THE UNIVERSITY OF MELBOURNE
DEPARTMENT OF ECONOMICS
GROUP PROJECT COVER SHEET

SUBJECT CODE:	**SUBJECT NAME:**
ECOM30004	TIME SERIES ANALYSIS AND FORECASTING
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Is Cryptocurrency the Sanctuary the World Needs?

1. Introduction

The 2008 global financial crisis had everyone questioning the inherently stable and manipulative free “regulated” financial system we live by. Its global repercussion has brought along social unrest sky-rocketed unemployment and created political turmoil. The public’s confidence in conventional financial infrastructure has since taken a huge downwards spiral, urging investors to be in search for another “Independent Financial Instrument” where a decentralized system is in place. Gold has always been the answer investors turn to, but the spotlight in the last decade has shifted towards a more unconventional class of asset, a digital currency known as ‘cryptocurrency'.

Owing to its anonymous and decentralizing characteristics coupled with relatively low transaction rates, the economy has seen a surge in the number of users in Bitcoin (most popular cryptocurrency) over the last few years (Joshi, 2017). Due to its rising acceptance and huge periodical fluctuations, this has induced many scholars to study its ricochet on the economy. Some studies riveted on investigating the properties of the digital currency compared to established fiat money (Barber et al. 2012; Bell 2013; Glaser et al. 2014), with findings indicating that Bitcoin possesses none of the characteristics of an exchangeable tangible asset such as gold, nor does it have any fiat money traits. Others focused on examining the underlying factors driving the price of Bitcoin (Buchholz et al. 2012; Kristoufek 2013; van Wijk 2013; Dyhrberg 2016), with evidence pointing towards components such as the appeal to investors, recognition in the media, market demand and supply forces.

Also, in view of the proliferating approval on multiple fronts of cryptocurrencies into more conventional financial markets; (e.g. In 2017, the CME Group has introduced cryptocurrencies future contracts, where it is now averaging $370 Million in trading per day (Forbes, 2019)), we have seen studies pertaining to the significance of incorporating Bitcoin into investors’ portfolios alongside other forms of asset classes gaining more traction (Briere et al. 2013; Eisel et al. 2015; Bouri et al. 2017a). With that, Bitcoin is now intertwined with traditional markets more than ever. The generated network flow and inter-connections suggest a high possibility that any shocks in these assets may send a wave of reactions throughout the entire financial system.

This has motivated us to investigate the connectedness between the “new age currency” Bitcoin and other forms of traditional financial market instruments and assets.

We have examined some significant studies that investigated on volatility spillover effects between oil and similar asset classes like stocks, bonds and futures (Aftab et al. 2015), However, little to none of the literature involve empirical studies dealing with the spillover effects of Bitcoin markets across other classes of assets. This literature gap is another reason for us to examine the spillover effect Bitcoin has on major asset classes.

The main focus and hypothesis of this paper is to investigate if Bitcoin as a new form of asset class is subjected to, or induces spillover effects to other forms of major conventional assets such as gold, oil and multiple stock indexes. With the sheer number and severity of crises in these markets in recent decades, the findings will further deliver a valuable insight for both investors and regulators with regards to the influences they have on one another and on the stability of Bitcoin markets.

We organize the balance of the paper as follows. Section 2 describes the data that was used in this study. Section 3 describes the methodology used in this study, Section 4 presents the empirical findings and Section 5 concludes the study with some of its implications.

2. Data Collection and Description

To perform our analysis, we collect the daily realized volatility data for eight major stock indices as well as the daily price series for Bitcoin, gold and crude oil, primarily due to the lack of access to their realized volatilities respectively. Our sample period starts from 08/10/2015 to 07/17/2019. Next, we discuss the data cleaning approach and the descriptive statistics for each variable.

2.1. Data Cleaning

The price series of Bitcoin is continuous since Bitcoin trades 24/7. However, the realized volatility series and the commodity price series are only available on working days. In order to deal with data mismatch in our project, we set the weekend missing data for the traditional financial assets as the average value of the Friday and consecutive Monday. This data cleaning method is frequently used in many related papers in the literature.

2.2. Data Description for Equity Index Realized Volatilities

In this study, we have considered nine stock indices which are the All Ordinaries Index (AORD), the Financial Times Stock Exchange (FTSE), the Hang Seng Index (HSI), the NASDAQ Composite (IXIC), the Korea Composite Stock Price Index (KS11), the Nikkei 225 Index (N225), S&P 500 (SPX), the SSE Composite Index (SSEC) and EURO STOXX 50 (STOXX50E). The realized volatilities for these equity indices are obtained from the Oxford-Man Institute of Quantitative Finance Realized Library, which is based on underlying high-frequency data (i.e. five minute intervals) through Thomson Reuters Tick History. We provide the summary statistics for all realized volatilities for each equity index in Table 1.

Table 1. Summary statistics of realized volatilities for nice stock indices

	AORD	FTSE	HSI	IXIC	KS11	N225	SPX	SSEC	STOXX50E
Mean	0.000039	0.000073	0.000056	0.000059	0.000034	0.000076	0.000055	0.000113	0.000090
Median	0.000023	0.000041	0.000041	0.000030	0.000026	0.000034	0.000022	0.000054	0.000050
Maximum	0.000790	0.005739	0.000925	0.002091	0.000777	0.002318	0.003730	0.003369	0.005405
Minimum	0.000003	0.000001	0.000005	0.000003	0.000007	0.000004	0.000001	0.000006	0.000000
Std. Dev.	0.000052	0.000205	0.000060	0.000104	0.000037	0.000155	0.000145	0.000196	0.000205
Skewness	5.872456	19.325750	6.902832	8.590339	9.796662	7.124172	15.143930	6.224267	16.486530
Kurtosis	58.274850	468.486100	78.937600	128.323000	150.770200	69.681410	328.825500	68.508590	367.634600

Based on the summary statistics table, the SSE Composite Index (SSEC) shows the highest average realized volatility level (0.000113), which is reasonable as the emerging market equity index is generally exposed to greater uncertainty compared to other developed economies. In contrast, the All Ordinaries Index (AORD) shows the lowest average realized volatility (0.000039), which reflects that Australian stock market is relatively well-developed and stable. In terms of the skewness level, all of the nine realized volatilities series show evidence of positive skewness, which means there would be a higher chance to observe lower levels of volatility from those indices and only a small chance to observe extremely high volatilities as outliers.

