Malaysian Journal of Economic Studies 56(2): 201–225, 2019 ISSN 1511-4554

Are Cryptocurrencies Affected by Their Asset Class Movements or News Announcements?

Ikhlaas Gurrib[a]
Canadian University Dubai

Qian Long Kweh[b]
Canadian University Dubai

Mohammad Nourani[c]
Universiti Sains Malaysia

Irene Wei Kiong Ting[d]
Universiti Malaysia Pahang

Abstract: This study analyses whether returns of top market capitalised cryptocurrencies are affected by their movements or major global macroeconomic news. Daily data are collected for the leading 10 cryptocurrencies from July 2017–December 2018. This study, (i) tests whether lagged variables can help predict other variables' returns through a vector autoregression (VAR) model, (ii) analyses the response of cryptocurrencies to one standard deviation shock on Bitcoin's returns, and (iii) decomposes factors that contribute to variance and tests for structural breaks. Findings show that most cryptocurrencies do not significantly affect other variances, except for Monero, which represented between 19% and 45% of the variances of five cryptocurrencies. Autoregressive (AR) models are superior in forecasting one day ahead return forecasts, compared to the VAR model, whereas the random walk (RW) model ranked last. Although remarkable structural breaks are observed via impulse response functions during December 2017–January 2018, no major news announcements were released on the same day the breaks occurred. Overall, this study suggests the need for high-frequency cryptocurrency prices to tackle the issue of the relationship between intraday news release and cryptocurrencies.

Keywords: cryptocurrency, news announcements, VAR, impulse response, structural break
JEL classification: G15, G17, G19

[a] Faculty of Management, Canadian University Dubai, P.O. Box 117781, 1st Interchange, Sheikh Zayed Road, Dubai, United Arab Emirates. Email: ikhlaas@cud.ac.ae
[b] Faculty of Management, Canadian University Dubai, P.O. Box 117781, 1st Interchange, Sheikh Zayed Road, Dubai, United Arab Emirates. Email: qlkweh@cud.ac.ae, qlkweh@gmail.com (Corresponding author)
[c] School of Management, Universiti Sains Malaysia, 11800 Penang, Malaysia. Email: nourani@usm.my
[d] Faculty of Industrial Management, Universiti Malaysia Pahang, 26300 Gambang, Pahang, Malaysia. Email: irene@ump.edu.my

Article Info: *Received* 14 November 2018; *Revised* 22 May 2019; *Accepted* 26 August 2019
https://doi.org/10.22452/MJES.vol56no2.2

1. Introduction

One of the most distinct features of cryptocurrencies, as opposed to traditional currencies, relates to the fact that cryptocurrencies do not have physical representations (Folkinshteyn, Lennon, & Reilly, 2015). No intrinsic value like other traditional currencies, proportionately higher volatilities, and no volatility spill over with alternative assets (Berentsen & Schar, 2018; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Phillip, Chan, & Peiris, 2018), make cryptocurrencies an interesting candidate to study when it comes to whether macroeconomic events affect their returns. In the literature, the effect of global news on various investment products vary. For example, prior studies have found significant relationships between stock returns and money growth (Cornell, 1983), between different interest rates and stock returns (Chan, Karceski, & Lakonishok, 1998) and between major US global financial condition indices and net positions of actively traded USD foreign currency futures (Gurrib, 2018). However, Burniske and White (2017) reported that despite Bitcoin (BTC) retaining the lead in terms of usage as found in most wallets and exchanges, BTC has also been dubbed as an ineffective tool in managing price volatility due to its low correlation with major currencies like the US dollar, Euro and the British Pound, and commodities such as gold. Moreover, Yermack (2015) reported macroeconomic changes, which cause movements in exchange rates, are not captured by BTC's price movements.

This study thus aims to test whether the top ten cryptocurrencies are influenced by their asset class returns or global major news announcements.[1] The scope of this study would thus also cover major news announcements that originate from the US, Europe and the UK. Due to the decentralised feature of cryptocurrencies, and relatively few studies on cryptocurrencies' price formations, this study focusses mainly on news coming from the most developed economies such as the US, UK and Europe. This is in line with the EUR/USD and GBP/USD being some of the most actively traded currencies globally. The use of global events, like news from the US or Europe, is also supported by Liu and Tsyvinski (2018) who found similar exposures to BTC risk when examining different regions which includes the US, Europe, Japan, Canada and Asia (excluding Japan). Although studies, such as Kumar and Smith (2017) support the notion that cryptocurrencies should not affect monetary policy actions in relation to interest rates and inflation control measures, the effect of changes in interest rates and inflation-related announcements on major cryptocurrencies has yet to be analysed. BTC open source allows the creation of new cryptocurrencies daily, which further fuels the need to investigate whether alternative investments, such as BTC, affect the returns of other cryptocurrencies and/or are affected by global financial news.

Our study contributes to the existing literature by closing the gap in two main areas. The study is the first to present a vector autoregression (VAR) model to help predict the returns of leading cryptocurrencies using one step ahead forecasts. The Granger causality and impulse responses are carried out to analyse the impact of cryptocurrency's returns on each other's return. The VAR model is the first one to be compared to the autoregressive (AR) and random walk (RW) models. The superiority

[1] See https://coinmarketcap.com/ for more information about the market capitalisation of cryptocurrencies.

of the AR model as compared with the VAR model provides information on the relative non-importance of any cryptocurrency in affecting the return and variances of others, instead of relying only on its own lags. The relatively poor forecasting ability of a RW model suggests the returns for cryptocurrencies can be better forecasted using a VAR model. Second, ours is the first study to analyse the presence of structural breaks within a VAR framework. This notion is important due to the volatility spikes noticed during December 2017–January 2018 in most cryptocurrencies. The presence of considerable structural changes within the cryptocurrencies' returns adds further value because they provide information that cryptocurrencies, such as other alternative investments, can be affected structurally. This effect can be caused by own asset class movements or external factors, such as macroeconomic events. The study investigates the potential effect of major news announcements on the leading ten cryptocurrencies, instead of focussing on BTC only. This inclusion allows for improved generalisation of results. This paper explores the major news announcements released in the US, Europe and the UK after being categorised into three groups, namely, inflation/interest rates-related, unemployment and economic growth-related news, which also enables the possibility of detecting whether any specific groups are prone to affect cryptocurrencies' returns.

The current study has added value for active wallet users, whose number doubled to nearly 6 million over 2013–2018. Knowledge on the drivers of cryptocurrencies' returns to the investor can be important. As such, this knowledge sheds light on whether cryptocurrencies' returns are largely affected by their and other cryptocurrencies' returns compared with other external factors, such as macroeconomic news, which typically affect other asset classes, such as equity, currencies and commodities. This study also has important policy implications for regulatory bodies, such as the Security Exchange Commission (SEC) and CFTC (Commodity Futures Trading Commission). Furthermore, this study will help shed light on whether cryptocurrencies are affected by major macroeconomic events and/or the movements of specific cryptocurrencies. Large price changes were observed in major cryptocurrencies, such as BTC, since its launch in 2009. Thus, the findings suggest whether certain cryptocurrencies' returns should be supervised closely and whether volatility spikes are detrimental to the returns of cryptocurrency investors. Government bodies are also concerned with the use of these digital currencies to channel illegitimate money as observed in the Silk Road case due to the decentralised and anonymous nature of cryptocurrency systems (Newton-Small, 2013). As postulated by Hoskinson (2013), converting cryptocurrencies from and then to fiat money, with increased regulated exchanges, would potentially provide better information on the use of cryptocurrencies.

The remainder of the paper provides a literature review, breakdown of data under analysis, methodology, descriptive statistics, and analysis. Certain conclusive remarks are made at the end of the study.

2. Literature Review

While different regulatory bodies such as the Commodity Futures Trading Commission (CFTC) defines cryptocurrencies as commodities, with the Security Exchange Commission (SEC) defining it as a currency, or a new asset class (Burniske & White, 2017), cryptocurrencies share some commonalities with equities. Conrad, Custovic, and Ghysels (2018) compared the financial asset capabilities of Bitcoin and observed several similarities to gold and the U.S dollar. Common features with the equity market include the size of cryptocurrencies which is based on market capitalisation; cryptocurrency trades transacting both on spot prices, with even some cryptocurrencies trading on futures and options markets like the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME).

