

bradscholars

Liquidity dynamics between virtual and equity markets

Item Type	Article
Authors	Huang, Sherena S.
Citation	Huang SS (2023) Liquidity dynamics between virtual and equity markets. Journal of International Financial Markets, Institutions and Money. 91: 101917.
DOI	https://doi.org/10.1016/j.intfin.2023.101917
Rights	© 2023 The Author. Published by Elsevier B.V. This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).
Download date	2025-09-10 18:58:45
Link to Item	http://hdl.handle.net/10454/19767

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Liquidity dynamics between virtual and equity markets

Sherena S. Huang

Room 0.06, Pemberton Building, Accounting, Finance and Economics Centre (AFE), University of Bradford, Richmond Road, Bradford, West Yorkshire BD7 1DP, United Kingdom

ARTICLE INFO

Keywords:

Crypto asset
Cryptocurrency
Systemic risk
Global market
Financial stability
Monetary policy

ABSTRACT

This paper estimates liquidity dynamics between virtual and real assets from multiple dimensions, namely market capacity, transaction cost and market efficiency. The data covers transaction information of crypto markets and four equity exchanges (US, UK, EU and Japan) between January 2019 and December 2022. The first result shows a two-way liquidity risk feedback loop between virtual and real markets, and the second result confirms dynamic liquidity interactions between them. The US market is identified as a transmitter rather than a receiver of liquidity risk but may not escape cumulative liquidity shocks.

1. Introduction

Developments in 2008 have concentrated regulatory attention on systemic liquidity risks—a vicious circle or illiquidity spiral between funding and market liquidity (Brunnermeier & Pedersen, 2008; Acharya & Viswanathan, 2011; In, et al., 2012; Strahan, 2012; Katsiampa, et al., 2019; Sensoy, 2016). Studies of liquidity interactions have primarily focused on real assets, such as equities and equity-like instruments, which often influence each other due to their underlying relationships. The advent of crypto¹ in 2008 brought up a new form of asset that is neither equity nor an underlying asset—it is independent and largely affected by speculation. While the relatively small virtual asset market may not have a direct impact on the prices and volumes of real assets, liquidity interactions may exist as major market liquidity providers—speculators—move funds from one venue to another in pursuit of higher margins (Brunnermeier & Pedersen, 2008). Where funds are limited, high liquidity in one market may cause illiquidity in another indicating the possibility of liquidity flows between virtual and real assets. However, an empirical framework for the liquidity dynamics between virtual and real assets has not yet been established.

The digital nature of virtual assets makes them available to investors worldwide through the internet, accompanied by investment bubbles (BIS, 2008; 2011; 2020). Strong liquidity interactions between virtual and real assets may incur systemic liquidity shocks, which generalises the importance of this study. This paper contributes to the literature by estimating liquidity dynamics between virtual and real assets represented by crypto and equity markets, respectively. It employs robust methods to quantify 1) Does liquidity co-move between cryptos and global markets? 2) If so, is the direction of liquidity risk transmission mono- or bi-directional? and 3) do external shocks (the COVID-19 pandemic) affect liquidity interaction among assets? By addressing these questions, this paper aims to provide a multi-dimensional estimation of the above-mentioned regulatory concerns and verify global financial stability in terms of market liquidity.

The post-crisis amplifies the distrust between the public and financial institutions and leads to calls for financial decentralisation. The pioneer crypto asset—Bitcoin, is one of the outcomes. Bitcoins are issued, granted and transferred on a peer-to-peer network based

E-mail address: s.huang18@bradford.ac.uk.

¹ This paper follows official definitions and uses crypto or crypto asset for crypto products, such as cryptocurrency—the popular term on markets.

<https://doi.org/10.1016/j.intfin.2023.101917>

Received 25 May 2023; Accepted 23 December 2023

Available online 23 December 2023

1042-4431/© 2023 The Author. Published by Elsevier B.V. This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>).

on Blockchain, one type of Distributed Ledger Technology, which tries to overcome the problems of information asymmetry between individuals without the involvement of an intermediary, the banks (Nakamoto, 2008). Its simple but rigorous algorithms make transactions faster, more economical and more secure (Holloway, 2017; Reyes, 2017). This challenges the role of financial institutions.

Although authorities have defined cryptos as financial instruments and separated them from legal tender (FCA, 2019), the arrival of Bitcoin has opened a new market for speculation; more crypto assets have been created using various algorithms and attracted many speculators. This raises concerns over financial stability in terms of liquidity (BIS, 2008; 2020; 2011). Recent examples reflect the impact of speculative trading on the crypto market. The Terra Luna Coin collapse in May 2022 highlights the extreme volatility of crypto asset trading—the Luna coin price slumped from over 150 USD in April 2022 to near zero in May; approximately 90 % of its market value evaporated within 50 days. The bankruptcy of a crypto exchange, FTX, in November 2022 incurs a more severe case—billions of dollars are trapped and investors are not allowed to withdraw (BBC, 2022). This may lead to liquidity shortfalls in both equity and crypto markets.

This paper utilises the concept of commonality in liquidity made popular by Chordia et al. (2000) which suggests the covariance in liquidity of individual assets follows from a common or systemic liquidity factor. Since the systemic factor is non-diversifiable, such commonality in liquidity implies that shocks will produce market-wide effects and may affect the functioning of financial markets (Hasbrouck & Seppi, 2001). In addition, this paper employs three measures to estimate commonality for multifaceted estimates of liquidity, namely liquidity depth (Amihud, 2002; 2018), tightness (Sarr & Lybek, 2002) and resilience (Roll, 1984) and observes liquidity dynamics between virtual and real assets using Dynamic Conditional Correlation (DCC) Multivariate Generalised Autoregressive Conditionally Heteroskedastic (M–GARCH) Model (Engle & Granger, 1987; Engle, 2002). The estimates include exchanges in the United States (US), United Kingdom (UK), European Union (EU) and Japan (JP) which are the active markets for both equity and crypto trading.

This paper contributes to the literature in a number of ways. It extends the liquidity commonality estimations to cross-sectional and identifies the dynamics between virtual and real assets. Second, it testifies the sensitivity of three liquidity measures to the liquidity dynamics across assets, which will help to select estimators for future research. Third, the econometric approach analyses liquidity risk dynamics both within and beyond external shocks, such as the Covid-19 lockdowns. Fourth, it establishes a new measure that can be used as an indicator of liquidity risk transmission.

I document the existence of a bidirectional liquidity risk transmission between virtual and real assets—liquidity shortfalls in crypto markets can transmit into equity markets, and vice versa. Such liquidity distress may ripple across the markets. The US market appears capable of absorbing liquidity shocks exacerbated by the virtual market, however, it is not immune to the liquidity risk accumulated in equity markets. Furthermore, it confirms the significant effects of economic conditions and policy measures on market liquidity.

2. Literature review

2.1. Value recognition of virtual assets

The definition of value continues to evolve as the industry develops. Adam Smith (1776) categorises value into “value of use” and “value of exchange” and goods that hold higher value in use have less value in exchange, and vice versa—this differentiates between the value of goods and the value of currencies. Later on, Baier (1966) defines value as “the capacity of good, service, or activity to satisfy a need or provide a benefit to a person or legal entity”. Furthermore, Porter (1985) quantifies value as “the price a buyer is willing to pay”, which makes it possible to price non-physical items.

The first recognition of virtual items as property was through a legal case of a computer game at the Supreme Court of the Netherlands—case number 0/00101 J. In 2007, two teenage boys were involved in a dispute over a digital amulet and helmet robbery in an online role-playing game, RuneScape. In 2012, the court recognised these digital objects as property (Wildman & McDonnell, 2020; Wolswijk, 2012). This case sparked an argument in the legal community over whether imaginary “things” have value and can be traded. Nevertheless, regardless of legal status, virtual assets in the online gaming industry are primarily traded through in-game tokens, and their value is determined by players’ preferences and reflected in the token prices.

Similar to gaming tokens, crypto assets can be purchased using official currencies and traded on the issuers’ networks or exchange platforms. Theoretically, virtual markets are independent of real markets as the two markets trade different types of assets: one values long-term investment in company performance, whilst the other profits from price fluctuations. However, crypto assets satisfy a small strand of speculators who pursue volatility returns causing liquidity to flow from one market to another. These speculators establish a link between the virtual and real markets. Equity markets with a large number of participants, competitive transaction costs and efficient procedures (implying high liquidity) are expected to be able to withstand small outflows, which is what this paper examines.

2.2. The development of the crypto market

Crypto tokens are originally a digital reward for verifying online transactions on a distributed ledger network (Nakamoto, 2008; Drescher, 2017). It has grown alongside the development of the internet and has been treated as an object for investments and speculations in recent years. As of 2nd August 2022, the market capital of cryptos reached over one trillion US Dollars and Bitcoin, the original and by far the most well-known crypto asset launched in January 2008, holds most of the market shares (CoinMarketCap, n. d.).