We also provide the plots of all the nine realized volatility series over the sample period, which are shown in Appendix 1.

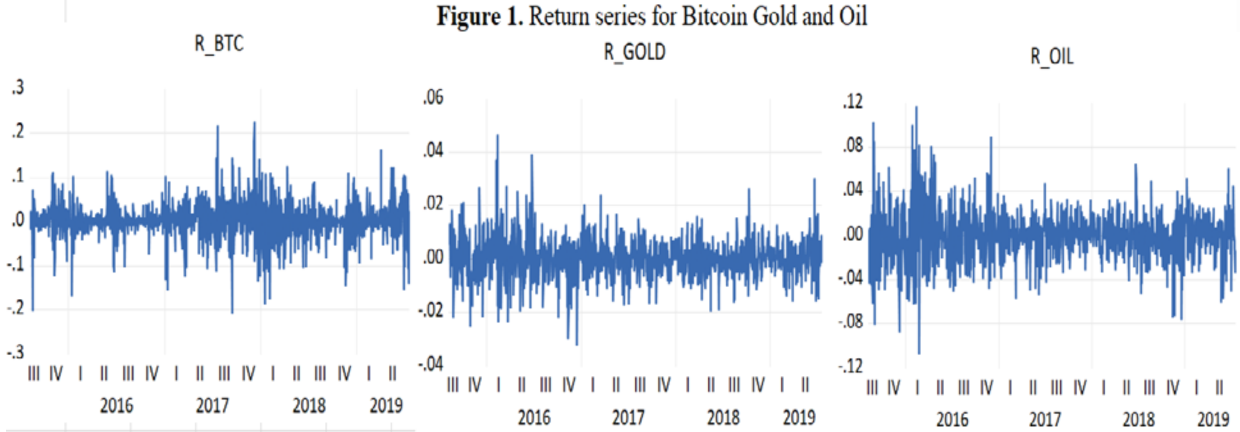
2.3. Data Description for Bitcoin, Gold and Oil

We collect the price series of gold and oil from DataStream and the price series of Bitcoin from Coinmarketcap.com, which is frequently cited in professional publications such as Wall Street Journal. The price series and summary statistics table of Bitcoin, gold and oil are listed in Appendix 2, Table 2.

2.3.1. Return Series and Summary Statistics

We measure returns as the log change in price series. Below are the plots and summary statistics table of the return series for Bitcoin, gold and oil over the entire sample period:

Figure 1. Return series for Bitcoin Gold and Oil



In Figure 1, since all three series hover around a horizontal line of approximately zero graphically, this may suggest all three assets are stationary in mean. The variance however appears to be non-stationary from a graphical point of view. We can see all three series exhibit different levels of volatility throughout the sample period. For example, in the case of Bitcoin, the return series is more volatile between 2017Q2 and 2018Q1, which corresponds to the period when Bitcoin price increases to its all-time high. We thus conclude there is evidence of volatility clustering and thus, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model could be used to better capture the variance dynamics.

Table 3. Summary statistics of daily returns of three assets

	R_BTC	R_GOLD	R_OIL
Mean	0.0026	0.0001	0.0003
Median	0.0029	0.0000	0.0000
Maximum	0.2251	0.0453	0.0803
Minimum	-0.2075	-0.0347	-0.0766
Std. Dev.	0.0418	0.0057	0.0142
Skewness	-0.12	0.29	-0.54
Kurtosis	6.85	11.62	8.22
J-B	719.90*	3607.05*	1375.67*
Obs.	1,437	1,437	1,437

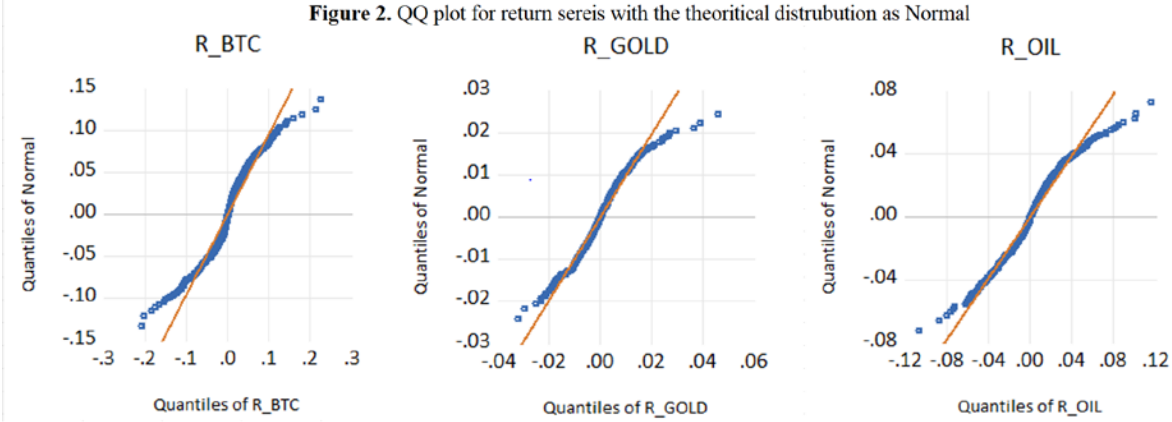
Note: J-B: Jarque–Bera statistic. *, ** denotes the rejection of the null hypothesis at the 1 and 5% significance levels, respectively.

Table 3 shows the descriptive statistics table for all three series. We can observe that the average daily return of Bitcoin is the highest (0.26%), which is 26 times larger than that of gold. However, in terms of the standard deviation, Bitcoin seems to be the most volatile asset (0.0418), which is almost 8 times larger than that of gold. In terms of the skewness level, all three series show a less skewed pattern, but the Bitcoin and oil returns show negative skewness while the return of gold is positively skewed. Based on kurtosis figures, we can conclude that all three series show fatter tails compared to tails associated with a normal distribution. This is consistent with the results of the

Jarque-Bera test, which tell us that we can reject the null hypothesis that these three series are normally distributed at the 1% level of significance.