Liu and Tsyvinski (2018) also looked at whether cryptocurrencies and equity markets behave in the same fashion, by analysing if BTC, Ripple's (XRP) and Ethereum (ETH) returns are compensated by risk factors derived from equity markets. Their findings suggest sizable betas from the capital asset pricing model, with however significant alphas. The interconnectivity among cryptocurrencies is supported by Phillip et al. (2018) who reported that 225 cryptocurrencies display many diverse stylized facts including long memory and heteroscedasticity while Katsiampa, Corbet, and Lucey (2019) who examined the volatility spillover effects provided evidence that time-varying conditional correlations exist and are mostly positive. Corbet et al. (2018) found cryptocurrencies markets to have only limited connectivity with other asset classes such as commodity, bonds and equity markets. In view of the rather inconclusive evidence regarding discernable relationships between cryptocurrencies and asset classes, this study would look into whether macroeconomic events can affect returns of the top ten leading cryptocurrencies, based on market capitalisation.

Among all the features of digital currencies captured by Ciaian and Rajcaniova (2016), such as low transaction costs, anonymity, no inflationary pressures, lack of regulation, and price volatility, the latter has particularly attracted investors' attention. Firstly, digital currencies are stored and accessible through software or hardware wallets. For instance, BTC can be purchased either by exchanging them for standard fiat money such as the US dollar or Euro, by acquiring them from the sales of goods and services denominated in BTC, or through a mining. Secondly, although cryptocurrencies do not have any intrinsic values as they are fiat currencies with no underlying consumption or production value as observed in commodities like gold, cryptocurrencies are not the sole currencies with no intrinsic value, since global currencies such as the US dollar and Euro also share the same feature, being fiat currencies created under government rulings. Thirdly, the volatility exhibited in global currencies is also present in cryptocurrencies, with ±20% fluctuation in Euro/US dollar prices over 2009–2015, but more pronounced fluctuations for the BTC which fluctuates from $0 to $1,100, before plunging back to $225 over the same period.

Features of cryptocurrencies like virtual monetary units with no physical representation, no central authority to keep an exclusive right to hold or monitor accounts, and relatively higher volatility in prices, are the main ones distinguishing traditional assets with these digital assets (Berentsen & Schar, 2018). With each cryptocurrency having predetermined supply, which can only be changed through a massive consensus among market participants, changes in market expectations are expected to be driven mostly by demand factors. It is thus an empirical question on whether these digital asset prices are affected by their own or external events such as macroeconomic news. With a significant proportion of wallet users and wallet providers being based in the

US and Europe (Hileman & Rauchs, 2017), the study of macroeconomic news onto cryptocurrencies from these regions is warranted.

Findings regarding the relationship between cryptocurrencies and macroeconomic factors are mixed in the literature. On the one hand, Kristoufek (2013) studied the formation of BTC price and proposed that the latter cannot be explained by macroeconomic factors mainly because cryptocurrencies are not issued by a specific government or central bank, suggesting that global news may play more important roles than local news. This notion was supported by Bouoiyour and Selmi (2015), who also found BTC to be a speculative bubble rather than being related to market forces. Wang and Vergne (2017) used newspaper mentions of BTC as a proxy for "buzz" and found that high "buzz" was followed by low BTC returns. On the other hand, Van Wijk (2013) focussed on macroeconomic factors, such as stock market indices, oil prices and exchange rates, and found that certain foreign currency pairs, such as Euro/USD and oil prices, share significant relationships with BTC in the long run. Lee (2014) explored the relationship between the attractiveness of BTC and its demand and found this relationship was dependent on the type of news released at a specific period. Liu and Tsyvinski (2018) analysed the exposure of BTC, ETH and XRP returns to macroeconomic factors and found low and statistically non-significant relationships.

These studies lacked concentration in three areas. First, some studies focussed mainly on analysing solely BTC's price, which can lead to poor generalisation of results for other cryptocurrencies because it is the leading cryptocurrency. As observed earlier, other cryptocurrencies have been growing at different rates, thereby suggesting an imperfect synchronicity with BTC price movements. Using price as opposed to returns also shows certain weaknesses in that comparing returns across asset classes is more useful compared to price actions. Returns also tend to be stationary at certain levels, which can be useful for statistical inferences. Second, the non-testing of structural breaks points to potential weaknesses in terms of stability in the adopted models. Third, although studies, such as Van Wijk (2013) and Ciaian, Rajcaniova and Kancs (2016) investigated certain macroeconomic factors, they focussed largely on factors such as equity market indices, oil prices and foreign currencies. Interpreting news announcements is also subject to the investor's expectations. Any difference between actual news information and set expectations can lead to a change in asset prices. Our study relies exclusively on the potential effects of major economic news on leading cryptocurrencies. Thus, the scope of this paper will not differentiate between positive and negative news at this juncture.

3. Data and Methodology

3.1 Data Collection

The leading cryptocurrencies in terms of each cryptocurrency's market capitalisation weight relative to the whole market capitalisation over July 2017–September 2018 as identified from https://coinmarketcap.com/ were BTC, ETH, Bitcoin cash, Litecoin, XRP, Dash (DASH), NEM (XEM), Monero (XMR), IOTA (MIOTA), and NEO. Although data are available for BTC and LTC from 28 April 2013, prices for the ten cryptocurrencies are available only from 23 July 2017. As previously mentioned, with most wallet providers and users being in North America and Europe, the major news selected come from the US, the UK and Europe. Daily data were collected from 23 July 2017 to 1 September 2018 from CoinMarketCap. Major news announcements were collected from the St. Louis Federal Reserve Economic Database (FRED) and Forex Factory's Market Data Application (MDA).

To capture as many important news as possible, all inflation, interest rates, growth and unemployment-related news are collected and categorised as inflation/ interest rate, growth and unemployment announcements. If news from different categories are released on the same day, these are excluded from the later analysis because different news could potentially have varied impacts on asset prices. This limitation could be eliminated in future research if high frequency data are available for all cryptocurrencies. Statements by policy makers or central banks are disregarded due to their qualitative nature. However, if released with another news item from a different category on the same day, both news items are disregarded. Finally, whenever quantitative news from the same category are released on the same day, the more important one is captured. For example, when inflation-related Core CPI m/m and CPI m/m are released on the same day (such as 11 August, 2017), only Core CPI m/m is retained for future analysis because traders pay further attention to the data that are adjusted for fluctuations in food and energy prices. The time zone is set to the Coordinated Universal Time (UTC) to match news announcements with cryptocurrencies' returns.

3.2 Methodology

The methodology adopted in this study centres on first adopting a VAR model using the cryptocurrencies under study. VARs have extensively been used in the literature. For instance, Watson (1994) and Waggoner and Zha (1999) summarised different VAR techniques; Mills (1999) and Tsay (2001) applied VAR models onto financial data. Sims (1980) vigorously supported that VAR models are valid tools in the econometrics of data description, forecasting, structural inference and policy analysis. Stock and Watson (2001) found VARs are robust tools in forecasting and data description and recommended the use of economic theory or institutional knowledge in relation to differentiating between causation and correlation.

Our study addresses the issue of excessive variables by optimising the lag structure and updating the model from a general to a parsimonious model by removing insignificant coefficients form the lag structures. A reduced and a recursive form VAR model are adopted in this study because of the lack of economic theory between cryptocurrencies and news announcements. The reduced form VAR model is specified as follows:

$$\begin{bmatrix} BTC_t \\ ETH_t \\ \cdots \\ NEO_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \cdots \\ \alpha_{10} \end{bmatrix} + \begin{bmatrix} BTC_{t-1} \\ ETH_{t-1} \\ \cdots \\ NEO_{t-1} \end{bmatrix} \begin{bmatrix} \pi_{11}^1 & \cdots & \pi_{1x}^1 \\ \vdots & \ddots & \vdots \\ \pi_{x1}^1 & \cdots & \pi_{xn}^1 \end{bmatrix} + \ldots + \begin{bmatrix} BTC_{t-N} \\ ETH_{t-N} \\ \cdots \\ NEO_{t-N} \end{bmatrix} \begin{bmatrix} \pi_{11}^N & \cdots & \pi_{1x}^N \\ \vdots & \ddots & \vdots \\ \pi_{x1}^N & \cdots & \pi_{xn}^N \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \cdots \\ \varepsilon_{10t} \end{bmatrix} \quad (1)$$

where BTC_t, ETH_t,…,NEO_t are the ten cryptocurrencies prices and $\alpha_{1…10}$ represents the intercepts in the system. BTC_{t-1}, ETH_{t-1},…,NEO_{t-1} are the ten cryptocurrencies prices, which are lagged by 1 day. Each dependent variable is a function of its own lagged variables, in addition to other lagged dependent variables, thereby allowing for only endogenous variable in the system. For example, NEO_{t-N} is NEO lagged by N days, where N represents the number of lags after optimising the lag structure. π represents the coefficients of the independent variables and ε_{1t},ε_{2t},…,ε_{10t} are the error terms of the individual equations.