The novelty of cryptos has also drawn the attention of authorities. As early as 2014, the Organisation for Economic Co-operation and Development (OECD) addressed the potential issues of crypto assets in consumer protection, such as value volatilities and market

manipulation (Blundell-Wignall, 2014). Additionally, the International Monetary Fund (IMF) discussed the risks of crypto assets at the Law and Financial Stability Seminar taking place in September 2018 in the US and emphasised its rising issues in market volatility. The Financial Conduct Authority of the UK (FCA) issued a guide on crypto business regulations in 2019 (FCA, 2019) and the EU integrated requirements for crypto businesses in its Fifth Anti-Money Laundering Directives (5AMLD), accordingly in 2020. These regulations focus on the registration and compliance of crypto businesses, speculative activities are not yet well-monitored.

The crypto market is incredibly volatile: the price of Bitcoin climbed from 1,000 USD in 2017 to over 60,000 USD in 2021 and dumped to 20,000 USD in May 2022 following a stable coin (Luna coin) crash that evaporated 90 % of its market value within 50 days. The later FTX (the former second largest crypto exchange) bankruptcy in November 2022 exacerbated the market panic and pulled the Bitcoin price down to, approximately, 16,000 USD. Such volatility highlights the instability of the virtual assets—the traded assets have no physical values; their price variation extensively relies on news and rumours, as well as speculative trading.

The drastic price variations of cryptos can affect funds inflows and outflows of both virtual and real assets. Therefore, evaluating the liquidity risk dynamics between crypto and exchanges can be vital for financial stability.

2.3. Commonality in liquidity

Liquidity dynamically echoes with money supply, market efficiency and economic policies that signal market variation and investment portfolios (Brunnermeier & Pedersen, 2008; Nikolaou, 2009; Sensoy, 2016; Bai & Qin, 2015). Even if the liquidity risk of a single asset can be diversified (Fernando, 2003), if not resolved in a timely manner, the cumulative liquidity shortages may trigger systemic risks and spread globally (Nikolaou, 2009; Panagiotou, et al., 2022; Domowitz, et al., 2005). The 2007 global financial crisis witnessed this possibility (Frank, et al., 2008). Studies summarise the common factors affecting market liquidity into three categories: liquidity depth, liquidity tightness and liquidity resilience, which respectively represent market capacity, transaction costs and market efficiency, and affect the mobility of funds from three dimensions. Greater market capacity and efficiency and lower transaction costs attract funds, thereby increasing market liquidity (Nikolaou, 2009; Brunnermeier & Pedersen, 2008; BIS, 2008; BIS, 2020; Ince, 2022; Ben Cheikh, et al., 2020). The speculative nature of virtual assets makes them more sensitive to these common factors (Akyildirim, et al., 2020; Katsiampa, et al., 2019; Mandaci & Cagli, 2022).

The liquidity covariance or commonality in liquidity seen as a component of systemic liquidity shocks has been discussed intensively in post-crisis research (Chordia, et al., 2000; Nikolaou, 2009; Karolyi, et al., 2012; Korajczyk & Sadka, 2008). Studies find that commonality in liquidity within a market is associated with inventory risks and market inefficiency (Chordia, et al., 2000, 2005), investor heterogeneity (Fernando, 2003) and high portfolio correlation (Coughenour & Saad, 2004). Studies also find commonality in liquidity between stock exchanges (Brockman, et al., 2009; Karolyi, et al., 2012), assets (Gopalan, et al., 2012), and markets (Banti & Phylaktis, 2015; Goyenko & Ukhov, 2009). These studies estimate liquidity co-movement from different perspectives and signify associated risks, such as liquidity depth, tightness or resilience. This paper aims to provide a complete estimate of liquidity conditions from all three perspectives and shed light on the impact of the novelty financial instrument, crypto asset, on global equity market liquidity. Further estimates of liquidity dynamics between virtual and real assets may assist in addressing the regulatory concerns about systemic liquidity risk posed by crypto assets.

3. Methodology and data

3.1. Basic framework

The estimation is structured into two steps: first, estimate liquidity indicators of cryptos and markets in three dimensions, namely liquidity depth, tightness and resilience, which represent market capacity, transaction costs and information efficiency (Nikolaou, 2009); second, identify the liquidity interactions and dynamics between markets. My sample data is stationary and cointegrated and has correlated error terms. Therefore, I use the Newey-West estimator to verify liquidity interactions (White, 1980; Newey & West, 1987) and the Dynamic Conditional Correlation (DCC) Multivariate GARCH model (Engle, 2002) to observe liquidity dynamics.

3.2. Liquidity indicators

Due to the lack of a generally accepted single definition of market liquidity, I follow convention and use proxy indicators of three aspects, liquidity depth, tightness and resilience, to estimate the commonality in liquidity between cryptos and global markets.

Liquidity depth refers to the existence of abundant orders on either side of the price at which security now trades (Sarr & Lybek, 2002), which sees the impact of order flow on price. I follow Amihud (2002) and estimate stock illiquidity as an absolute (percentage) price change of daily trading volume. The illiquidity ratio in equation (1) shows trading volume is inverse to market illiquidity premiums and the larger the trading volume, the weaker the price impact.

$$\text{Liquidity Depth (Illiq)} = \frac{1}{D_{iy}} * \sum_{d=1}^{D_{iy}} \frac{|R_{idy}|}{\text{Volume}_{idy}} \quad (1)$$

Where R_{idy} and Volume_{idy} are the daily return and trading volume of asset i on day d and year y . D_{iy} is trading days of asset i in year y . $R_{idy} = \ln(\text{price})_t - \ln(\text{price})_{(t-1)}$ (Amihud, 2002; Amihud & Mendelson, 1986; Amihud, et al., 2005).

The second liquidity indicator is tightness, which refers to transaction costs, such as the difference between bid and ask prices, as

well as implicit costs (Sarr & Lybek, 2002). I employ the *Relative Spread (R spread)* to proxy liquidity tightness, which measures market liquidity based on the ratio of the bid-ask spread to its average price. A smaller R-spread implies lower transaction costs and by inference, lower market liquidity risk.

$$\text{Liquidity Tightness (Rspread)}_i = \frac{(ask_i - bid_i)}{(ask_i + bid_i)/2} \quad (2)$$

The third liquidity indicator is resilience. Liquidity resilience measures the characteristics of resilient markets in which new orders flow quickly to correct order imbalances, which can move prices away from values justified by fundamentals. Following Roll (1984), I calculate the covariance of successive daily returns to discover market resilience as follows:

$$\text{Liquidity Resilience (Roll)} = 2\sqrt{-cov_i} \quad (3)$$

Where $cov_i = \text{covariance}(return_t, return_{(t+1)})$ is the covariance of consecutive daily returns. If $cov_i = 0$, there is no covariance between succeeding price changes caused by the arrival of new information, which infers the informational efficiency of the market. Greater market transparency increases confidence in trade and reduces implicit transaction costs, leading to higher market liquidity.

The three liquidity indicators represent three dimensions of market liquidity with larger values indicating higher liquidity risks. This paper estimates the three indicators using daily data and aggregates the indicators to a weekly frequency for the measurement of liquidity co-movement.

3.3. Commonality in liquidity/liquidity co-movement

The preferred methodological approaches require tests for autocorrelation and heteroskedasticity among variables. The test results detect autocorrelation but not all tests find heteroskedasticity. Thus, I choose the Newey-West estimator to estimate liquidity co-movement, which overcomes autocorrelation and heteroscedasticity in the errors (Newey & West, 1987). Since the Newey-West estimates are from single-equation models, I use the DCC M–GARCH Model (Engle, 2002) to observe dynamics in liquidity risk transmission.

3.3.1. Newey West estimator

The Newey-West estimator estimates the covariance matrix for a regression that accounts for serial correlation in the error terms (Newey & West, 1987). Serial correlation, also known as autocorrelation, occurs when the error terms in a regression are correlated over time. This violates the assumption of independence of errors (White, 1980). The Newey-West estimator adjusts for correlated error terms—which appear in the sample data for this paper. The estimator solves heteroskedastic and possibly autocorrelated error terms and approaches a normal distribution as the sample size increases (asymptotically normal distribution).

The model has the following specifications. For cryptos, the dependent variable is an indicator of the liquidity at time t with the main independent variable of interest being the lag of the liquidity indicator of a market. I repeat the exercise for selected markets, respectively, using the liquidity of cryptos as the dependent variable. A vector of macroeconomic indicators augments the model. I estimate separate models for the three liquidity indicators (see Equation (4) and (5)).

$$\text{liquidity}_{CY_t} = \alpha \sum_{m=1}^3 \text{liquidity}_{MK_{(t-m)}} + \beta \sum_{m=1}^3 \text{Macro}_{i(t-m)} + \varepsilon_t^{liq} \quad (4)$$

$$\text{liquidity}_{MK_t} = \alpha \sum_{m=1}^3 \text{liquidity}_{CY_{(t-m)}} + \beta \sum_{m=1}^3 \text{Macro}_{i(t-m)} + \varepsilon_t^{liq} \quad (5)$$

Where Liquidity_{CY_t} and Liquidity_{MK_t} are liquidity indicators of cryptos and global markets in week t , respectively. m is the optimal lag. $\text{Macro}_{i(t-m)}$ is the vector of variables controlling for the macroeconomic environment of markets, accordingly. I specify the year-on-year Consumer Price Index (CPI) and the onset of Covid-19 to proxy the availabilities of individual funds for speculative activities (virtual assets) and use the Major Banks Prime Lending Rates to proxy the availabilities of funds for equity investments (real assets). Batini and Nelson (2001) reaffirm a one-year lag effect between interest rates and inflation as interest rates are a policy reaction to present market conditions, therefore, the impact of inflation and interest rates are different on individuals and businesses. ε is the random noise.