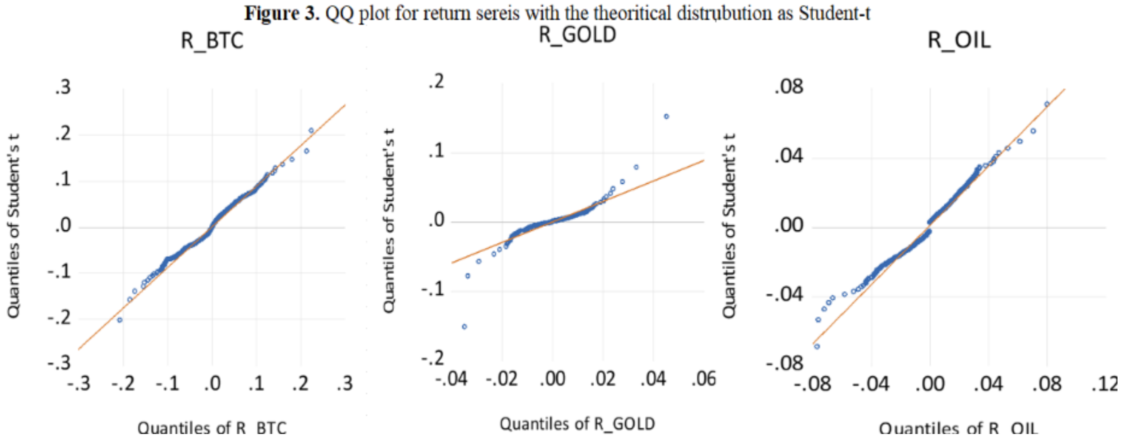
2.3.2. Quantile-Quantile (QQ) Plot

Figure 2. QQ plot for return sereis with the theoritical distrubution as Normal



Graphically, based on the QQ-plot results, we can observe that, compared with a theoretical normal distribution, the quantile of our return series is less (greater) than that of the theoretical distribution when the quantile value of the return distribution approaches to a high (low) level. That suggests that our return series may have fatter tails, which is consistent with the facts in Table 2 that returns have higher values of kurtosis. Thus, it makes sense if we consider switching our theoretical distribution to a Student's t.

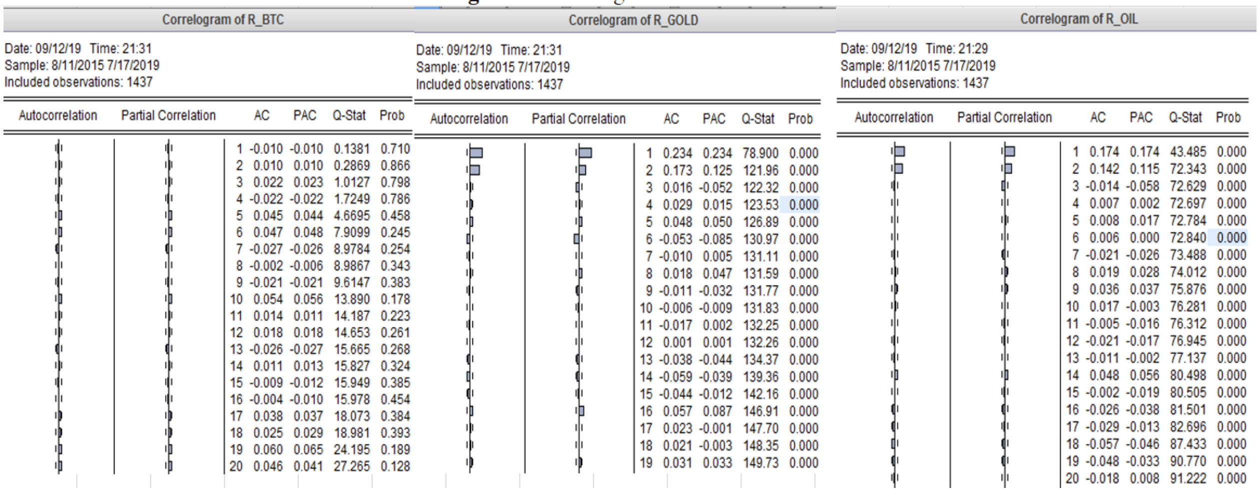
Figure 3. QQ plot for return sereis with the theoritical distrubution as Student-t



Based on Figure 3, we can observe that after switching to a theoretical Student's t distribution, the quantile plots of Bitcoin and oil return series fit well with the quantile plot of the Student's t distribution, which has an implication on the model constructing process in the rest of our paper. On the other hand, the quantile for gold returns is greater (less) than that of the theoretical distribution when the return quantile approaches a high (low) level. That suggests that the theoretical distribution tends to over-compensate the tail fatness of the gold return distribution. Thus, we would suggest an adjusted Student's t distribution for the gold return series and standard Student's t distribution for the others.

2.3.3. Correlogram

Figure 4. Correlogram for return series



Correlogram of R_BTC

Date: 09/12/19 Time: 21:31
Sample: 8/11/2015 7/17/2019
Included observations: 1437

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.010	-0.010	0.1381	0.710
		2	0.010	0.010	0.2869	0.866
		3	0.022	0.023	1.0127	0.798
		4	-0.022	-0.022	1.7249	0.786
		5	0.045	0.044	4.6695	0.458
		6	0.047	0.048	7.9099	0.245
		7	-0.027	-0.026	8.9784	0.254
		8	-0.002	-0.006	8.9867	0.343
		9	-0.021	-0.021	9.6147	0.383
		10	0.054	0.056	13.890	0.178
		11	0.014	0.011	14.187	0.223
		12	0.018	0.018	14.653	0.261
		13	-0.026	-0.027	15.665	0.268
		14	0.011	0.013	15.827	0.324
		15	-0.009	-0.012	15.949	0.385
		16	-0.004	-0.010	15.978	0.454
		17	0.038	0.037	18.073	0.384
		18	0.025	0.029	18.981	0.393
		19	0.060	0.065	24.195	0.189
		20	0.046	0.041	27.265	0.128

Correlogram of R_GOLD

Date: 09/12/19 Time: 21:31
Sample: 8/11/2015 7/17/2019
Included observations: 1437

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.234	0.234	78.900	0.000
		2	0.173	0.125	121.96	0.000
		3	0.016	-0.052	122.32	0.000
		4	0.029	0.015	123.53	0.000
		5	0.048	0.050	126.89	0.000
		6	-0.053	-0.085	130.97	0.000
		7	-0.010	0.005	131.11	0.000
		8	0.018	0.047	131.59	0.000
		9	-0.011	-0.032	131.77	0.000
		10	-0.006	-0.009	131.83	0.000
		11	-0.017	0.002	132.25	0.000
		12	0.001	0.001	132.26	0.000
		13	-0.038	-0.044	134.37	0.000
		14	-0.059	-0.039	139.36	0.000
		15	-0.044	-0.012	142.16	0.000
		16	0.057	0.087	146.91	0.000
		17	0.023	-0.001	147.70	0.000
		18	0.021	-0.003	148.35	0.000
		19	0.031	0.033	149.73	0.000