To remove redundant lags in the model, lags are optimised after conducting the Wald coefficient test. Conventional diagnostic testing is performed to check for normality (Jarque–Bera normality test), and serial correlation (Breusch-Godfrey LM test) in residuals. The reduced form and recursive VARs are used to summarise any significant covariance between the cryptocurrencies' returns. The Granger causality test is used to examine if lagged values of one variable help to predict another variable. It shows the p-values associated with the F-statistics to test if relevant sets of coefficients are zero. The Granger causality test is modelled as follows:

$$y_t = \alpha_1 + \sum_{i=1}^{n} \pi_i x_{t-i} + \sum_{j=1}^{n} \pi_j x_{t-j} + \varepsilon_t \tag{2}$$

where $\pi_{i…n}$ represent the impacts of other cryptocurrencies' lagged returns onto one specific returns and $\pi_{j…n}$ represent the impacts of one cryptocurrency's lagged return onto its own cryptocurrency's returns. y_t represents the ten cryptocurrencies' returns. The paper then moves to analyse shocks within the VAR system by examining the effect of one standard deviation change in the error terms of determining BTC over different cryptocurrencies' returns.

Jordà (2005) provided a breakdown of the methodology of impulse responses by local projections. The impulse response function of the selected cryptocurrencies' returns y_t to BTC_t returns, that is, up to 10 days after its occurrence, is calculated as the residual between the following two forecasted estimations:

$$IRF\ (z) \equiv E[y_{t+z-1}|BTC_{t-1} = 1, y_s, BTC_{t-1}, s > t]$$

$$E[y_{t+z-1}|BTC_{t-1} = 0, y_s, BTC_{t-1}, s > t] \tag{3}$$

where the impulse responses are based on the best mean squared multi-step-ahead forecasts. Several proponents of the use of impulse response by local projections onto financial markets include Furceri and Zdzienicka (2012) who analysed the effect of debt crises onto GDP and Bernal-Verdugo, Furceri, and Guillaume (2013) who analysed the effect of labour reforms and bank crises onto unemployment.

Forecast error decompositions, which capture the proportion of variance in the error made in forecasting a variable due to a specific shock over a given horizon, are also reported. Findings suggest considerable interaction among cryptocurrencies. The reduced form VAR can also be used to forecast the return of cryptocurrencies and evaluate their performance against certain benchmarked models. Multi-step-ahead forecast is computed by estimating the VAR through a given day.

To compare the forecasting ability of the VAR model, out-of-sample forecasts are compared with the AR(p) and RW models. The root mean squared forecast error (RMSE) is calculated as the root of the average squared value of the forecast error over the out-of-sample period. The rationale behind AR(p) models is that it can explain the current value of cryptocurrency's prices, θ_t, by a function of historical p values. In the vector notation, the AR(p) model is expressed as:

$$\theta_t = \pi\boldsymbol{\theta}'_{\boldsymbol{t-i}} + \epsilon_t \tag{4}$$

where $\pi = (\pi_1, \pi_2, \ldots, \pi_p)$, $\boldsymbol{\theta}_{\boldsymbol{t-i}} = (\theta_{t-1}, \theta_{t-2} \ldots, \theta_{t-p})$ and $\epsilon_t \sim N(0, \sigma^2)$. If the mean is not zero, then the AR(p) model is updated to include an intercept α, where $\alpha = \mu(1 - \pi_1 - \ldots\pi_p)$. However, the RW model assumes that the cryptocurrency's returns move away from their present position in a random fashion and is presented as follows:

$$\theta_t = \theta_{t-1} + \omega_t \tag{5}$$

where $\omega_t \sim N(0, \sigma^2)$. The RW model has the same form as an AR(1) model except that it is non-stationary because $\pi = 1$. Following Jordà (2005), the number of lags under AR(p) is optimised using Akaike information criterion (AIC).

4. Research Findings

4.1 Descriptive Statistics

Figure 1 and Figure 2 display the monthly US dollar prices of the leading crypto-currencies for July 2017–September 2018. For clear presentation of fluctuations in cryptocurrency prices, we divide them into three groups and two charts displayed in Figure 1 and Figure 2. Figure 1 shows two groups of cryptocurrencies including BTC in one group and ETH, BCH, LTC, DASH, XMR and NEO in another group. The secondary

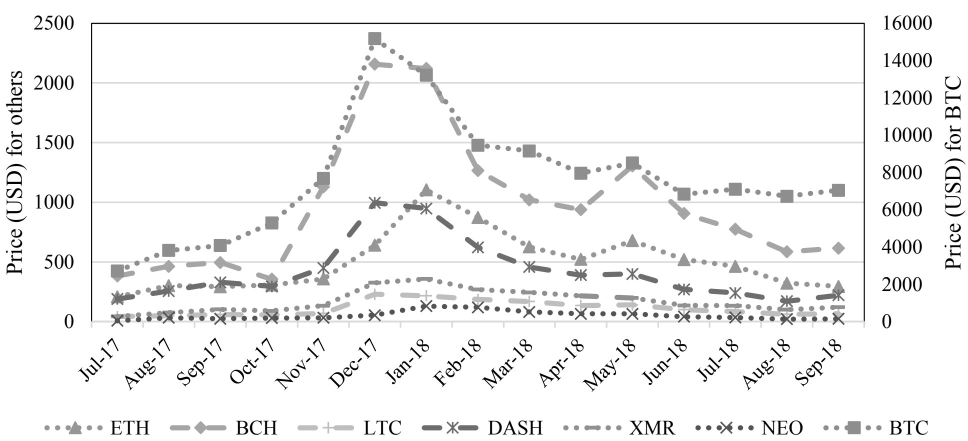

Figure 1. Prices of leading high-price cryptocurrencies in US$ (July, 2017–September, 2018).
Source: https://coinmarketcap.com/

axis on the right-hand side of the graph shows that BTC experienced considerable price increases to $15,175 in December 2017 (highest price recorded was $19,500). Notably, the others also witnessed similar price trends over the period under study. This trend can be explained by the correlation coefficients, as observed in Table 1, where the selected cryptocurrencies shared relatively high positive correlation coefficients that range from 0.61 to 0.9. Figure 2 shows the three low-price cryptocurrencies, namely XRP, NEM and MIOTA, having lower values as compared to others. The untabulated descriptive statistics show that the mean value of BTC was the highest at $7,959, whereas NEM's was the lowest at $0.36. BTC also had the highest risk with a standard deviation of $3,406, compared with NEM, which had the lowest risk with a standard deviation value of $0.31. All cryptocurrencies were positively skewed and leptokurtic. The low values in the Jarque–Bera normality test (results are not reported) suggest the cryptocurrencies' prices are not normally distributed.