3.3.2. Dynamic multivariate GARCH model

An alternative and popular method to deal with autocorrelation and heteroscedasticity among variables is the Multivariate Generalized Auto-Regressive Conditional Heteroskedasticity (M–GARCH) model that treats each element of the time-varying conditional correlation matrix as a linear function of its past and past shocks. Bollerslev, Engle, and Wooldridge (1988) introduce a Diagonal VEC-GARCH model and generalise a VECH term that stacks the lower diagonal elements of a symmetric matrix into a column vector. Engle (2002) extends the VEC-GARCH model to a Dynamic Conditional Correlation (DCC) M–GARCH Model that employs a nonlinear combination of univariate GARCH models with time-varying cross-equation weights to model the conditional covariance matrix of the errors. The conditional quasi-correlation parameters follow the GARCH-like process and estimate the parameters by maximum likelihood (ML). DCC M–GARCH is more flexible and parsimonious than the Diagonal VEC-GARCH model (StataCorp, 2021) and allows predetermined or exogenous variables in the model (Engle, 2002). Thus, this paper employs the DCC M–GARCH

Table 1
Summary statistics of variables.

Variable	Description	Obs	Mean	Median	Min	Max	Sd.	CV
Crypto Depth	Liquidity depth of cryptos	208	0.118	0.097	0.01	0.504	0.084	0.709
US Depth	Liquidity depth of Dow Jones	208	0.023	0.021	0.004	0.111	0.013	0.556
UK Depth	Liquidity depth of FTSE	208	0.011	0.008	0.002	0.333	0.023	2.104
EU Depth	Liquidity depth of DAXI	208	0.122	0.106	0.015	2.606	0.18	1.478
JP Depth	Liquidity depth of Nikkei 225	208	0.124	0.121	0.025	0.269	0.049	0.396
Crypto Tightness	Liquidity Tightness of cryptos	208	0.137	0.131	0.079	0.274	0.031	0.229
US Tightness	Liquidity Tightness of Dow Jones	208	0.013	0.011	0.004	0.073	0.009	0.654
UK Tightness	Liquidity Tightness of FTSE	208	0.014	0.011	0.005	0.078	0.009	0.618
EU Tightness	Liquidity Tightness of DAXI	208	0.014	0.012	0.005	0.076	0.008	0.582
JP Tightness	Liquidity Tightness of Nikkei 225	208	0.011	0.009	0.004	0.056	0.006	0.546
Crypto Resilience	Liquidity resilience of cryptos	208	9.365	8.77	5.928	27.274	2.485	0.265
US Resilience	Liquidity resilience of DJI	208	1.219	0.85	0.04	17.689	1.571	1.289
UK Resilience	Liquidity resilience of FTSE	208	1.02	0.868	0.003	8.868	0.858	0.842
EU Resilience	Liquidity resilience of DAXI	208	1.246	0.957	0.077	10.096	1.124	0.903
JP Resilience	Liquidity resilience of Nikkei 225	208	1.315	1.054	0.093	7.55	1.049	0.798
US CPI	YOY Consumer Price Index of the US	208	3.9	2.3	0.1	9.1	2.9	0.7
UK CPI	YOY Consumer Price Index of the UK	208	3.6	2.0	0.2	11.1	3.5	1.0
EU CPI	YOY Consumer Price Index of the EU	208	3.1	1.4	-0.3	10.6	3.3	1.1
JP CPI	YOY Consumer Price Index of Japan	208	0.8	0.5	-1.3	4	1.2	1.5
US Lending Rate	Major banks prime lending rate of the US	208	4.23	3.44	3.25	7.27	1.15	0.27
UK Lending Rate	Major banks prime lending rate of the UK	208	1.65	1.63	1.1	4.5	0.75	0.46
EU Lending Rate	Major banks prime lending rate of the EU	208	-0.25	-0.42	-0.58	1.89	0.57	-2.24
JP Lending Rate	Major banks prime lending rate of Japan	208	2.82	2.3	0.4	6.7	2.00	0.71
Covid	Dummy: 1 in lockdown, 0 otherwise	208	0.495	0	0	1	0.50	1.01

Data of indexes and cryptos is from Yahoo Finance. DJI is the Dow Jones index of US exchanges; FTSE is the FTST 100 Index of the London Exchange; DAXI is the DAX Performance-Index of the Frankfurt Stock Exchange. N225 is the Nikkei 225 Index of Japan Exchange; CPI is the Consumer Price Index for All Urban Consumers; Lending Rate is the major banks prime lending rate of the region; both CPI and lending rate are collected from DataStream. The covid lockdown period is between 16th March 2020 and 8th March 2022. Liquidity indicators are calculated based on daily data. All variables are integrated or converted into weekly frequency; CV: coefficient of variation (sd/mean).

model to verify the dynamics in liquidity between virtual and real assets.

$$h_{ij,t} = \rho_{ij,t} \sqrt{h_{ii,t} h_{jj,t}} \quad (6)$$

$$Y_t = CX_t + \varepsilon_t \quad (7)$$

$$\varepsilon_t = H_t^{1/2} v_t$$

$$H_t = D_t^{1/2} R_t D_t^{1/2}$$

$$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2}$$

$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \widetilde{\varepsilon}_{t-1} \widetilde{\varepsilon}_{t-1}' + \lambda_2 Q_{t-1} \quad (8)$$

$h_{ii,t}$ and $h_{jj,t}$ are the diagonal elements and follow univariate GARCH processes of H_t and $\rho_{ij,t}$ follows the dynamic process and varies with time.

Y_t is a $m \times 1$ vector of dependent variables—liquidity indicators in this case;

C is an $m \times k$ matrix of parameters;

X_t is a $k \times 1$ vector of independent variables—liquidity indicators and exogenous variables in this case;

$H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t that depends on lagged error terms ε_{t-1} ;

v_t is an $m \times 1$ vector of normal, independent, and identically distributed innovations;

D_t is a diagonal matrix of conditional variances, in which each $\sigma_{ii,t}^2$ evolves according to a univariate GARCH model;

R_t is a matrix of conditional quasi-correlations;

$\widetilde{\varepsilon}_t$ is an $m \times 1$ vector of standardized residuals, $D_t^{-1/2} \widetilde{\varepsilon}_t$; and

λ_1 and λ_2 are parameters that govern the dynamics of conditional quasi-correlations. λ_1 and λ_2 are nonnegative and satisfy $0 < \lambda_1 + \lambda_2 < 1$. From equation (8), λ_1 shows the correlation with shocks (ε_{t-1}) and λ_2 shows the correlation with its own variation (Q_{t-1}). The parameters of interest of this analysis are λ_1 and λ_2 —the dynamic adjustment coefficients.

The exogenous variables employed in the DCC M-GARCH model are the same as those used in the Newey West regressor, which are

Table 2
Statistical tests for autocorrelation and heteroskedasticity.

Liquidity indicator	Market	Obs	Lags	df	Cumby-Huizinga test for autocorrelation H0: $\rho = 0$ (serially uncorrelated)		LM test for autoregressive conditional heteroskedasticity (ARCH) H0: no ARCH effects		Breusch-Pagan/Cook-Weisberg test for heteroskedasticity H0: Constant variance		White's test H0: Homoskedasticity	
					Chi2	p-val	Chi2	p-val	chi2(1)	Prob > chi2	chi2(8)	Prob > chi2
Liquidity Depth	US	208	1-1	1	3.780*	0.052	0.121	0.728	16.25***	0.000	7.89	0.444
			1-2	2	4.680*	0.096	0.139	0.933				
	UK	208	1-1	1	5.085**	0.024	0.006	0.939	12.36***	0.000	7.34	0.500
			1-2	2	7.350**	0.025	0.062	0.970				
	EU	208	1-1	1	5.240**	0.022	0.063	0.802	14.25***	0.000	14.25	0.442
			1-2	2	7.260**	0.027	0.081	0.960				
	Japan	208	1-1	1	22.178***	0.000	0.432	0.511	2.94*	0.086	5.04	0.754
			1-2	2	27.791***	0.000	0.451	0.798				
Liquidity Tightness	US	208	1-1	1	35.793***	0.000	20.475***	0.000	17.81***	0.000	32.34***	0.000
			1-2	2	40.500***	0.000	21.484***	0.000				
	UK	208	1-1	1	32.525***	0.000	23.609***	0.000	19.89***	0.000	35.64***	0.000
			1-2	2	36.786***	0.000	24.881***	0.000				
	EU	208	1-1	1	34.343***	0.000	22.005***	0.000	20.31***	0.000	34.56***	0.000
			1-2	2	38.824***	0.000	23.364***	0.000				
	Japan	208	1-1	1	28.716***	0.000	19.841***	0.000	21.65***	0.000	21.77**	0.005
			1-2	2	31.819***	0.000	21.485***	0.000				
Liquidity Resilience	US	208	1-1	1	14.535***	0.000	8.480**	0.004	74.35***	0.000	22.51**	0.004
			1-2	2	15.134***	0.001	8.635**	0.013				
	UK	208	1-1	1	14.130***	0.000	4.742**	0.029	132.99***	0.000	42.10***	0.000
			1-2	2	15.244***	0.001	4.725*	0.094				
	EU	208	1-1	1	13.997***	0.000	4.485**	0.034	125.48***	0.000	57.97***	0.000
			1-2	2	15.943***	0.000	4.627*	0.099				
	Japan	208	1-1	1	12.807***	0.000	0.865	0.352	42.04***	0.000	13.48*	0.096
			1-2	2	13.762***	0.001	0.872	0.647				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan: Nikkei 225 Index of Japan Exchange.