Correlogram of R_OIL

Date: 09/12/19 Time: 21:29
Sample: 8/11/2015 7/17/2019
Included observations: 1437

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.174	0.174	43.485	0.000
		2	0.142	0.115	72.343	0.000
		3	-0.014	-0.058	72.629	0.000
		4	0.007	0.002	72.697	0.000
		5	0.008	0.017	72.784	0.000
		6	0.006	0.000	72.840	0.000
		7	-0.021	-0.026	73.488	0.000
		8	0.019	0.028	74.012	0.000
		9	0.036	0.037	75.876	0.000
		10	0.017	-0.003	76.281	0.000
		11	-0.005	-0.016	76.312	0.000
		12	-0.021	-0.017	76.945	0.000
		13	-0.011	-0.002	77.137	0.000
		14	0.048	0.056	80.498	0.000
		15	-0.002	-0.019	80.505	0.000
		16	-0.026	-0.038	81.501	0.000
		17	-0.029	-0.013	82.696	0.000
		18	-0.057	-0.046	87.433	0.000
		19	-0.048	-0.033	90.770	0.000
		20	-0.018	0.008	91.222	0.000

Based on Figure 4 above, the ACF and PACF of gold and oil return series show significant spikes at lags 1 and 2, suggesting some evidence that we need a higher order autocorrelation function to capture their dynamics at levels. On the other hand, the ACF and PACF of Bitcoin returns shows no evidence of significant autocorrelation that can be observed up to 20 lags. That may suggest that we do not need a higher order autocorrelation function to capture its dynamics at levels.

3. Methodology

3.1. Autoregressive Moving Average (ARMA) Models

We use the ARMA class of models to model our return series by imposing structure on Wold's representation, thus being able to describe the dynamics of the series with only one or two parameters for both its own past values and past errors or shocks.
An ARMA(p, q) process is described as:

$$y_t = \phi_0 + \varepsilon_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

This can be simplified to AR and MA models by restricting p and q to 0. For example, an AR(p) model is written as:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t$$

And a MA(q) model is written as:

$$y_t = \phi_0 + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Estimation of model parameters is done through maximum likelihood estimation, where assuming $\varepsilon_t \sim N(0, \sigma^2)$, we optimise the set of parameters $\Theta = \{\phi_0, \theta_1, \theta_2, \ldots, \theta_q, \sigma^2, \phi_1, \ldots, \phi_p\}$ that maximises the following log-likelihood function $\log L = -\frac{1}{2}\log 2\pi - \frac{1}{2}\log \sigma^2 - \frac{1}{2\sigma^2 T}\sum_{t=1}^{T} \varepsilon_t^2$ where $\varepsilon_t = y_t - \hat{y}_t$. However, we may need to adjust our assumptions to better reflect our findings in the QQ-plots and JB tests, such as assuming a standard or adjusted Student's t distribution.

3.2. Generalised Autogressive Conditional Heteroskedasticity (GARCH) Models

Persistence in variance over time of a random variable describes the property of momentum in conditional variance, that is, past volatility explains current volatility. Engle (1982) and Bollerslev (1986) developed the GARCH model to capture this dynamic in variance level by essentially applying the autoregressive (ARMA) model to the error variance.

Consider a GARCH(p, q) model:

$$y_t = x'_t\beta + \varepsilon_t$$
$$\varepsilon_t = z_t\sigma_t$$
$$(\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2}, \dots) \sim N(0, \sigma_t^2)$$

And

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i\, \sigma^2{}_{t-i}$$

Where z_t is i.i.d., $E(z_t) = 0, var(z_t) = 1$.

Here, our error term with respect to our mean equation is now heteroskedastic, and the GARCH(p, q) model allows the conditional variance (σ_t^2) of the random error terms to depend linearly on the past squared errors ε_t^2 (the ARCH terms). Although the GARCH(p, q) facilitates the choice of optimal lag structure for ARCH and GARCH terms (σ_t), the parsimonious GARCH(1, 1) specification has proven to be a sufficient representation for most financial data.

3.3. GARCH-M Variants, TGARCH, PGARCH

However, there are certain limitations in the GARCH model. For example, GARCH processes do not allow for asymmetrical volatility responses and fail to allow for any feedback between the variance and mean. Research has suggested that most financial markets exhibit an asymmetric volatility response, perhaps due to the leverage effect, and that there is some level of volatility feedback, as we typically expect that higher levels of risk should result in higher returns as compensation. As a result, we compare various GARCH models, more specifically the Threshold GARCH (TGARCH), the Power GARCH (PGARCH) as different ways to capture asymmetries, and the GARCH in mean (GARCH-M) to capture potential volatility feedback.

More specifically, TGARCH models are represented as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i\varepsilon_{t-i}^2 + \gamma_i\varepsilon_{t-i}^2 I_{t-i}) + \sum_{j=1}^{p} \beta_j\sigma_{t-j}^2$$

Where $I_{t-i} = 1$ if $\varepsilon_{t-i} < 0$ and $I_{t-i} = 0$ otherwise. The only difference is that we have introduced a dummy variable that tells us whether the shock is positive or negative. γ_i gives an estimation of the asymmetric effects that (may) exist between negative and positive shocks, where $\gamma_i > 0$ typically indicates that a leverage effect exists.

PGARCH models are represented as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j\sigma_{t-j}^\delta$$

Where $\delta > 0$, $|\gamma_i| \leq 1$ and $\gamma_i = 0$ for $i > r$ and $r \leq p$. We see asymmetry effects through γ_i. We see that the PGARCH model reduces down to a GARCH model when $\delta = 2$ and $\gamma_i = 0$ for all i. We define the power $\delta = 1$ in this study to ensure our model has economic intuition.

The GARCH-M specification adds a heteroskedasticity term in the mean equation:

$$y_t = x'_t\beta + \varepsilon_t + \lambda\sigma_{t-1}$$

All conditional variance equations including GARCH-M, TGARCH-M and PGARCH-M remain the same, the only difference is the addition of the explanatory variable in the mean equation, allowing for volatility to have an impact on the next period return. Estimation of GARCH models again involves maximum likelihood estimation.