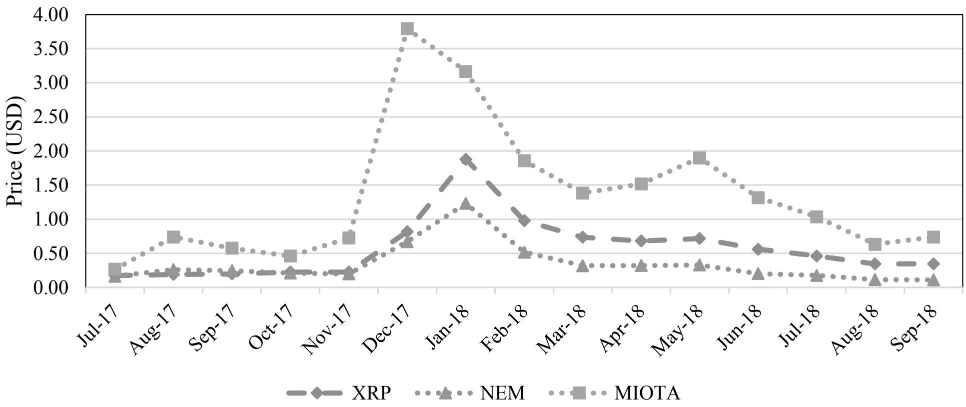

Figure 2. Prices of leading low-price cryptocurrencies in US$ (July, 2017–September, 2018).
Source: https://coinmarketcap.com/

Table 1. Correlation among leading cryptocurrencies

	BTC	ETH	BCH	LTC	XRP	DASH	NEM	XMR	MIOTA	NEO
BTC	1									
ETH	0.75	1.00								
BCH	0.88	0.78	1.00							
LTC	0.90	0.84	0.86	1.00						
XRP	0.71	0.84	0.78	0.78	1.00					
DASH	0.87	0.75	0.93	0.86	0.75	1.00				
NEM	0.73	0.81	0.82	0.77	0.90	0.87	1.00			
XMR	0.90	0.87	0.88	0.94	0.82	0.90	0.81	1.00		
MIOTA	0.92	0.76	0.89	0.87	0.72	0.88	0.79	0.88	1.00	
NEO	0.61	0.94	0.63	0.75	0.75	0.64	0.71	0.80	0.61	1.00

The Im-Pesaran-Shin (IPS), Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) stationarity tests support that cryptocurrencies' prices are stationary after first order differencing (results are not reported). Log returns, computed as $\log\left(\frac{p_t}{p_{t-1}}\right)$, were found to be stationary at 99 percent confidence level. The log returns are used for the remainder of the study because they are stationary and convey additional interest to the investor who wants to compare the returns among different asset classes. We did not pursue a vector error correction model because all variables were stationary at all levels. As per Equation (1), the VAR model should be optimised for the number of lags. The results of AIC test supported an optimal lag structure of two. Hence, we used two lags in the analyses.

Granger causality tests are carried out to determine whether the lagged returns of one cryptocurrency is useful in predicting other cryptocurrencies' returns. Table 2 displays the *p*-values associated with the *F*-statistics for testing if the relevant regressor coefficients are zero. Numbers in italics are significant at the 5% level. Out of the 90 p-values displayed, 37 were less than or equal to 5%, which suggests that approximately 40% of the regressors are significant in predicting cryptocurrencies' returns. Upon close inspection, all cryptocurrencies' returns have p-values less than 5%, which suggests that they help in predicting BTC's returns. Conversely, BTC returns are significant in predicting only two cryptocurrencies' returns including BCH and NEM. XMR is found to be significant at the 5% level in predicting the other nine cryptocurrencies' returns. Only DASH was found to be a significant contributor of XMR returns with a p-value of 0.038.

With two lags per each dependent variable and 10 cryptocurrencies, a need to move from a generic to a parsimonious model arose. Following the Wald coefficient tests, redundant coefficients were removed from the VAR system. Table 3 summarises the findings under the parsimonious VAR model. With two lags, 10 cryptocurrencies

Table 2. Granger causality tests

		Dependent variable									
		BCH	BTC	DASH	ETH	LTC	MIOTA	NEM	NEO	XMR	XRP
Regressor	BCH	–	*0.000*	*0.043*	0.313	0.158	0.500	0.743	0.121	0.656	0.952
	BTC	*0.007*	–	0.450	0.690	0.211	0.263	*0.003*	0.209	0.696	0.661
	DASH	*0.040*	*0.000*	–	0.247	0.401	*0.030*	*0.015*	0.954	*0.038*	0.116
	ETH	*0.008*	*0.000*	0.987	–	0.295	0.054	*0.045*	*0.032*	0.784	0.826
	LTC	*0.001*	*0.000*	0.878	0.822	–	0.088	0.083	0.223	0.363	0.584
	MIOTA	*0.004*	*0.000*	0.848	0.248	0.190	–	0.419	*0.040*	0.191	0.159
	NEM	0.155	*0.000*	0.923	0.459	0.071	0.142	–	0.826	0.112	0.130
	NEO	*0.005*	*0.000*	0.433	0.815	0.134	0.617	0.253	–	0.426	0.341
	XMR	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	–	*0.000*
	XRP	*0.000*	*0.000*	*0.037*	*0.017*	*0.169*	*0.003*	*0.010*	*0.004*	0.441	–

Note: The table shows the *p*-values of the *F*-statistics for testing if the coefficients are zero. A two-day lag is used in the Granger causality test based on the AIC test. Numbers in italics are significant at the 5% level and suggest that the regressor helps to predict the return of the dependent variable.

and 1 intercept in each time series equation, the general model stood at 210 variables for 403 observations. The highly positive correlations among the cryptocurrencies as observed in Table 1 suggest that a reduction in form is plausible. Although not reported in Table 3, the parsimonious model results were reached by removing more than half

Table 3. VAR results

Dependent variable	*p*-value of own lag (1st lag)	*p*-value of own lag (2nd lag)	*p*-value of LM test	Structural break dates	
				Sequential	Repartition
BCH	*0.0012*	*0.0006*	0.4720	11/10/2017	11/22/2017
				2/1/2018	1/30/2018
				6/12/2018	6/12/2018
BTC	*0.0024*	0.4745	0.1406	11/2/2017	11/26/2017
				3/9/2018	1/31/2018
				5/24/2018	5/24/2018
DASH	*0.0000*	*0.0000*	0.0533	5/22/2018	9/21/2017
				11/20/2017	11/29/2017
				1/30/2018	1/30/2018
				9/21/2017	5/23/2018
MIOTA	0.3282	0.2909	0.3108	11/28/2017	12/1/2017
				1/30/2018	1/30/2018
				6/12/2018	4/13/2018
				4/13/2018	6/12/2018
ETH	0.6282	0.5729	0.2526	12/11/2017	10/12/2017
				3/10/2018	12/12/2017
				6/22/2018	3/8/2018
				10/12/2017	6/22/2018
LTC	0.3183	0.8586	0.9916	12/8/2017	10/9/2017
				3/26/2018	12/9/2017
				6/12/2018	3/13/2018
				10/9/2017	6/12/2018
NEM	*0.0000*	*0.0003*	0.2424	3/16/2018	12/12/2017
				6/10/2018	2/10/2018
				12/12/2017	6/10/2018
NEO	0.7493	0.3492	0.2151	12/14/2017	9/27/2017
				3/14/2018	1/2/2018
				6/10/2018	3/12/2018
				9/27/2017	6/10/2018
XMR	*0.0319*	0.5740	0.7372	11/21/2017	9/22/2017
				3/13/2018	12/4/2017
				5/24/2018	3/12/2018
				9/22/2017	5/24/2018
XRP	*0.0021*	0.1371	0.1295	12/14/2017	10/4/2017
				2/22/2018	12/21/2017
				6/12/2018	2/21/2018
				10/4/2017	6/12/2018

Note: *p*-values are reported only for the two-day lag of dependent variables. Numbers in italics are significant at the 5% level.

of the lagged independent variables after conducting the Wald coefficient test and removing any coefficient not significantly different from zero at the 5% level. For brevity, only the *p*-values of own lags are reported, although other independent variables were significant in explaining the current dependent variable. The 1-day lag returns of BCH, BTC, DASH, NEM, XMR and XRP and 2-day lag returns of BCH, DASH and NEM were statistically significant in explaining the current returns of BCH, DASH, LTC, NEM, NEO, XMR and XRP, respectively. The LM serial correlation test (Breusch-Godfrey test) is not significant at 5 percent significance level, which suggests the absence of autocorrelation in the models. BTC had the highest R-squared value of 0.58, followed by DASH (0.51) and ETH (0.47). Furthermore, this study conducts Bai-Perron tests of L+1 vs. L sequentially determined breaks (Bai & Perron, 1998) because the Bai-Perron test allows us to test for possible multiple structural breaks at unknown dates. The structural break dates are also reported in Table 3. An observation is that the common dates include November and December for shocks.

As also observed in the residual graphs in Figure 3, all residuals were close to zero as expected, except during December 2017 to January 2018, where some volatility spikes were noted. The next four sections inspect impulse responses, forecast error decompositions, evaluate the forecasting ability of the VAR model and compare the results with the AR(p) and RW models.