CPI and Covid for virtual assets and Lending Rate for real assets, respectively.

3.4. Data selection

My dataset contains information on 100 cryptos and four exchanges between January 2019 and December 2022. The data sources are Yahoo Finance for both cryptos and market indices, and Eikon DataStream for macroeconomic statistics. I set up a dummy variable, "Covid", to indicate the lockdown periods between 16th March 2020 and 8th March 2022 (The Institute for Government, 2022). I remove observations that have missing values in stock volumes to avoid zero denominators. The estimation uses weekly data; the total number of observations is 208. The data description and summary statistics on three liquidity indicators and environmental variables are in Table 1. The correlation among variables is presented in Appendix Table A1 and Table A2.

I employ the Cumby-Huizinga test (Cumby & Huizinga, 1992), Breusch-Pagan/Cook-Weisberg test (Breusch & Pagan, 1979) and White's test (White, 1980) to verify autocorrelation and heteroskedasticity and use LM test to observe arch effect among variables. The test results are in Table 2. The results show that autocorrelation, heteroskedasticity and arch effect exist in liquidity tightness and resilience. However, despite the autocorrelation among variables, the LM test and White's test results accept the null hypothesis for liquidity depth—the data is homoscedasticity and has no arch effect. Therefore, the M-GARCH model is probably only suitable for liquidity tightness and resilience.

The sample data shows that the weekly liquidity depth of cryptos became tepid during the early stage of the lockdown between April 2020 and December 2020, whereas resumed high liquidity risks in January 2021. The average liquidity depth of global markets manifests a disparate pattern: higher liquidity depth of the Dow Jones Index is discovered before the lockdown (week 11, 9th–15th March 2020) reflecting fund fleeing. However, this situation does not last long—the liquidity depth of Dow Jones gradually goes back to its pre-lockdown level in the middle of 2021; the liquidity depth of the UK's FTSE 100 and German DAX Indexes show similar trends; a spike in liquidity depth appears in the week that the British government announced pandemic ease and economic recovery (week 11, 15th–21st March 2021). The Japan Nikkei 225 Index is uncoordinated with cryptos and volatile throughout the sample period (see Fig. 1).

The liquidity tightness of cryptos and global markets (Fig. 2) vary reversely before and during the lockdown, whereas move parallelly afterwards. This may reveal the mutual restraint of funding between the two assets—funding goes to either crypto or equity markets that have lower transaction costs. The liquidity tightness indicators of both crypto and equity markets illustrate spikes before the lockdown in week 10 of 2020. The changing pattern of liquidity tightness after the lockdown may reflect growth in speculative

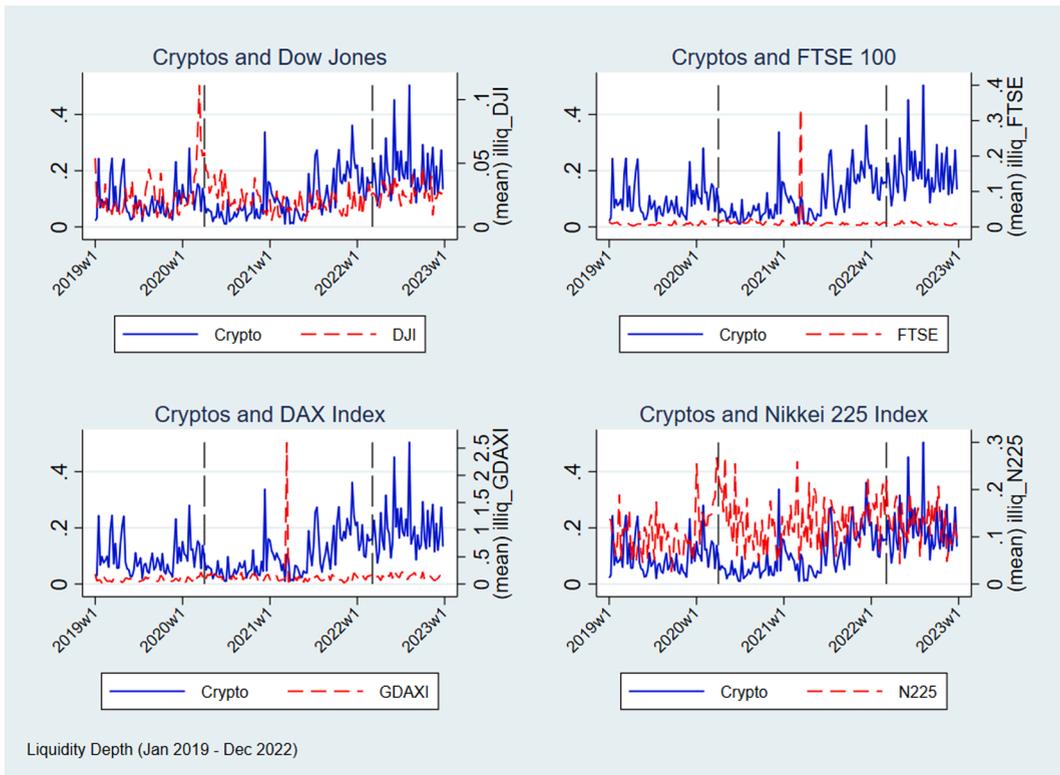


Fig. 1. Liquidity depth of virtual and equity markets.

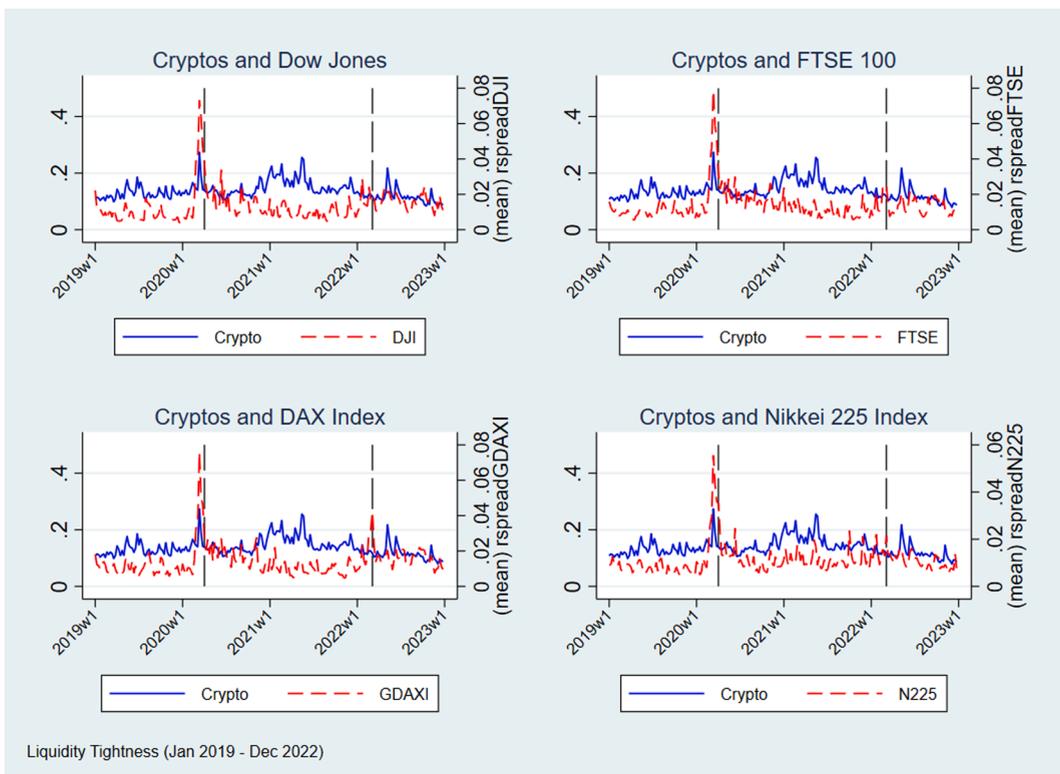


Fig. 2. Liquidity tightness of virtual and equity markets.