3.6. Structural GARCH

Particularly with daily return series, difficulties may exist when the sum of the parameters in the GARCH model sum or exceed one. This typically implies that the GARCH model estimates are inconsistent since conditional variance is explosive in nature and results in an undefined unconditional variance. Lamoureux and Lastrapes (1990) proposed that such phenomenon might be caused by presence of structure breaks in volatility levels. They also show that the overall stickiness of volatility, measured by the sum of estimated coefficients for GARCH and ARCH terms, are inconsistently estimated if there are structural breaks in volatility level. Therefore, they proposed an augmented GARCH model to incorporate structure break features by introducing dummy variables:

$$\sigma_t^2 = \omega' + \delta_1 D_{1t} + \cdots + \delta_k D_{kt} + \lambda\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2$$

Where D_{it} $(i = 1, \ldots, k)$ are dummy variables that correspond to periods over which the GARCH process is stationary. The break dates could be detected by graphical analysis or tests such as the Bai and Perron (2003) multiple break test on squared return series. One potential difficulty would be ensuring the subsamples are large enough to generate reasonable statistical inference, yet small enough to explicitly capture all possible structural changes in ω.

3.7. Vector Autoregression (VAR) Models, Generalised Variance Decomposition and DY Spillover Index

We employ the spillover index approach by Diebold and Yilmaz (2012) based on generalised variance decomposition to determine the direction and relative intensity of spillovers across the analysed stock, commodity and cryptocurrency markets.

For a N-variate process $Y_t = (y_{t,1}, \ldots, y_{t,n})$ in a Vector Autoregressive system VAR (p) at $t = 1, \ldots, T$:

$$\Phi(L)Y_t = \varepsilon_t$$

While the Diebold-Yilmaz spillover index approach allows the process to be both mean and variance level processes, since our main interest lies in understanding the volatility spillover effects, we refer to Y_t as the variance series (e.g. the realized volatilities for stock indices and GARCH-proxied volatilities for cryptocurrencies) for the rest of the paper.

Since Y_t is stationary, we could obtain a MA (∞) representation:

$$Y_t = \Psi(L)\varepsilon_t$$

Where $\Psi(L)$ is an $N \times N$ infinite lag polynomial matrix of coefficients.
Diebold and Yilmaz (2012) proposed the 'own' and 'across' variance share concept, where the own variance share is defined as the fractions of the H-step-ahead forecast error variance for y_j raised due to own past shocks, for $j = 1, \dots,$ n, and the across variance share (or spillover) is defined as the fractions of the H-step-ahead forecast error variance for y_j raised due to shocks from other (variance) series y_k, for $k = 1, \dots,$ n and $k \neq j$. This concept could be formulated in the form:

$$(\theta_H)_{j,k} = \left((\Sigma)_{k,k}\right)^{-1} \sum_{h=0}^{H-1} \left((\Psi_h \Sigma)_{j,k}\right)^2 / \sum_{h=0}^{H-1} (\Psi_h \Sigma \Psi_h')_{j,j}$$

Where Ψ_h is again a $N \times N$ coefficients matrix with lag h, and $(\Sigma)_{k,k} = \sigma_{kk}$. The parameter $(\theta_H)_{j,k}$ captures the Pearson-Shin GFEVD partial contribution from asset k to j and $\sum_{h=0}^{H} \theta_{j,k} \neq 1$ by definition. In this way, the pairwise-directional connectedness, $C_{j \leftarrow k}(H)$, could be derived as the standardised $\left(\widetilde{\theta_H}\right)_{j,k}$:

$$C_{j \leftarrow k}(H) = \left(\widetilde{\theta_H}\right)_{j,k} = (\theta_H)_{j,k} / \sum_{k} (\theta_H)_{j,k}$$

The total directional spillovers from a variable k to the others in the system is then defined as:

$$C_{j \leftarrow}(H) = 100 \times \sum_{j \neq k, j=1}^{n} C_{j,k}(H) \,/ \sum_{j,k=1}^{n} C_{j,k}(H)$$

The total directional spillovers form the other variables in the system to a variable j is defined as:

$$C_{\leftarrow k}(H) = 100 \times \sum_{j \neq k, k=1}^{n} C_{j,k}(H) \,/ \sum_{j,k=1}^{n} C_{j,k}(H)$$

As a representative for the overall connectedness of the whole system, the total spillover index (TSI) is defined as the share of forecast error variances for all variables in the system which are not contributed by its own errors.

$$C_H = 100 \times \frac{\sum_{j \neq k} \left(\widetilde{\theta_H}\right)_{j,k}}{\sum \left(\widetilde{\theta_H}\right)_{j,k}} = 100 \times \left(1 - \frac{\mathrm{Tr}\{\widetilde{\theta_h}\}}{\sum \widetilde{\theta_h}}\right)$$

4. Findings

4.1. Conditional Mean Equation

The mean equation selection results are presented below. For Bitcoin (Panel A), both information criteria AIC (-3.603) and SC (-3.599) are the lowest for the ARMA(0, 0) model, which suggest the best model for the conditional mean equation is simply a random variable with no lag structure i.e. its past returns cannot predict its future returns. This is consistent with the correlogram of Bitcoin presented in the data section.

For the mean equation of the gold return (Panel B), AIC (-7.114) and SC (-7.099) both suggest that the MA(2) model best captures the dynamics of the series. Estimated MA(1) and MA(2) terms have t-statistics of 0.183 (p-value = 0) and 0.218 (p-value = 0) respectively, indicating both estimated parameters are significant at the 5% significance level.

For the mean equation of the crude oil (Panel C), we choose ARMA(1, 1) model due to the low AIC (-4.889) and the high log-likelihood value. Similarly, the choice of this mean equation is consistent with the correlogram for crude oil, which suggested a higher order of autoregressive structure.