4.1.1 Structural breaks

As shown in Figure 3 and observed in Figure 4, excessive noise was noted during October 2017 and February 2018 and were mostly concentrated during December 2017 to January 2018. Notably, abrupt changes were observed in all cryptocurrencies around December 2017. This finding requires the need to check for potential structural breaks in the model, which can be the result of major news announcements. We identified three inflation/central bank categorised news, four employment-related news, and three growth-related news, outlined in Table 4, which were released during this period.

Using the Bai–Perron multiple breakpoint tests, breakpoint dates were captured for each cryptocurrency. Using the Chow breakpoint test, these breakpoint dates were tested for structural breaks. As displayed in Table 5, the zero-probability value of the *F*-statistics reject the null hypothesis of no structural breaks at these specific dates. Therefore, the significant news announcement for each cryptocurrency are identified for further analysis. In line with Table 4, which categorised major news announcements, these structural break dates were matched with potential news releases on these specific dates. We specified a maximum of 10 days for a news to be a significant event in a cryptocurrency price break. The closely related news were for BCH (zero day Manufacturing Production m/m – UK and one day Non-Farm Employment Change –US), LTC (one day Unemployment Claims – US), NEM (one day Manufacturing Production m/m – UK) and XRP (zero day Final GDP q/q – US). Although this finding suggests that other categorised news, such as inflation and interest rate related announcements, did not have any noticeable impact on cryptocurrency's returns, the relatively thin amount of macroeconomic news as captured in this study from December to January suggests a need for higher frequency cryptocurrency data. As mentioned in the Data section,

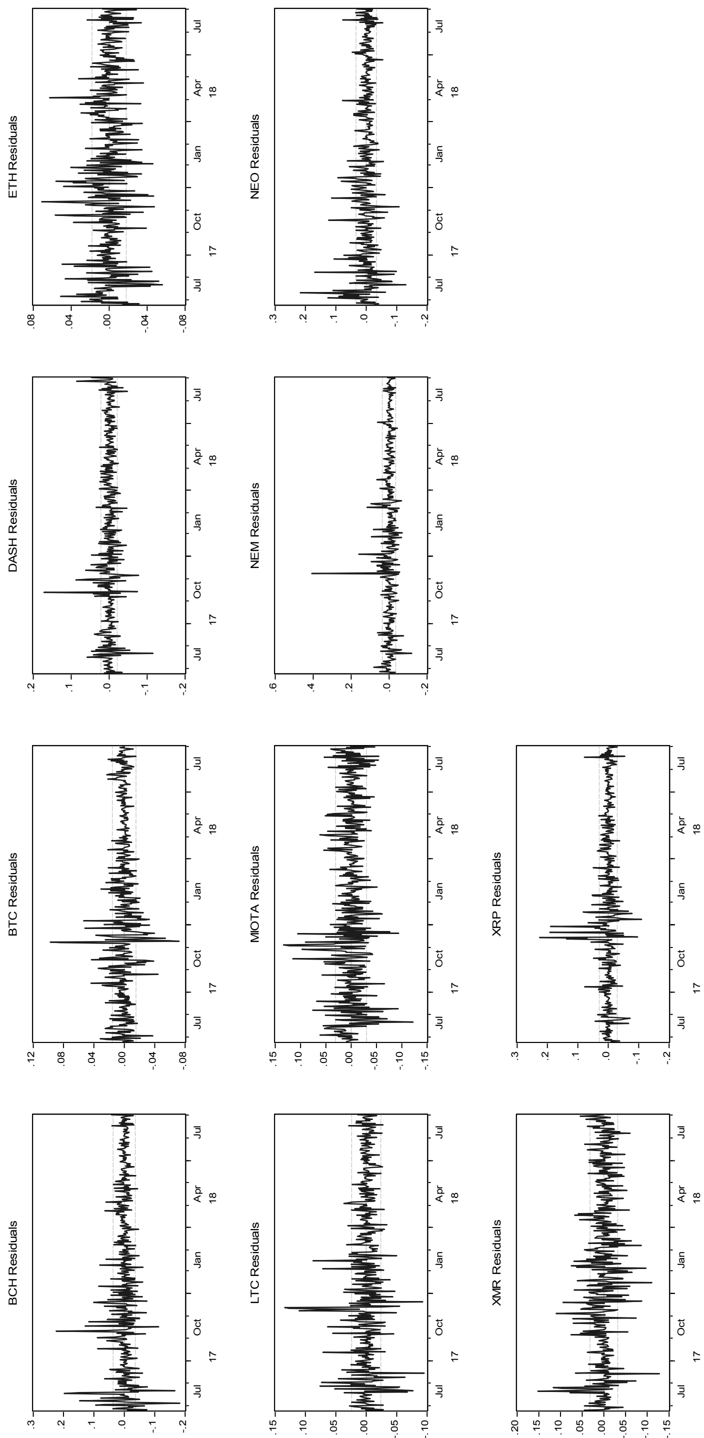

Figure 3. Residuals of VAR system

Note: The figure shows the residuals of BCH, BTC, DASH, MIOTA, ETH, LTC, NEM, NEO, XMR and XRP in the VAR system from December, 2017 to September, 2018.

Table 4. Categorisation of news announcements

News category	Inflation/Interest rate	Unemployment	Growth
News content	Average Earnings Index – UK (*5*)	ADP Non-Farm Employment Change – US (*5*)	Advance GDP q/q – US (*3*)
	Core CPI m/m – US (*1*)	Non-Farm Employment Change – US (*10*)	Current Account – UK (*3*)
	CPI y/y – UK (*7*)	Unemployment Claims – US (*5*)	Core Durable Goods Orders m/m – US (*5*)
	PPI m/m – US (*5*)		Core Retail Sales m/m – US (*3*)
	Second Estimate GDP q/q – UK (*1*)		Final GDP q/q – US (*3*)
			GDP m/m – UK (*1*)
			Manufacturing Production m/m – UK (*6*)
			Prelim GDP q/q – US (*2*)
			Retail Sales m/m – UK (*5*)
News count	19	20	31

Source: Author, FRED.

Table 5. Structural breakpoint dates and news announcements

	Chow breakpoint	Structural break dates	News announcements
BTC	*0.0000*	11/2/2017	–
	0.0405	3/9/2018	–
	0.0004	5/24/2018	–
	0.0000	11/26/2017	Second Estimate GDP q/q – UK (+3 day)
	0.9680	1/31/2018	–
BCH	*0.0000*	11/10/2017	Manufacturing Production m/m – UK (0 days)
	0.0490	2/1/2018	Non-Farm Employment Change – US (+1 day)
	0.0000	6/12/2018	–
	0.0000	11/22/2017	–
	0.0678	1/30/2018	–
DASH	*0.0000*	5/22/2018	–
	0.0000	11/20/2017	Manufacturing Production m/m – UK (+10 days)
	0.0000	1/30/2018	Average Earnings Index – UK (+6 days)
	0.0000	9/21/2017	–
	0.0000	11/29/2017	Second Estimate GDP q/q – UK (+6 days)
	0.0000	5/23/2018	–
MIOTA	*0.0000*	11/28/2017	Second Estimate GDP q/q – UK (+5 days)
	0.1803	1/30/2018	–
	0.0000	6/12/2018	–
	0.0401	4/13/2018	–
	0.0000	12/1/2017	Second Estimate GDP q/q – UK (+8 days)
ETH	*0.0000*	12/11/2017	Unemployment Claims – US (+4 days)
	0.0961	3/10/2018	–
	0.0000	6/22/2018	–
	0.0000	10/12/2017	Manufacturing Production m/m – UK (+2 days)
	0.0000	12/12/2017	Unemployment Claims – US (+5 days)
	0.1301	3/8/2018	–
LTC	*0.0000*	12/8/2017	Unemployment Claims – US (+1 days)
	0.0020	3/26/2018	–
	0.0000	6/12/2018	–
	0.0000	10/9/2017	Non-Farm Employment Change – US (+3 days)
	0.0000	12/9/2017	Unemployment Claims – US (+2 days)
	0.0298	3/13/2018	–
NEM	*0.0000*	3/16/2018	–
	0.0000	6/10/2018	–
	0.0000	12/12/2017	Unemployment Claims – US (+5 days)
	0.0000	2/10/2018	Manufacturing Production m/m – UK (+1 days)
NEO	*0.0000*	12/14/2017	Unemployment Claims – US (+7 days)
	0.0005	3/14/2018	–
	0.0000	6/10/2018	–
	0.0000	9/27/2017	–
	0.0000	1/2/2018	Unemployment Claims – US (+5 days)
	0.0010	3/12/2018	–

Table 5. Continued

	Chow breakpoint	Structural break dates	News announcements
XMR	*0.0000*	11/21/2017	–
	0.0011	3/13/2018	–
	0.0000	5/24/2018	–
	0.0000	9/22/2017	–
	0.0000	12/4/2017	–
	0.0014	3/12/2018	–
XRP	*0.0000*	12/14/2017	Unemployment Claims – US (+7 days)
	0.7211	2/22/2018	–
	0.0005	6/12/2018	–
	0.0000	10/4/2017	–
	0.0000	12/21/2017	Final GDP q/q – US (+0 days)
	0.7815	2/21/2018	–

Note: Values in italics are probabilities of the *F*-statistic test of *p*-values with structural break. Plus (+) means the structural break occurred after the news. Maximum 10 days events were evaluated.

only news released within one specific category are captured. The effect of news from different categories, such as growth and unemployment, that are released on the same day but at different hours are not studied because their individual effect is not measurable due to the use of only daily cryptocurrency data.