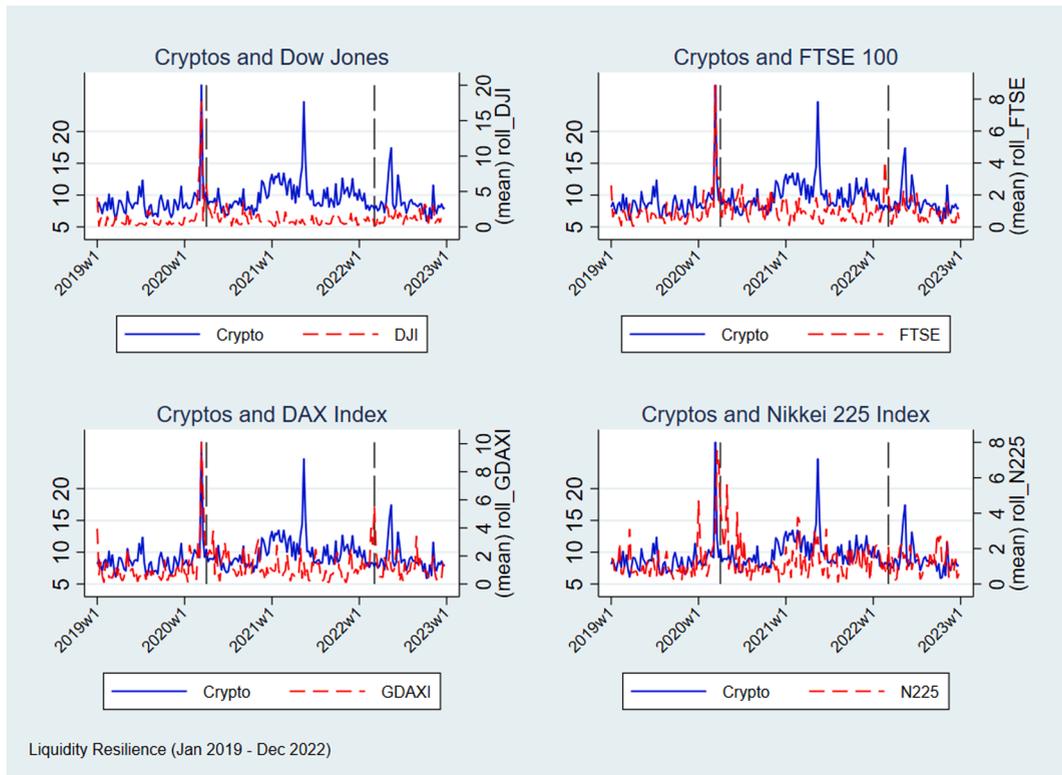


Fig. 3. Liquidity resilience of virtual and equity markets.

trading in both markets under uncertainty of economic recovery.

Fig. 3 shows that the liquidity resilience of cryptos and global markets is more turbulent. Both cryptos and global markets faced liquidity risk raises before the lockdown. The liquidity resilience of the Dow Jones Index remains calm during the lockdown. The liquidity resilience of the UK's FEST 100 and German DAX Indexes move alike and both markets exhibit liquidity shortfalls around the reopening time in 2022. The liquidity resilience of the Japan Nikkei 225 Index is incoordinate with cryptos and volatile throughout the sample period; this pattern is similar to other Asian markets, such as Korean and Hong Kong exchanges.

4. Results

4.1. Liquidity trajectory

I look at whether liquidity indicators capture statistical interactions between virtual and real assets. The results are presented in two tables. Table 3 shows the impact of real asset liquidity on crypto liquidity and Table 4 identifies the reversed influence. The result tables have three main columns for liquidity depth, tightness and resilience, respectively, and each main column has four sub-columns for the equity markets. The coefficients of interest are in row 1 of each table.

The regression results uncover a significant and bidirectional liquidity risk transmission between real and virtual assets in liquidity tightness and resilience. Coefficients for liquidity tightness (Column B1 and B2) and resilience (Column C1 and C2) indicate a positive and significant relationship between the two asset classes in both directions: liquidity risk arising in equity markets can be amplified in virtual markets; the reverse effect is smaller but also significant. For instance, liquidity tightness, as measured by transaction costs, arising from the Japanese exchange may result in a liquidity shortage in crypto markets that is more than five times greater; reverse liquidity transmission is about 9 % (see Column B1-(4) and B2 (4)). This statistically indicates that the transaction costs and market efficiency of both asset classes are crucial to each other—liquidity shortfalls in equity markets can trigger liquidity distress in the virtual market, and vice versa.

The liquidity depth indicator also captures a liquidity feedback loop between crypto and the Japanese exchange and mono-directional liquidity movement from the US market to crypto (Column A1 (1)) and from crypto to the UK and EU markets (Column A2 (2) and A2 (3)).

Additionally, the environmental variables present a significant impact on the liquidity risks of virtual and real assets. The rise in CPI and the COVID-19 lockdown have significantly pushed up liquidity risks of crypto in all three dimensions, except for the insignificant impact of COVID-19 in the US (Table 3). This indicates that adverse economic conditions (rising inflation) and unexpected events (COVID-19 lockdown) have put pressure on speculative trading.

Table 3
The impact of market liquidity on cryptos.

	(A1) Liquidity Depth				(B1) Liquidity Tightness				(C1) Liquidity Resilience			
	(1) US	(2) UK	(3) EU	(4) Japan	(1) US	(2) UK	(3) EU	(4) Japan	(1) US	(2) UK	(3) EU	(4) Japan
Market	1.278*** (5.76)	0.349 (1.50)	0.050 (1.26)	0.440*** (5.73)	3.491*** (4.99)	3.863*** (4.33)	4.142*** (4.98)	5.765*** (4.08)	1.320*** (7.82)	2.520*** (7.33)	1.872*** (6.55)	1.659*** (3.43)
CPI	0.021*** (14.76)	0.021*** (17.15)	0.022*** (14.72)	0.046*** (7.55)	0.009*** (6.25)	0.008*** (5.74)	0.006*** (4.05)	0.021*** (3.69)	0.924*** (13.40)	0.737*** (14.29)	0.755*** (12.16)	2.459*** (7.50)
Covid	0.002 (0.17)	0.052*** (6.20)	0.054*** (6.16)	0.040** (2.97)	0.071*** (8.01)	0.075*** (6.56)	0.079*** (7.53)	0.077*** (5.18)	5.315*** (9.38)	5.614*** (10.21)	6.150*** (10.64)	7.619*** (11.34)
N	208	208	208	208	208	208	208	208	208	208	208	208

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Lags = 2; US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan: Nikkei 225 Index of Japan Exchange; Lending Rate: major banks prime lending rate of each region; CPI: YoY Consumer Price Index of each region.

Table 4
The impact of crypto liquidity on markets.

	(A2) Liquidity Depth				(B2) Liquidity Tightness				(C2) Liquidity Resilience			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	US	UK	EU	Japan	US	UK	EU	Japan	US	UK	EU	Japan
Crypto	0.0160 (1.55)	0.022* (2.07)	0.685*** (9.23)	0.508*** (10.63)	0.071** (3.28)	0.092*** (5.39)	0.106*** (13.42)	0.088*** (8.62)	0.148 (1.63)	0.121*** (4.18)	0.134*** (8.73)	0.137*** (10.72)
Lending Rate	0.005*** (11.42)	0.004*** (4.53)	-0.044* (-2.13)	0.017*** (10.06)	0.001 (1.43)	0.001 (0.72)	0.003** (3.03)	-0.000 (-1.33)	-0.031 (-0.19)	-0.072 (-0.61)	0.055 (0.54)	-0.001 (-0.03)
N	208	208	208	208	208	208	208	208	208	208	208	208

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Lags = 2; US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan; Nikkei 225 Index of Japan Exchange; Lending Rate: major banks prime lending rate of each region; CPI: YoY Consumer Price Index of each region.

Table 5
Dynamics impact of real asset liquidity on cryptos.

	(D1) Liquidity Depth				(E1) Liquidity Tightness				(F1) Liquidity Resilience			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	US	UK	EU	Japan	US	UK	EU	Japan	US	UK	EU	Japan
Market	-0.674*	0.876***	0.154***	0.374***	4.492***	2.327***	3.832***	4.548***	-0.147	2.922***	-0.61**	-0.189
	(-2.29)	(3.70)	(3.75)	(3.84)	(10.17)	(4.74)	(13.87)	(29.18)	.	(9.04)	(-3.18)	(-0.99)
CPI	0.023***	0.018***	0.020***	0.044***	0.012***	0.010***	0.008***	0.023***	0.939	0.845***	0.870***	2.090***
	(14.20)	(13.71)	(7.24)	(5.60)	(14.57)	(13.75)	(13.83)	(12.81)	.	(22.41)	(24.32)	(20.25)
Covid	0.016	0.069***	0.049***	0.054***	0.076***	0.104***	0.105***	0.115***	5.707***	7.214***	7.324***	8.532***
	(1.43)	(11.84)	(7.11)	(4.36)	(18.32)	(23.33)	(27.02)	(31.01)	(24.32)	(24.16)	(28.87)	(29.01)
Adjustment												
λ_1	0.196***	0.355***	0.300***	0.352***	0.652***	0.639***	0.762***	0.750***	0.342***	0.530***	0.279***	0.106
	(3.52)	(4597.34)	(8.73)	(5.55)	(10.87)	(9.40)	(15.99)	(13.19)	(4.46)	(7.26)	(3.29)	(1.79)
λ_2	0.746***	0.645	0.683***	0.589***	0.269***	0.293***	0.159**	0.170**	0.602***	0.315***	0.554***	0.753***
	(10.84)	.	(15.76)	(7.83)	(4.18)	(3.72)	(3.13)	(2.74)	(6.62)	(3.85)	(3.93)	(6.58)
N	208	208	208	208	208	208	208	208	208	208	208	208

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Lags = 2; US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan: Nikkei 225 Index of Japan Exchange; Lending Rate: major banks prime lending rate of each region; CPI: YoY Consumer Price Index of each region. A “.” denotes convergence not achieved.