Table 4. Mean equation selection

Panel a. Bitcoin								
	LL	**AIC**	**SIC**	**AR(1)**	**AR(2)**	**MA(1)**	**MA(2)**	**Residual WN**
NA	2589.486	-3.60263	-3.59896					Y
AR(1)	2589.555	-3.59994	-3.58894	-0.00979				Y
				0.5748				
AR(2)	2589.629	-3.59865	-3.58398	-0.0097	0.010161			Y
				0.578	***0.6259***			
MA(1)	2589.554	-3.59994	-3.58893			-0.00959		Y
						0.5823		
MA(2)	2589.639	-3.59866	-3.58399			-0.01018	0.011195	Y
						0.5597	***0.5901***	
ARMA(1,1)	2589.567	-3.59856	-3.58389	-0.15723		0.146774		Y
				0.9368		***0.941***		
Panel b. Gold								
	LL	**AIC**	**SIC**	**AR(1)**	**AR(2)**	**MA(1)**	**MA(2)**	**Residual WN**
NA	5060.594	-7.04189	-7.03822					Y
AR(1)	5101.111	-7.09549	-7.08449	0.23424				Y
				0				
AR(2)	5112.457	-7.10989	-7.09522	0.204953	0.125287			Y
				0	***0***			
MA(1)	5091.571	-7.08221	-7.07121			0.180546		Y
						0		
MA(2)	5115.175	-7.11367	-7.099			0.183403	0.217897	Y
						0	***0***	
ARMA(1,1)	5108.627	-7.10456	-7.08989	0.547964		-0.32791		Y
				0		***0***		
Panel c. Crude Oil								
	LL	**AIC**	**SIC**	**AR(1)**	**AR(2)**	**MA(1)**	**MA(2)**	**Residual WN**
NA	3482.718	-4.84582	-4.84215					Y
AR(1)	3504.805	-4.87377	-4.86277	0.174199				Y
				0				
AR(2)	3514.367	-4.88569	-4.87102	0.15416	0.11518			Y
				0	***0***			
MA(1)	3500.137	-4.86728	-4.85627			0.137606		Y
						0		
MA(2)	3514.8	-4.87991	-4.8744			0.163846	0.154194	Y
						0	***0***	
ARMA(1,1)	3516.8	-4.88907	-4.86524	0.510125		-0.33997		Y
				0		***0***		

Note: Y in the Residual WN column means the residuals in the regression is a white noise process. Selected models are highlighted in red.

4.2. Conditional Variance Equation

Concerning the variance-feedback GARCH variants (i.e. GARCH(1, 1)-M, TGARCH(1, 1)-M and PGARCH(1, 1)-M), none of the variance-feedback terms in any of the aforementioned variant models were significant at the conventional significance level of 10%. Therefore, we rule out these variant models as the best fit for our return volatilities. In other words, our results in Table 5 below suggest there are no feedback effects (no return premium compensated for higher risk) in all models for the three assets.

Table 5. Variance equation selection

					Panel a. Bitcoin						
NA	**LL**	**AIC**	**SIC**	**ARCH**	**GARCH**	**Asymmetry term**	**|RESID(-1)|**	**GARCH(-1)^0.5**	**VAR feedback term**	**LR test**	**True to reject Null**
GARCH(1,1)	2791.11	-3.876283	-3.854278	0.119373	0.839017						
				0.0009	*0*						
GARCH(1,1)-M	2791.139	-3.874933	-3.84926	0.11967	0.838731				0.01508	0.058	FALSE
				0.001	*0*				*0.7835*		
TGARCH(1,1)	2506.306	-3.478506	-3.452833	0.113325	0.816225	-0.020488				-569.608	FALSE
				0.0134	*0*	*0.8209*					
TGARCH(1,1)-M	2506.372	-3.477205	-3.447865	0.114294	0.816109	-0.022631			0.045309	0.132	FALSE
				0.013	*0*	*0.8013*			*0.8105*		
PGARCH(1,1)	2828.435	-3.929624	-3.911287			-0.058975	0.142145	0.8563		74.65	TRUE
						0.5845	*0*	*0*			
PGARCH(1,1)-M	2828.454	-3.928259	-3.906253			-0.060766	0.142376	0.856165	0.012193	0.038	FALSE
						0.5783	*0*	*0*	*0.8577*		
					Panel b. Gold						
ARMA(0,2)	**LL**	**AIC**	**SIC**	**ARCH**	**GARCH**	**Asymmetry term**	**|RESID(-1)|**	**GARCH(-1)^0.5**	**VAR feedback term**	**LR test**	**True to reject Null**
GARCH(1,1)	5264.4	-7.317189	-7.291516	0.045419	0.938274						
				0.0037	*0*						
GARCH(1,1)-M	5246.556	-7.292353	-7.26668	0.035901	0.949927				-0.072312	-35.688	FALSE
				0.0092	*0*				*0.5865*		
TGARCH(1,1)	5240.268	-7.283602	-7.257929	0.049906	0.946914	-0.027343				-48.264	FALSE
				0.0153	*0*	*0.2003*					
TGARCH(1,1)-M	5240.33	-7.282297	-7.252956	0.049569	0.946636	-0.026967			-0.090651	0.124	FALSE
				0.0166	*0*	*0.2086*			*0.4932*		
PGARCH(1,1)	5243.054	-7.287479	-7.261806			-0.230695	0.049118	0.950985		-42.692	FALSE
						0.1597	*0.0011*	*0*			
PGARCH(1,1)-M	5243.072	-7.286113	-7.256773			-0.229491	0.048974	0.950882	-0.025437	0.036	FALSE
						0.1624	*0.0011*	*0*	*0.8458*		
					Panel c. Crude Oil						
ARMA(1,1)	**LL**	**AIC**	**SIC**	**ARCH**	**GARCH**	**Asymmetry term**	**|RESID(-1)|**	**GARCH(-1)^0.5**	**VAR feedback term**	**LR test**	**True to reject Null**
GARCH(1,1)	3634.072	-5.053025	-5.031007	0.061885	0.922686						
				0.0002	*0*						
GARCH(1,1)-M	3634.425	-5.052124	-5.026436	0.06363	0.920672				0.099868	0.706	FALSE
				0.0001	*0*				*0.5058*		
TGARCH(1,1)	3644.567	-5.06625	-5.040562	0.024144	0.932966	0.066776				20.99	TRUE
				0.0947	*0*	*0.0015*					
TGARCH(1,1)-M	3644.853	-5.065254	-5.035897	0.024126	0.930981	0.066871			0.080951	0.572	FALSE
				0.0935	*0*	*0.0015*			*0.5486*		
PGARCH(1,1)	3652.425	-5.077194	-5.051506			0.728626	0.050939	0.949518		36.706	TRUE
						0.0105	*0.0008*	*0*			
PGARCH(1,1)-M	3652.589	-5.07603	-5.046672			0.725228	0.051054	0.947493	0.054163	0.328	FALSE
						0.0107	*0.0008*	*0*	*0.6386*		

Note: Last column summarizes the Likelihood Ratio (LR) test's result on whether to reject the null hypothesis, ARCH and GARCH denote the ARCH and GARCH terms in the variance equation respectively and the selection of baseline mean equation is denoted on the upper left corner respectively.