The unrestricted VAR model from Equation (1) is tested for structural changes in returns by imposing dummy variables of 1 as exogenous variables for the break dates found significant in the above analysis. The results are shown in Table 6. There are no significant changes in the *p*-values of own lags for individual cryptocurrencies except that first lag of LTC becomes significant and first lags of NEM and XRP become insignificant after including the dummy variables into the models. Surprisingly, a majority of break dates are found to be insignificant when included into the VAR model. The only six significant dates found to be within the period of 26 November 2017 to 14 December 2017 are mostly related to Unemployment Claims in the US. However, there were no news announcements released on the same day the breaks occurred. This finding suggests that cryptocurrencies' returns witness structural changes around end November and early to middle of December.

The findings are supported by Kristoufek (2013) and Bouoiyour and Selmi (2015) who argued that cryptocurrencies' prices, such as BTC, cannot be explained by macroeconomic indicators because these financial products are disconnected from economic policies. The results are also in line with those of Ciaian et al. (2016) who found macro-financial developments, such as exchange rates and oil, are not driving BTC prices in the long run. Our findings are also in support of those of Yermack (2015) and Liu and Tsyvinski (2018) who found that macroeconomic events, which tend to affect major currencies similarly, does not appear to affect cryptocurrencies, such as BTC. The relatively poor association of news announcements with important structural breaks in cryptocurrencies' returns suggest that macroeconomic factors were not associated

Table 6. Unrestricted VAR with structural break dates

Dependent variable	*p*-value of own lag (1st lag)	*p*-value of own lag (2nd lag)	News announcements		
BCH	*0.0018*	*0.0000*	11/26/2017 (0.4502)	1/2/2018 (0.4590)	–
BTC	*0.0039*	0.7789	*26/11/2017 (+3) (0.0387)*	–	–
DASH	*0.0000*	*0.0002*	20/11/2017 (0.7902)	30/1/2018 (0.8066)	29/11/2017 (0.1801)
MIOTA	0.2558	0.3644	*28/11/2017 (+5)* (*0.0116*)	1/12/2017 (0.0833)	–
ETH	0.9585	0.9601	*11/12/2017 (+4) (0.0289)*	12/10/2017 (0.9911)	*12/12/2017 (+5) (0.0050)*
LTC	*0.0292*	0.1187	*8/12/2017 (+1) (0.0166)*	9/10/2017 (0.1237)	9/12/2017 (0.9713)
NEM	*0.0860*	*0.0002*	12/12/2017 (0.6497)	10/2/2018 (0.6527)	–
NEO	0.7839	0.1324	14/12/2017 (0.7978)	1/2/2018 (0.5749)	–
XMR	*0.0131*	0.3779	–	–	–
XRP	0.4117	0.3326	*14/12/2017 (+7) (0.0000)*	21/12/2017 (0.8596)	–

Note: *p*-values are reported only for the two-day lag of dependent variables. Numbers in italics are significant at the 5% level.

with the noise observed in these technology-driven markets. This finding suggests that regulatory bodies, such as the CFTC and SEC, capture higher frequency data and render these data publicly available as part of sustaining transparency in the financial markets. Higher frequency data on cryptocurrencies would allow for broadly available news release to be mapped against cryptocurrency movements. The only few significant break dates in the unrestricted VAR model reveal that the price volatility during early December could have been caused by the unemployment claims in the US for certain cryptocurrencies, i.e. ETH, LTC and XRP. The weak results on break dates could infer the relatively unimportant macroeconomic news on cryptocurrency price movement.

4.1.2 Impulse responses

We observed a relatively higher importance of BTC in the cryptocurrency market and a strongly positive correlation in Table 1. Thus, we investigated the impact of a shock on BTC over other leading cryptocurrencies' returns. The impulse response functions are calculated for the nine cryptocurrencies following one standard deviation shock to BTC's returns in unrestricted VAR system with the inclusion of the structural breaks as

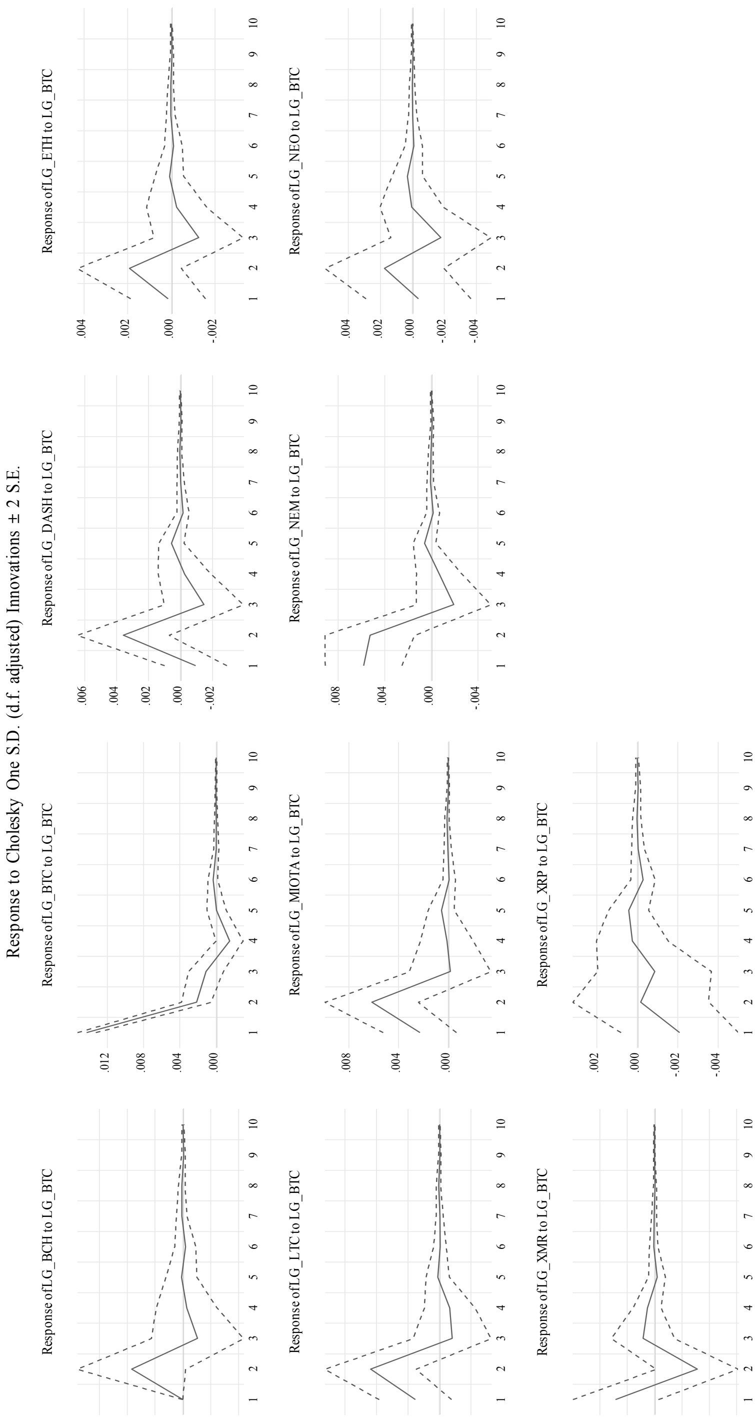

Figure 4. Response of cryptocurrencies to a one standard deviation shock in BTC

Note: The graphs show the effect of all crypto returns following a one standard deviation shock in BTC's returns. The response over 10 days is captured. The dotted lines represent the 95% confidence intervals.

exogenous variables. The dotted lines represent the 95% confidence intervals in Figure 4. Based on the results in Figure 4, all other cryptocurrencies experienced a positive increase in returns on the 1st day following the one standard deviation shock to BTC's returns, except for XRP and DASH. However, the effect was short-lived, with all returns dropping slightly below their pre-shock state, before stabilising to their initial state within four days following the initial shock. This finding suggests that despite the shock from BTC, which produced an initial positive effect on most cryptocurrencies' returns, this effect lasted no longer than four days. This result is supported by earlier findings in Table 2, where the one-day lagged returns of BTC were essential in explaining the current returns for only three cryptocurrencies. The steepest effect was observed with BTC, where the latter dropped 1.6% within two days following its own shock.