Table 6
Dynamics impact of virtual asset liquidity on markets.

	(D1) Liquidity Depth				(E1) Liquidity Tightness				(F1) Liquidity Resilience			
	(1) US	(2) UK	(3) EU	(4) Japan	(1) US	(2) UK	(3) EU	(4) Japan	(1) US	(2) UK	(3) EU	(4) Japan
Crypto	-0.023 (-1.80)	0.204*** (15.14)	1.893*** (11.75)	0.560*** (8.01)	0.063*** (5.97)	0.095*** (7.08)	0.112*** (16.07)	0.107*** (8.74)	0.084* (2.32)	0.048 (0.77)	0.126 (1.09)	-0.020 (-0.45)
Lending rate	0.005*** (16.72)	0.001*** (3.37)	0.004 (0.36)	0.020*** (12.92)	0.001*** (3.95)	0.002 (1.33)	0.002** (2.85)	-0.000 (-0.09)	0.003 (0.13)	0.152*** (9.77)	0.230*** (11.79)	0.183*** (8.24)
Adjustment												
λ_1	0.313*** (5.04)	0.839*** (31.34)	0.434*** (9.90)	0.215*** (4.72)	0.775*** (13.84)	0.611*** (9.15)	0.703*** (10.96)	0.611*** (6.89)	0.162 (1.74)	0.502*** (6.84)	0.547*** (5.87)	0.035 (1.23)
λ_2	0.535*** (5.97)	0.158*** (5.91)	0.559*** (12.16)	0.690*** (11.78)	0.035 (0.54)	0.260*** (3.34)	0.141 (1.76)	0.167 (1.70)	0.609** (2.66)	0.342*** (4.44)	0.186 (1.77)	0.836*** (10.75)
N	208	208	208	208	208	208	208	208	208	208	208	208

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Lags = 2; US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan: Nikkei 225 Index of Japan Exchange; Lending Rate: major banks prime lending rate of each region; CPI: YoY Consumer Price Index of each region.

Table 7
Model Adequacy (Standard Errors).

Regressors	Market	Obs	(G) Impact of market on crypto			(H) Impact of crypto on market		
			Newey West(α)	DCC M–GARCH		Newey West(α)	DCC M–GARCH	
				(C)	(λ_1)		(C)	(λ_1)
Liquidity Depth	US	208	0.22	0.29	0.06	0.01	0.01	0.06
	UK	208	0.23	0.24	0.00	0.01	0.01	0.03
	EU	208	0.04	0.04	0.03	0.07	0.16	0.04
	Japan	208	0.08	0.10	0.06	0.05	0.07	0.05
Liquidity Tightness	US	208	0.70	0.44	0.06	0.02	0.01	0.06
	UK	208	0.89	0.49	0.07	0.02	0.01	0.07
	EU	208	0.83	0.28	0.05	0.01	0.01	0.06
	Japan	208	1.41	0.16	0.06	0.01	0.01	0.09
Liquidity Resilience	US	208	0.17	.	0.08	0.09	0.02	0.09
	UK	208	0.34	0.32	0.07	0.03	0.02	0.07
	EU	208	0.29	0.19	0.08	0.02	0.02	0.09
	Japan	208	0.48	0.19	0.06	0.01	0.02	0.03

Statistics are standard errors. Parameters are consistent with equation (4), 5, 7 and 8. US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan; Nikkei 225 Index of Japan Exchange. A “.” denotes convergence not achieved.

The increase in lending rates has significantly worsened the market liquidity conditions in the US, UK, Japan (liquidity depth) and the EU (liquidity tightness). However, its impact on liquidity resilience is insignificant (Table 4). This suggests that market capacity and transaction costs are more sensitive to policy measures.

4.2. Liquidity dynamics

Since liquidity depth indicators accept the null hypothesis (homoskedasticity) of the LM test and White’s test, but the alternative hypothesis (heteroskedasticity) of Breusch–Pagan/Cook–Weisberg test, this section discusses the DCC M–GARCH model results of all three liquidity indicators. Meanwhile, the analytical results exhibit a similar pattern for both one and two lags, thus, Arch (1/1) and GARCH (1) are used.

The results are in Table 5 and Table 6. Table 5 shows the impact of real asset liquidity on crypto liquidity and Table 6 identifies the reversed influence. The result tables have three main columns for liquidity depth, tightness and resilience, respectively, and each main column has four sub-columns for the four equity markets. The coefficients of interest are the main result of liquidity indicators and the adjustment variable λ_1 shows the correlation with shocks (StataCorp, 2021).

The DCC M–GARCH model discovers similar patterns to the Newey West regressor and confirms a two-way feedback loop of liquidity between virtual and equality markets. The bidirectional feedback loop of liquidity is prominent in liquidity depth and tightness except for the US market (liquidity depth). The liquidity resilience indicator captures a mono-directional liquidity transmission from the UK to crypto and a reverse movement from crypto to the US.

The dynamic adjustment variable λ_1 reveals the liquidity risk spiral between virtual and real assets in all three dimensions except Japan (liquidity resilience) and the interactions are positive and significant. The liquidity risk arising in the equity markets can lead to the liquidity risk of the virtual market to increase by approximately 20–36 % (liquidity depth), 64–76 % (liquidity tightness) and 28–53 % (liquidity resilience) in three dimensions, respectively. Meanwhile, the equity market liquidity synergises with the crypto market liquidity by about 22–84 % (liquidity depth), 61–78 % (liquidity tightness) and 16–55 % (liquidity resilience), respectively. Among them, liquidity tightness sees the greatest liquidity risk transmission.

The dynamic adjustment variable λ_2 identifies a self-feedback channel of individual markets, which means that these markets also interact with their own liquidity turbulence.

4.3. Model adequacy

I verify the adequacy of the Newey West model and the DCC M–GARCH model using Standard Errors (Table 7), which allow comparison of the two models. The standard errors indicate that both models perform better in identifying the impact of crypto on equity markets (column H) with the standard errors less than 10 %. The Newey West model performs better on the main explanatory variables (α), while the DCC M–GARCH model can provide an appropriate explanation for the dynamic adjustment coefficients (λ_1).

In contrast, both models have high standard errors in estimating the impact of equity markets on crypto liquidity, except for the dynamic adjustment coefficients of the DCC M–GARCH model; the standard errors do not improve when adjusting for the environmental/exogenous variables. Additionally, the liquidity tightness estimator produces the largest standard errors compared to the other two liquidity indicators.

Therefore, the two models are more adequate in identifying liquidity risk transmission from the virtual to the real markets—the Newey West estimator can verify the mono-directional relationship and the DCC M–GARCH model can observe the dynamic adjustment between them.

Table 8
Liquidity dynamics among equity markets.

Equation	Excluded	df	(I) Liquidity Depth		(J) Liquidity Tightness		(K) Liquidity Resilience	
			chi2	p	chi2	p	chi2	p
US	UK	2	0.53	0.768	3.50	0.174	2.73	0.255
	EU	2	0.73	0.694	1.93	0.381	3.54	0.170
	Japan	2	0.86	0.650	0.40	0.817	1.27	0.530
	ALL	6	2.00	0.919	13.52	0.035	16.05**	0.013
UK	US	2	0.82	0.664	2.39	0.302	34.53***	0.000
	EU	2	6.14**	0.046	3.71	0.156	2.80	0.247
	Japan	2	17.95***	0.000	0.57	0.752	5.03*	0.081
	ALL	6	23.39**	0.001	4.72	0.580	36.76***	0.000
EU	US	2	1.32	0.517	2.44	0.295	41.34***	0.000
	UK	2	6.11**	0.047	4.77*	0.092	5.64**	0.060
	Japan	2	16.75***	0.000	0.40	0.817	2.58	0.275
	ALL	6	23.11**	0.001	10.99	0.089	56.33***	0.000
Japan	US	2	6.54**	0.038	0.96	0.618	15.71***	0.000
	UK	2	1.22	0.543	9.78**	0.008	3.09	0.213
	EU	2	2.14	0.343	3.71	0.157	0.31	0.854
	ALL	6	13.02**	0.043	24.97***	0.000	62.66***	0.000

Liquidity dynamics among markets are estimated using VAR and Granger Causality Test. US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan: Nikkei 225 Index of Japan Exchange. ALL: collective impact of all three markets.

