Bitcoin can forecast the trend of the cryptocurrency uncertainty index to some extent, although the real index reflects more uncertainty. The main economic events that have occurred since February 2021 that might affect the price of Bitcoin, or cause the Cryptocurrency Uncertainty Index to fluctuate, have been labeled in the graphic. For example: A. March: a series of sanctions against Russia, including a ban on access to the global banking system SWIFT, B. July: $530 million of unlocked shares in the Grayscale Bitcoin Trust (GBTC) affected the price of Bitcoin, while over 16,000 BTC were unlocked, C. September: The People's Bank of China acknowledged a sustained crackdown on cryptocurrencies. Bitcoin sinks to a low of over $40,000 as the market collapses, and D. November: the highly anticipated Bitcoin upgrade Taproot takes effect; Bitcoin rises to a fresh all-time high of $69,000. This proves that these related financial events do influence the price movement of Bitcoin, and the Cryptocurrency Uncertainty Index will likewise be affected according to our forecast.

5. Conclusion and evaluation

This paper uses intraday trading data from coinmarketcap.com and converts it to weekly data to examine liquidity spillovers in major cryptocurrency markets from 2017 to 2022. However, due to data collection constraints, this paper examines only five digital currencies: Bitcoin, Ethereum, Binance-coin, Tether, and Ripple. Whilst numerous academic published papers have explored volatility spillovers and transmission in cryptocurrency markets, very few empirical studies have been conducted on liquidity spillovers. This research project aims to fill this gap and improve our understanding of the digital currency market.

To begin, the researcher confirmed and quantified the liquidity of these five currencies using the Amihud illiquidity ratio. The results reveal that Tether is the least liquid currency, Ripple is the second least liquid, and Bitcoin is one of the most liquid assets in the financial market. Subsequently, the spillover of cryptocurrency liquidity is time-varying and directional using a spillover indicator based on a generalised variance decomposition. The net directional spillover impact varies between currencies, regardless of whether they are analysed individually or in pairs. On the one hand, at the level of individual currencies, Bitcoin and Ether act as net shock transmitters, whereas the remaining three currencies act as shock receivers. On the other hand, in terms of pairs, Ethereum-Bitcoin acts as a liquidity provider, while Tether-Bitcoin, Tether-Ethereum and Tether-Binance coin all act as receivers.

Finally, using the new method proposed by Lucey to quantify price and policy uncertainty in the cryptocurrency market, namely the policy (UCRY Policy) and price (UCRY Price) of the cryptocurrency uncertainty index, we discovered that the price of bitcoin moves similarly to this index. Thus, we used the price of bitcoin to forecast the uncertainty index. Four major events in the cryptocurrency market that could alter their patterns are discussed, but the accuracy of the forecast outcomes is contingent on the subsequent release of the uncertainty index. Furthermore, it may have a range of practical and policy implications for risk measurement in cryptocurrency markets. All in all, this article fills a gap in the existing literature on cryptocurrency liquidity spillovers and confirms that the cryptocurrency uncertainty index exhibits significant movement in response to rising cryptocurrency events. However, as this paper is the first to investigate the cryptocurrency liquidity spillover effects, the findings obtained require additional validation. It is recommended that future researchers investigate the two-way shock transmission effects between cryptocurrencies, potentially employing the Vector Error Correction approach and the Diagonal BEKK Multivariate GARCH model.

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