4.1.3 Variance decompositions

Variance decompositions are reported in Table 7 using a 1- to 5-day forecast horizon based on unrestricted VAR estimates with the inclusion of the structural breaks as exogenous variables. Excluding BTC, where its variance proportions relative to all cryptocurrencies are reported, for the remaining cryptocurrencies only the values greater than or equal to 5% in at least one period forecast are reported. As expected, in period one, all cryptocurrencies' volatilities in returns were composed primarily of their volatilities, which range from 60% to 100%. The Cholesky ordering was set from BTC, BCH, DASH ETH, LTC, MIOTA, NEM, NEO, XMR and XRP. As observed, BTC contributed only marginally to the volatility of other cryptocurrencies' returns. Other

Table 7. Variance decompositions by cryptocurrencies

Period	BCH	BTC	DASH	MIOTA	ETH	LTC	NEM	NEO	XMR	XRP
BTC										
1	3	97	0		0	0			0	
2	5	60	6		18	10			0	
3	4	38	4		11	8			30	
4	5	38	4		11	8			29	
5	5	38	4		11	8			29	
BCH										
1	100	0							0	
2	76	1							21	
3	75	1							20	
4	74	1							20	
5	74	1							20	
DASH										
1	14	0	86						0	
2	6	1	42						50	
3	7	1	40						49	
4	7	1	40						48	
5	7	1	40						48	

Table 7. Continued

Period	BCH	BTC	DASH	MIOTA	ETH	LTC	NEM	NEO	XMR	XRP
ETH										
1	8	0	11		80				0	
2	4	1	8		42				45	
3	4	1	8		41				45	
4	4	1	8		41				45	
5	4	1	8		41				44	
LTC										
1	5	1	6		28	60			0	
2	3	2	5		18	36			37	
3	3	2	5		17	35			36	
4	3	2	5		18	35			36	
5	3	2	5		18	35			36	
MIOTA										
1		0	7	73	16				0	
2		1	5	43	10				38	
3		1	5	42	10				37	
4		1	5	42	10				37	
5		1	5	42	10				37	
NEO										
1		0	5		17			72	0	
2		0	4		13			53	23	
3		0	4		14			51	23	
4		0	4		14			51	23	
5		0	4		14			51	23	
XMR										
1		0							99	
2		1							96	
3		1							94	
4		1							94	
5		1							94	
XRP										
1		0			11		6		1	76
2		0			9		5		28	51
3		0			9		5		28	50
4		0			9		5		27	49
5		0			9		5		27	49
NEM										
1	5	1	6		16		68		0	
2	3	5	6		11		50		19	
3	3	4	6		11		48		19	
4	3	5	6		11		48		19	
5	3	4	6		11		48		19	

Note: The table displays the error decompositions for the 10 cryptocurrencies using 1–5 day forecast horizons. With the exception of BTC's variance contribution that is displayed in all cryptocurrencies, only the significant values in relation to others are reported. The Cholesky ordering was set from BTC, BCH, DASH ETH, LTC, MIOTA, NEM, NEO, XMR and XRP. All values are in %.

cryptocurrencies also behaved similarly by contributing only marginally to other cryptocurrencies' variance. The only noticeable exception was XMR, which represented 29%-25% of BTC's variance, 20%-21% of BCH's variance, 48%-50% of DASH's variance, 44%-45% of ETH's variance, 36%-37% of LTC's variance, 37%-38% of MIOTA's variance, 23% of NEO's variance, 27%-28% of XRP's variance and 19% of NEM's variance over the two- to fifth-day forecast horizon. Although not reported, an impulse response test shows that DASH, ETH, XRP and BCH have a positive effect on their returns approximately on the second day following a one standard deviation shock in XMR. BTC returns also benefited from a positive effect in their returns around the third day. All cryptocurrencies dropped to their pre-shock state before stabilising around the fifth day.

4.1.4 Forecasts

Using RMSE, the VAR model is tested for its forecasting ability over one step ahead forecast. Due to the heightened volatility observed in crypto currencies and dynamic forecasting being more susceptible to a deterioration in forecasting results as the forecasting horizon is increased, we restrict our forecast to one step ahead forecast only, to allow the model to capture any recent data fluctuation. The results are compared with the AR and RW models. The out-of-sample forecast is set from 2 September 2018 till 30 September 2018. Using the Breusch-serial correlation LM test and Breusch-Godfrey-Pagan heteroscedasticity test, various AR equations were found to be not serially correlated and homoscedastic at the 5% significance level, except for XRP, LTC and MIOTA, which were found to be not serially correlated, but heteroscedastic. Table 8 shows the forecasting results using one day ahead forecasts, from 2nd September 2018 till the 30th October 2018, using the VAR, AR and RW models. We assume that a drift does not exist in the RW model. Among the three alternative models, the RW model ranked last for all cryptocurrencies. The AR model was superior in forecasting all cryptocurrencies' returns, with the VAR model ranking second on all occasions. The best VAR model was for XMR which had a slightly lower RMSE value of 0.0239 compared to the AR model yielding 0.0237.

Table 8. RMSE of one day ahead forecasts

	VAR	AR	RW		VAR	AR	RW
BCH	0.0310	0.0256	0.0358	MIOTA	0.0329	0.0245	0.0365
BTC	0.0150	0.0101	0.0131	NEM	0.0295	0.0238	0.0386
DASH	0.0291	0.0221	0.0337	NEO	0.0296	0.0252	0.0387
ETH	0.0325	0.0284	0.0411	XMR	0.0239	0.0237	0.0347
LTC	0.0246	0.0199	0.0293	XRP	0.0461	0.0394	0.0504

Note: The table reports the RMSE of the VAR, AR and RW models. The numbers of lags in the AR equation of each cryptocurrency are as follows: BCH (2), BTC (5), DASH (1), ETH (6), LTC (6), MIOTA (2), NEM (1), NEO (5), XMR (1) and XRP (2). The RW model assumes no drift.

4.2 Discussions

Regarding the potential comparison of the findings of this study with those in equity markets, the results from structural break tests which show insignificant alignment with the release of macroeconomic events, are supported by Kristoufek (2013) who postulated that the price creation of BTC cannot be explained by traditional economic theories because several determinants of price creations in the conventional theories, like being unregulated and trading in a digital economy, are absent in cryptocurrency markets and thus cannot be expected to be determined by traditional factors of supply and demand. Our results are also consistent with Bouoiyour and Selmi (2015) who found the Chinese market index (gold price) to significantly (insignificantly) impact BTC's prices, but more importantly, concluded that BTC's price is not affected by macro-economic fundamentals of a real economy but rather act as a digital asset driven by speculative behaviour. Our results differ from Van Wijk (2013) who used the Dow Jones Industrial Average (DJIA) equity index, FTSE 100 equity index, Euro/USD and oil price indices, as representatives of global macroeconomic and financial developments, and found a positive and significant impact of the value of DJIA on BTC's price, but negative impact of the Euro/US on BTC's price. The departure from the latter paper's results can be attributed to different periods under study, and also to the fact that the most significant break in cryptocurrencies took place in late 2017, a period not under study in the above-mentioned paper.