4.4. Spillover effect

Brockman, Chung and Pérignon (2009) suggest that liquidity risk is rarely a single-market matter; it can transfer from one market to another. As a result, crypto liquidity may spill over from one market to another. Thus, it is also important to identify the liquidity interactions between markets and observe the causal effect. Hence, the Vector Autoregressive (VAR) estimator and Granger Causality Test are employed for this purpose (Johansen, 1991; Lütkepohl, 2005). The Granger Causality Test results (in Table 8) identify liquidity dynamics among markets captured by at least one liquidity indicator. The liquidity depth indicator (market capacity) discovers significant liquidity co-movement between markets, except for the US. The liquidity tightness indicator (transaction cost) also indicates that liquidity risk may shift from the UK to the EU and Japan, and the causal effect is positive and significant. The liquidity resilience indicator (market efficiency) finds that the liquidity of a market co-moves with at least one other market, with the exception of the US, which is affected only by cumulative liquidity shocks. In sum, the Granger Causality tests reveal liquidity co-movements between markets, with the US market being the least affected; the US market appears to be a transmitter rather than a receiver of liquidity risk, but it may not escape cumulative liquidity shocks (column K).

5. Conclusion

Despite its minute market size compared to the equity exchanges, the rapid liquidity evaporation in virtual assets due to the extreme price fluctuations may lead to liquidity shortages across markets and spread risks on a global scale. This paper justifies the regulatory concerns about crypto-related liquidity risks (BIS, 2011) and verifies the possible channels of liquidity risk transmission. It extends liquidity estimation to multi-dimensions (Amihud, 2002; 2018; Sarr & Lybek, 2002; Roll, 1984) and establishes a comprehensive and robust framework for liquidity risk assessment (Newey & West, 1987; Engle, 2002).

The analytical results validate the existence of bidirectional liquidity risk transfer between the virtual and real markets from January 2019 to December 2022 and confirm the contagion of liquidity risk among equity markets, suggesting the possibility of systemic liquidity risk in the financial system. The vast capacity of the US market gives it the ability to absorb liquidity risks from crypto and other markets; however, cumulative liquidity shocks may be inescapable. In addition, adverse economic conditions, such as rising inflation and the pandemic have had a significant impact on crypto liquidity, while economic stimulus measures, such as leading rates, have significantly limited liquidity in the equity markets (except for the EU). This creates regulatory difficulties for authorities.

Assessing liquidity dynamics can help monitor liquidity risk across assets and markets and prevent systemic shocks. The established empirical framework is multidimensional, easily adaptable, and can provide immediate analytical results through programming and data visualisation. Policymakers may consider standardising the measurements and monitoring liquidity risk transmission regularly.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Table A1
Liquidity Correlation Matrix between Virtual and Real Assets.

	Crypto	Liquidity Depth	Liquidity Tightness	Liquidity Resilience
Market	US	0.03	0.12	0.32
	UK	-0.03	0.23	0.35
	EU	0.04	0.11	0.28
	Japan	0.13	0.33	0.18
Lending Rate	US	0.17	-0.46	-0.31
	UK	0.35	-0.48	-0.26
	EU	0.27	-0.43	-0.22
	Japan	-0.43	0.23	0.08
CPI	US	0.59	-0.20	0.01
	UK	0.58	-0.38	-0.12
	EU	0.58	-0.35	-0.10
	Japan	0.45	-0.51	-0.26
COVID		-0.21	0.44	0.31

Correlation matrix is estimated by Pearson correlation coefficients. US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan; Nikkei 225 Index of Japan Exchange. CPI is the Consumer Price Index for All Urban Consumers; Lending Rate is the major banks prime lending rate of the region; The COVID lockdown period is between 16th March 2020 and 8th March 2022. Liquidity indicators are calculated based on daily data. All variables are integrated or converted into weekly frequency.

Table A2
Liquidity Correlation Matrix between Markets.

		Liquidity Depth				Liquidity Tightness				Liquidity Resilience			
		US	UK	EU	Japan	US	UK	EU	Japan	US	UK	EU	Japan
Market	US	1	0.05	0.09	0.39	1	0.90	0.88	0.83	1	0.62	0.61	0.31
	UK	0.05	1	0.97	-0.01	0.90	1	0.91	0.82	0.62	1	0.75	0.29
	EU	0.09	0.97	1	0.04	0.88	0.91	1	0.77	0.61	0.75	1	0.41
	Japan	0.39	-0.01	0.04	1	0.83	0.82	0.77	1	0.31	0.29	0.41	1
Lending Rate	US	0.06	-0.10	-0.08	-0.22	-0.10	-0.19	-0.11	-0.28	-0.01	-0.21	-0.15	-0.13
	UK	0.10	-0.09	-0.01	-0.10	0.01	-0.15	-0.01	-0.21	0.01	-0.16	-0.08	-0.09
	EU	0.15	-0.06	0.02	-0.04	0.10	-0.04	0.06	-0.13	0.09	-0.11	-0.04	0.00
	Japan	-0.07	0.16	0.12	-0.12	0.01	0.14	0.02	-0.06	0.01	0.09	0.00	-0.03
CPI	US	-0.02	-0.08	0.04	0.16	0.04	-0.17	0.01	0.00	-0.07	-0.08	-0.03	-0.05
	UK	0.10	-0.10	0.03	0.10	0.13	-0.10	0.09	-0.03	0.02	-0.08	-0.01	-0.03
	EU	0.08	-0.08	0.05	0.12	0.11	-0.12	0.08	-0.03	0.00	-0.09	-0.02	-0.02
	Japan	0.17	-0.09	0.01	-0.01	0.13	-0.07	0.11	-0.10	0.06	-0.09	-0.02	-0.03
COVID		-0.07	0.11	0.09	0.20	0.10	0.20	0.09	0.26	0.03	0.21	0.15	0.15

Correlation matrix is estimated by Pearson correlation coefficients. US: Dow Jones Index; UK: FTSE100 of London Exchange; EU: German DAX Index; Japan; Nikkei 225 Index of Japan Exchange. CPI is the Consumer Price Index for All Urban Consumers; Lending Rate is the major banks prime lending rate of the region; The COVID lockdown period is between 16th March 2020 and 8th March 2022. Liquidity indicators are calculated based on daily data. All variables are integrated or converted into weekly frequency.

Appendix A

Table A. and Table A2..

References

- Acharya, V.V., Viswanathan, S., 2011. Leverage, Moral Hazard, and Liquidity. *J. Finan.* LXV I (1), 99–138. <https://doi.org/10.1111/j.1540-6261.2010.01627.x>.
- Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A., 2020. The relationship between implied volatility and cryptocurrency returns. *Financ. Res. Lett.* 33 (101212), 1–10. <https://doi.org/10.1016/j.frl.2019.06.010>.
- Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *J. Financ. Mark.* 5, 31–56. [https://doi.org/10.1016/S1386-4181\(01\)00024-6](https://doi.org/10.1016/S1386-4181(01)00024-6).
- Amihud, Y., 2018. Illiquidity and stock returns: A revisit. *Critical Finance. Review.*
- Amihud, Y., Mendelson, H., 1986. Asset Pricing and the Bid-Ask Spread. *J. Financ. Econ.* 17, 223. [https://doi.org/10.1016/0304-405X\(86\)90065-6](https://doi.org/10.1016/0304-405X(86)90065-6).
- Amihud, Y., Mendelson, H., Pedersen, L.H., 2005. Liquidity and Asset Prices. *Found. Trends Financ.* 1 (4), 269–364. <https://doi.org/10.1561/0500000003>.
- Bai, M., Qin, Y., 2015. Commonality in liquidity in emerging markets: Another supply-side explanation. *Int. Rev. Econ. Financ.* 39, 90–106. <https://doi.org/10.1016/j.iref.2015.06.005>.
- Baier, K., 1966. What is value? An analysis of the concept. In: B. a. Rescher, ed. *Value and the future: the impact of technological change on American values*. New York: The Free Press.
- Banti, C., Phylaktis, K., 2015. FX market liquidity, funding constraints and capital flows. *J. Int. Money Financ.* 56, 114–134. <https://doi.org/10.1016/j.jimonfin.2014.11.002>.
- Batini, N., Nelson, E., 2001. The Lag from Monetary Policy Actions to Inflation: Friedman Revisited. *International Finance* 4 (3), 381–400. <https://doi.org/10.1111/1468-2362.00079>.