For Bitcoin (Panel A), we choose the ARMA(0, 0) - GARCH (1, 1) model. The reason is that the asymmetry terms in both TGARCH(1, 1) and PGARCH(1, 1) models are insignificant at the 10% significance level with p-values of 0.821 and 0.585 respectively, suggesting there is no evidence of asymmetry effects in the volatility level for Bitcoin.

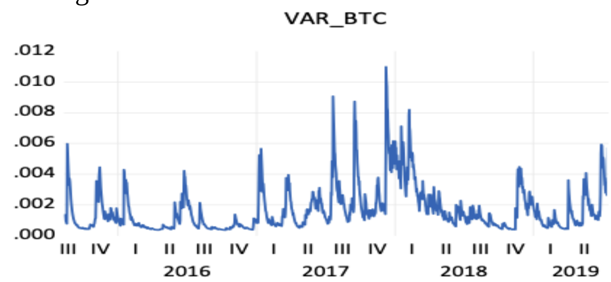
From Panel B, we choose the MA(2) - GARCH(1 ,1) model for gold. Similarly, there is no evidence on asymmetry effects as all asymmetric term parameters from the TGARCH and PGARCH models are insignificant at the 10% significance level. In addition, the model also yields lower AIC (-7.317) and SC (-7.292) estimates and the LR test statistics suggest that the GARCH(1, 1) model is hard to beat.

For crude oil (Panel C), we model the series using ARMA(1, 1) - PGARCH(1, 1) in the rest of the paper. The model is chosen as the LR test suggests that the PGARCH(1, 1) is better than the GARCH(1, 1) model, and also that the AIC (-5.077) and SC (-5.052) are lower for this model. In addition, the asymmetry term is significant at the 5% significance level with a t-statistic of 0.729 (p-value = 0.011), which suggests that the leverage effect exists for crude oil, i.e. ‘bad news’ appears to have a more pronounced effect on its variance than ‘good news’.

4.3. Variance of Bitcoin, Gold and Crude Oil

From the estimated conditional variance plot for Bitcoin, we see that the variance is more volatile from 2017 to 2018. This makes sense as during that time, Bitcoin was hitting its all-time high and experienced the unpresented crush soon after. The highest spike in the beginning of 2018 then corresponded to the 65% drop in price for Bitcoin.

Figure 5.1. Conditional Variance for Bitcoin

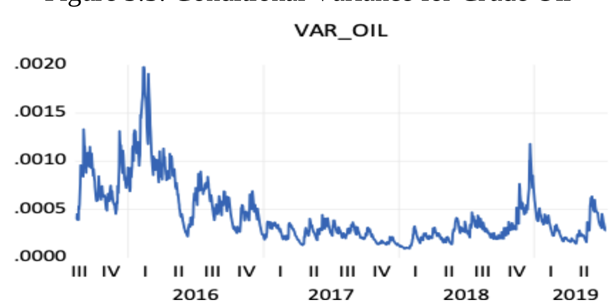


For gold, the GARCH estimated variance is relatively stable except for the spike observed in 2016 (Figure 5.2). The successful election for Donald Trump as president and the decision of the Brexit vote in the UK rattled investors on a global scale, where investors were inclined to hold gold as a ‘safe haven’. These events likely pushed the gold price to a two-year high in July. Afterwards, gold prices fell likely because of the hike in the U.S. Federal Reserve's interest rate in the second half of 2016 (Shawn, 2019).

Figure 5.2. Conditional Variance for Gold

Similar to gold, the conditional variance of crude oil is relatively volatile from 2014 to 2016, experiencing an unprecedented drop between mid-2014 and early 2016. The main reasons that contributed to these fluctuations were likely due to the boom of U.S. shale oil production and the decrease in the demand from oil importers. Overall, the supply glut and weakening demand together likely triggered the plunge in oil prices (Stocker, Baffes and Vorisek, 2018).

Figure 5.3. Conditional Variance for Crude Oil



4.4 Findings from Spillover Table

4.4.1 Total Connectedness

The total connectedness explains the overall degree of system connectedness. As shown in the bottom right corner of Table 6, a TSI of 5.8% represents that about 5.8% of the movements in the system we considered is due to spillovers across those markets. The following analysis will explain how the Bitcoin market is independent to other class of assets and financial market.

Table 6. Spill over effects between cryptocurrency market and other financial markets

	BTC	GOLD	OIL	SPX	FROM
BTC	99.6	0	0.3	0.1	0.4
GOLD	0.2	92.2	6.7	0.9	7.8
OIL	0.1	0.8	88.2	10.9	11.8
SPX	1.4	0.5	1.5	96.6	3.4
TO	1.6	1.30	8.50	11.90	
NET	**1.2**	**-6.50**	**-3.30**	**8.50**	**TSI=5.80%**

Note: TSI: Total Spillover Index. Column From sums up all spill overs from other assets to an asset j (named in the head of respective row). Row To sums up all spill overs from an asset k to other assets (named in the head of respective column).

4.4.2 Total Directional Connectedness

The "FROM" column of Table 6 gives the total directional connectedness from an asset i (named as the column head) to another asset j (named as the row head). The results from Table 6 show that the total directional connectedness in the "FROM" column ranges from 0.4% (BTC) to 11.8% (OIL). The lowest value of 0.4% is from the Bitcoin market, which means only 0.4% of the total forecast error variance of BTC is due to shocks from other asset classes, and the remaining 99.6% of the forecast error variances are explained by its own past innovations (own variance share), which illustrates that cryptocurrency markets do not appear to be impacted significantly and thus, are relatively independent from other financial markets.

The "TO" row records the total spillovers contributed by an asset j to an asset j. As seen from Table 6, the values in the row ranges between 1.3% (Gold) and 11.9% (SPX). The 1.6% for the Bitcoin market indicates that the shocks from the Bitcoin market only contribute to 1.6% of the forecast error variance of other financial markets. Therefore, Bitcoin exerts close to zero spillover effects to other commodity and equity markets.

The "NET" row is the difference between the total directional connectedness to others and from others for an asset j. The net total directional spillover of BTC is relatively trivial at 1.2%, again showing that the crypto-market appears to be isolated from other financial markets.