5. Conclusion

This study aims to shed further light into the return characteristics of cryptocurrencies and whether they are affected by their class asset movements or other factors, such as global macroeconomic news announcements. Major news was selected from the US, the UK and Europe because the highest number of wallet users and providers were localised in these countries. News announcements were categorised into three groups, namely, inflation/interest rates, unemployment and growth-related. Log returns were used because they were stationary at levels and more informative than using raw prices. This notion allows investors to compare returns across asset classes. All cryptocurrencies' prices shared an extremely strong and positive correlation with BTC prices. Although all cryptocurrencies' returns help to predict BTC's returns, BTC was non-significantly important in predicting most cryptocurrencies' returns. XMR, however, was significant in predicting nine of the other cryptocurrencies' returns. Under the VAR system, the one-day lag return was significant in explaining the current returns, except for BTC, MIOTA and ETH. Following a one standard deviation shock in BTC, all cryptocurrencies, except for XRP and DASH, experienced a small increase in their first day return. This finding was mostly reversed on the next day, where the effect stabilised to its pre-shock levels within four days. BTC and other cryptocurrencies contributed only marginally to one another's variances over a one- to five-day forecast horizon. The only noticeable exception was XMR, which weighted between 21% and 45% for the volatilities of certain cryptocurrencies. Using RMSEs, the AR model ranked superior in most cryptocurrencies compared to the VAR and RW models. The RW model ranked last for all return forecasts. The inclusion of a dummy variable to reflect the potential presence of structural changes in the VAR model was found significant at the 5% level, compared with a restricted model with no account of structural change. Significant structural break dates were found for the majority of the cryptocurrencies during December 2017–January 2018. No news announcement matched the occurrence of a structural break in the cryptocurrencies' returns. This result suggests that the selected macroeconomic news announcements were important factors that did not affect the volatility observed in the cryptocurrencies' prices. Importantly, higher frequency data are warranted for the cryptocurrencies' prices. The unavailability of higher frequency data for cryptocurrencies' prices denote that certain news collected from various categories were not captured in the study. Higher frequency cryptocurrency data would ensure that any specific news announcement is analysed against cryptocurrencies' returns in future research. This notion would allow the possibility of better matching the possible effect of timely news release onto cryptocurrencies' returns and cover a broad range of news release during different times of the day. Doing so would help regulatory institutions, such as the Security Exchange Commission, to examine the drivers of returns of cryptocurrencies as an alternative investment and enrich their knowledge in whether cryptocurrencies can affect or be affected by other asset classes, such as equity or commodities. Last but not least, synchronicity among cryptocurrencies can be better observed in high-frequency data series across time zone. As it demands another advanced proposal to work on, future research could probably examine hourly data when more information becomes available.

References

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica, 66*(1), 47-78. https://doi.org/10.2307/2998540

Berentsen, A., & Schar, F. (2018). A short introduction to the world of cryptocurrencies. *Review, 100*(1), 1-16. https://doi.org/10.20955/r.2018.1-16

Bernal-Verdugo, L. E., Furceri, D., & Guillaume, D. (2013). Banking crises, labor reforms, and unemployment. *Journal of Comparative Economics, 41*(4), 1202-1219. https://doi.org/10.1016/j.jce.2013.03.001

Bouoiyour, J., & Selmi, R. (2015). *What does Bitcoin look like?* (MPRA Paper No. 58091). Germany: University Library of Munich.

Burniske, C., & White, A. (2017). *Bitcoin: Ringing the bell for a new asset class*. Retrieved from http://research.ark-invest.com/thank-you-bitcoin-asset-class?submissionGuid=6c1d0a88-5312-462c-a5bb-265f43958f93

Chan, L.K., Karceski, J., & Lakonishok, J. (1998). The risk and return from factors. *Journal of Financial and Quantitative Analysis, 33*(2), 159-188. https://doi.org/10.2307/2331306

Ciaian, P., & Rajcaniova, M. (2016). The digital agenda of virtual currencies: Can BitCoin become a global currency? *Information Systems and e-Business Management, 14*(4), 883-919. https://doi.org/10.1007/s10257-016-0304-0

Ciaian, P., Rajcaniova, M., & Kancs, d. A. (2016). The economics of Bitcoin price formation. *Applied Economics, 48*(19), 1799-1815. https://doi.org/10.1080/00036846.2015.1109038

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. *Journal of Risk and Financial Management, 11*(2), 23-34. https://doi.org/10.3390/jrfm11020023

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*(April), 28-34. https://doi.org/10.1016/j.econlet.2018.01.004

Cornell, B. (1983). The money supply announcements puzzle: Review and interpretation. *American Economic Review, 73*(4), 644-657.

Folkinshteyn, D., Lennon, M.M., & Reilly, T. (2015). The Bitcoin mirage: An oasis of financial remittance. *Journal of Strategic and International Studies, 10*(2), 118-124.

Furceri, D., & Zdzienicka, A. (2012). How costly are debt crises? *Journal of International Money and Finance, 31*(4), 726-742. https://doi.org/10.1016/j.jimonfin.2012.01.012

Gurrib, I. (2018). Are key market players in currency derivatives markets affected by financial conditions? *Investment Management and Financial Innovations, 15*(2), 183-193. https://doi.org/10.21511/imfi.15(2).2018.16

Hileman, G., & Rauchs, M. (2017). *Global cryptocurrency benchmarking study*. Cambridge, UK: Cambridge Centre for Alternative Finance, University of Cambridge, Judge Business School.

Hoskinson, C. (2013, October 9). The Mathematician's defense of Bitcoin: It's just another option. *PBS Newshour*. Retrieved from https://www.pbs.org/newshour/economy/the-mathematicians-defense-of-bitcoin-its-just-another-option

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review, 95*(1), 161-182. https://doi.org/10.1257/0002828053828518

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*(June), 68-74. https://doi.org/10.1016/j.frl.2019.03.009

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports, 3*(3415), 1-7. https://doi.org/10.1038/srep03415

Kumar, A., & Smith, C. (2017, November). *Crypto-currencies – An introduction to not-so-funny moneys*. Reserve Bank of New Zealand Analytical Notes, No. AN2017/07. Wellington, N.Z.: Reserve Bank of New Zealand.

Lee, T.B. (2014, February 3). These four charts suggest that Bitcoin will stabilize in the future. *Washington Post*. Retrieved from https://www.washingtonpost.com/news/the-switch/wp/2014/02/03/these-four-charts-suggest-that-bitcoin-will-stabilize-in-the-future/

Liu, Y., & Tsyvinski, A. (2018). *Risks and returns of cryptocurrency* (NBER Working Paper No. 24877). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w24877

Mills, T.C. (1999). *The econometric modeling of financial time series* (Second Edition). Cambridge, UK: Cambridge University Press.

Newton-Small, J. (2013, October 21). The deep web. *Time Magazine*.

Phillip, A., Chan, J.S.K., & Peiris, S. (2018). A new look at Cryptocurrencies. *Economics Letters, 163*(February), 6-9. https://doi.org/10.1016/j.econlet.2017.11.020

Sims, C. (1980). Macroeconomics and reality. *Econometrica, 48*(1), 1-48. https://doi.org/10.2307/1912017

Stock, J.H., & Watson, M.W. (2001). Vector autoregressions. *Journal of Economic Perspectives, 15*(4), 101-115. https://doi.org/10.1257/jep.15.4.101

Tsay, R.S. (2001). *Analysis of financial time series*. Hoboken, NJ: John Wiley & Sons.

Van Wijk, D. (2013). *What can be expected from the Bitcoin?* (Working Paper No. 345986). Rotterdam: Erasmus Universiteit Rotterdam.

Waggoner, D.F., & Zha, T. (1999). Conditional forecasts in dynamic multivariate models. *Review of Economics and Statistics, 81*(4), 639-651. https://doi.org/10.1162/003465399558508

Wang, S., & Vergne, J.-P. (2017). Buzz factor or innovation potential: What explains cryptocurrencies' returns? *PloS ONE, 12*(1), 1-17. https://doi.org/10.1371/journal.pone.0169556

Watson, M. (1994). Vector autoregressions and cointegration. In R.F. Engle & D. McFadden (Eds.), *Handbook of Econometrics, Volume IV* (pp. 2843-2915). Amsterdam: Elsevier Science Ltd.
Yermack, D. (2015). Is Bitcoin a real currency? An economic appraisal. In K.C.D. Lee (Ed.), *The handbook of digital currency: Bitcoin, innovation, financial instruments, and big data* (pp. 31-43). Amsterdam: Elsevier.