- BBC, 2022. Crypto giant FTX collapses into bankruptcy. [Online] Available at: <https://www.bbc.co.uk/news/business-63601213> [Accessed 15 11 2022].
- Ben Cheikh, N., Ben Zaid, Y., Chevallier, J., 2020. Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Financ. Res. Lett.* 35 (101293), 1–9. <https://doi.org/10.1016/j.frl.2019.09.008>.
- BIS, 2008. Liquidity Risk: Management and Supervisory Challenges. Bank for International Settlements, Volume Banking Supervision, pp. 1–16.
- BIS, 2011. The transmission channels between the financial and real sectors: a critical survey of the literature. Bank for International Settlements, Volume Working Paper No.18, pp. 1–65.
- BIS, 2020. Designing a prudential treatment for cryptoassets. Basel Committee on Banking Supervision, Volume Discussion paper, pp. 1–14.
- Blundell-Wignall, A., 2014. The Bitcoin Question: Currency versus Trust-less Transfer Technology. *OECD Working Papers on Finance, Insurance and Private* 37, 1–21.
- Bollerslev, T., Engle, R., Wooldridge, J., 1988. A capital asset pricing model with time varying covariances. *J. Polit. Econ.* 96, 116–131. <https://doi.org/10.1086/261527>.
- Breusch, T.S., Pagan, A.R., 1979. A Simple Test for Heteroskedasticity and Random Coefficient Variation. *Econometrica* 47 (5), 1287–1294. <https://doi.org/10.2307/1911963>.
- Brockman, P., Chung, D.Y., Pérignon, C., 2009. Commonality in Liquidity: A Global Perspective. *J. Financ. Quant. Anal.* 44, 851–882. <https://doi.org/10.1017/S0022109009990123>.
- Brunnermeier, M.K., Pedersen, L.H., 2008. Market Liquidity and Funding Liquidity. *Rev. Financ. Stud.* 1–38. <https://doi.org/10.3386/w12939>.
- Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. *J. Financ. Econ.* 56, 3–28. [https://doi.org/10.1016/S0304-405X\(99\)00057-4](https://doi.org/10.1016/S0304-405X(99)00057-4).
- Chordia, T., Sarkar, A., Subrahmanyam, A., 2005. An Empirical Analysis of Stock and Bond Market Liquidity. *Rev. Financ. Stud.* 18 (1), 85–129. <https://doi.org/10.1093/rfs/hhi010>.
- CoinMarketCap, n.d. All Cryptocurrencies. [Online] Available at: <https://coinmarketcap.com/all/views/all/> [Accessed 2 August 2022].
- Coughenour, J.F., Saad, M.M., 2004. Common Market Makers and Commonality in Liquidity. *J. Financ. Econ.* 73, 37–69. <https://doi.org/10.1016/j.jfineco.2003.05.006>.
- Cumby, R.E., Huizinga, J., 1992. Testing the autocorrelation structure of disturbances in ordinary least squares and instrumental variables regressions. *Econometrica* 60 (1), 185–195. <https://doi.org/10.2307/2951684>.
- Domowitz, I., Hansch, O., Wang, X., 2005. Liquidity Commonality and Return Co-movement. *J. Financ. Mark.* 8 (4), 351–376. <https://doi.org/10.1016/j.finnar.2005.06.001>.
- Drescher, D., 2017. Blockchain Basics A Non-Technical Introduction in 25 Steps. 1st ed. s.l.:Apress. <https://doi.org/10.1007/978-1-4842-2604-9>.
- Engle, R.F., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.* 20, 339–350. <https://doi.org/10.1198/073500102288618487>.
- Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: Representation, estimation, and testing. *Econometrica* 55, 251–276. <https://doi.org/10.2307/1913236>.
- FCA, 2019. Guidance on Cryptoassets Feedback and Final Guidance to CP 19/3. Financial Conduct Authority, London.
- Fernando, C.S., 2003. Commonality in liquidity: transmission of liquidity shocks across investors and securities. *J. Financ. Intermed.* 12, 233–254. [https://doi.org/10.1016/S1042-9573\(03\)00041-X](https://doi.org/10.1016/S1042-9573(03)00041-X).
- Frank, N., González-Hermosillo, B., Hesse, H., 2008. Transmission of Liquidity Shocks: Evidence from the 2007 Subprime Crisis. *Int. Monetary Fund WP/08/200*, 1–21. <https://doi.org/10.5089/9781451870589.001>.
- Gopalan, R., Kadan, O., Pevzner, M., 2012. Asset Liquidity And Stock Liquidity. *J. Financ. Quant. Anal.* 47 (2), 333–364. <https://doi.org/10.1017/S0022109012000130>.
- Goyenko, R.Y., Ukhov, A.D., 2009. Stock and bond market liquidity: A long-run empirical analysis. *J. Financ. Quant. Anal.* 44 (1), 189–212. <https://doi.org/10.1017/S0022109009090097>.
- Hasbrouck, J., Seppi, D.J., 2001. Common Factor in Prices, Order Flows, and Liquidity. *J. Financ. Econ.* 59, 383–411. [https://doi.org/10.1016/S0304-405X\(00\)00091-X](https://doi.org/10.1016/S0304-405X(00)00091-X).
- Holloway, C., 2017. State of Illinois: Request for Information (RFI) Distributed Ledger and Blockchain Applications in the Public Sector. State of Illinois, s.l.
- In, F., Cui, J., Maharaj, E.A., 2012. The impact of a new term auction facility on Libor-OIS spreads and volatility transmission between money and mortgage markets during the subprime crisis. *J. Int. Money Financ.* 31, 1106–1125. <https://doi.org/10.1016/j.jimonfin.2011.12.013>.
- Ince, B., 2022. Liquidity components: Commonality in liquidity, underreaction, and equity returns. *J. Financ. Mark.* 60 (100730), 1–19. <https://doi.org/10.1016/j.finnar.2022.100730>.
- Johansen, S., 1991. Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica* 59 (6), 1551–1580. <https://doi.org/10.2307/2938278>.
- Karolyi, A., Lee, K.-H., Dijk, M.A., 2012. Understanding commonality in liquidity around the world. *J. Financ. Econ.* 105, 82–112. <https://doi.org/10.1016/j.jfineco.2011.12.008>.
- Katsiampa, P., Corbet, S., Lucey, B., 2019. High frequency volatility co-movements in cryptocurrency markets. *J. Int. Finan. Markets. Inst. Money* 62, 35–52. <https://doi.org/10.1016/j.intfin.2019.05.003>.
- Korajczyk, R.A., Sadka, R., 2008. Pricing the commonality across alternative measures of liquidity. *J. Financ. Econ.* 87, 45–72. <https://doi.org/10.1016/j.jfineco.2006.12.003>.
- Lütkepohl, H., 2005. New Introduction to Multiple Time Series Analysis. Berlin: Springer-Verlag. <https://doi.org/10.1007/978-3-540-27752-1>.
- Mandaci, P.E., Cagli, E.C., 2022. Herding intensity and volatility in cryptocurrency markets during the COVID-19. *Financ. Res. Lett.* 46 (102382), 1–7. <https://doi.org/10.1016/j.frl.2021.102382>.
- Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. [Online] Available at: <https://bitcoin.org/bitcoin.pdf> [Accessed 04 August 2022].
- Newey, W.K., West, K.D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55 (3), 703–708. <https://doi.org/10.2307/1913610>.
- Nikolaou, K., 2009. Liquidity (Risk) Concepts Definitions and Interactions. European Central Bank, Volume Working Paper No.1008, pp. 1–70. <https://doi.org/10.2139/ssrn.1333568>.
- Panagiotou, P., Jiang, X., Gavilan, A., 2022. The determinants of liquidity commonality in the Euro-area sovereign bond market. *Eur. J. Financ.* 1–43. <https://doi.org/10.1080/1351847X.2022.2100269>.
- Porter, M.E., 1985. *The Competitive Advantage: Creating and Sustaining Superior Performance*. Free Press, New York.
- Reyes, C., 2017. Conceptualizing Cryptolaw. *Nebraska Law Review*. <https://doi.org/10.2139/ssrn.2914103>.
- Roll, R., 1984. A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *J. Financ.* 39 (4), 1127–1139. <https://doi.org/10.1111/j.1540-6261.1984.tb03897.x>.
- Sarr, A., Lybek, T., 2002. Measuring Liquidity in Financial Markets. International Monetary Fund Volume WP/02/232, 1–62. <https://doi.org/10.5089/9781451875577.001>.
- Sensoy, A., 2016. Commonality in liquidity: Effects of monetary policy and macroeconomic announcements. *Financ. Res. Lett.* 16, 125–131. <https://doi.org/10.1016/j.frl.2015.10.021>.
- Smith, A., 1776. *The wealth of nations*. Bibliomania.com Ltd., Oxford, England.
- StataCorp, 2021. Dynamic conditional correlation multivariate GARCH models. Stata 17 Base Reference Manual.
- Strahan, P. E., 2012. Liquidity Risks and Credit in the Financial Crisis. Federal Reserve Bank of San Francisco, Volume Economic Letter 2012-15, pp. 1-4.
- The Institute for Government, 2022. Timeline of UK government coronavirus lockdowns and restrictions. [Online] Available at: <https://www.instituteforgovernment.org.uk/charts/uk-government-coronavirus-lockdowns> [Accessed 25 July 2022].

- White, H., 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* 48 (4), 817–838. <https://doi.org/10.2307/1912934>.
- Wildman, N., McDonnell, N., 2020. The Puzzle of Virtual Theft. *Analysis* 80 (3), 493–499. <https://doi.org/10.1093/analys/anaa005>.
- Wolswijk, H., 2012. Theft: Taking a Virtual Object in RuneScape. *The Journal of Criminal Law* 76 (6), 459–462. <https://doi.org/10.1350/1740-5580-76.6.459>.