4.4.3 Pairwise Directional Connectedness

The off-diagonal elements represent the pairwise directional connectedness between the markets. We mainly focus on the pairwise directional connectedness between Bitcoin and other financial markets. From Table 6, we can see that the pairwise directional connectedness between Bitcoin and other markets appears to be very low.

The pairwise directional connectedness from BTC to other financial markets ranges from 0.2% to 1.4%. More specifically, the forecast error variances of gold, oil and SPX due to shocks from BTC are 0.2%, 0.1% and 1.4% respectively. The numbers are close to zero, which implies that shocks from Bitcoin have a very limited effect on other financial markets. On the other hand, the pairwise directional connectedness from each of the other financial markets to BTC are also low. The values are 0%, 0.3% and 0.1% respectively for the gold, oil and SPX. This means that about 0% of the forecast error variance of BTC is due to the shocks from gold, 0.3% is due to the shocks from oil and 0.1% is due to the shocks from SPX.

Overall, we can see that the crypto-market neither exerts nor receives significant spillovers from other financial markets. Therefore, we could conclude that the crypto-market has almost no connection with other financial markets we have examined in this paper.

4.5 Robustness Check: Spillover Table with Expanded Scope

In the Table 6, we use S&P500 as the only proxy for the equity market. In order to ensure there is no bias for using S&P500 and the result is reliable, we add additional equity market indices in the expanded version of spillover table (Table 7) as a robustness check.

Table 7. Spill over effects between cryptocurrency market and other financial markets (Expanded Scope)

	BTC	GOLD	OIL	SPX	IXIC	FTSE	STOXX50E	AORD	NIKKEI	KOSPI	HSI	SSEC	FROM
BTC	98.7	0.1	0.3	0	0.2	0	0	0.1	0	0.1	0	0.5	1.3
GOLD	0.1	47.4	4	0.7	0.6	10.5	12.3	5.9	9.1	6	3.2	0	52.6
OIL	0.1	0.4	73.5	8.1	7.5	2.2	3.7	2.2	0	0.8	0.6	0.9	26.5
SPX	0.5	0.1	0.4	39.7	35.2	5.6	7.2	2.4	0.2	4.6	0.7	3.6	60.3
IXIC	0.5	0.2	0.7	34.6	45.9	3.3	4	2.4	0.2	4.6	1	2.9	54.1
FTSE	0.2	0	0.1	4.9	2.8	25.6	24.4	10.1	7.6	15.3	8.2	0.8	74.4
STOXX50E	0.2	0	0.3	5.8	3.3	23.8	26.3	9.7	6.9	14.6	8	1	73.7
AORD	0.4	0	1	10.1	8.7	13	13.8	24	7.2	11.4	7.8	2.5	76
NIKKEI	0.2	0.3	1.7	4.8	4.4	12.2	12.1	9.2	32.4	12.8	9.6	0.3	67.6
KOSPI	0.2	0	0	6.9	6.1	16.7	16.1	8.3	7.9	25.1	10.8	2	74.9
HSI	0.1	0	0.1	10.4	8.8	10.9	11.2	7.1	7.6	14.3	25.3	4.4	74.7
SSEC	0.2	0.1	1.1	15.4	9.7	2.1	3.8	4.2	0.4	4.3	9	49.6	50.4
TO	2.7	1.20	9.80	101.60	87.30	100.30	108.5	61.6	47.00	88.70	59.00	18.80	
NET	1.4	-51.4	-16.7	41.3	33.2	25.9	34.8	-14.4	-20.6	13.8	-15.7	-31.6	**TSI=57.20%**

Note: TSI: Total Spillover Index. Column From sums up all spill overs from other assets to an asset j (named in the head of respective row). Row To sums up all spill overs from an asset k to other assets (named in the head of respective column).

The pairwise directional connectedness from BTC to other equity markets ranges from 0.1% to 0.5%. All the values are relatively small, providing evidence that the shocks from Bitcoin market have approximately no effects on other financial markets. From other equity markets to BTC, the pairwise directional spillovers are quite low also, with estimates ranging from 0% to 0.5%, further verifying our hypothesis that the cryptocurrency market does not receive much impact from the other financial markets.

From the expanded Table 7, the results are consistent to what we found in Table 6. In summary through the robustness check, we could conclude with more confidence that the crypto-market is relatively isolated from the other financial markets.

4.6 Robustness Check: Spillover Table under Sub-Period Test

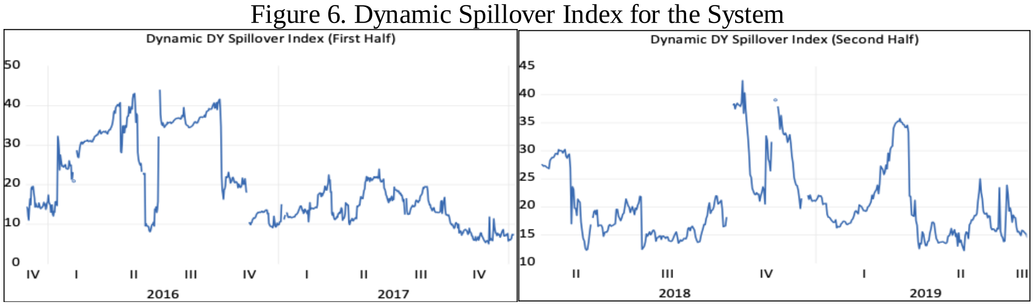
From 2017 to 2018, the Bitcoin market transitioned from a bull market to a bear market. To capture the apparent structural breaks in Bitcoin prices, we conducted a sub-period robustness test separating the bull and bear market periods to prove that the aforementioned spillover estimates, such as TSI, are not low as a net effect across the bull and bear markets. The results are shown in Table 8. The dynamic spillover index plots for the two periods are shown as well.

Table 8. Subperiod test: Spill over effects across markets

Panel a. First half					
	BTC	**GOLD**	**OIL**	**SPX**	**FROM**
BTC	99.5	0	0.4	0.1	0.5
GOLD	0.3	89.7	8.8	1.2	10.3
OIL	0	0.7	87.8	11.5	12.2
SPX	1.3	0.4	1.8	96.5	3.5
TO	1.7	1.10	11.00	12.80	
NET	**1.2**	**-9.20**	**-1.20**	**9.30**	**6.60%**
Panel b. Second half					
	BTC	**GOLD**	**OIL**	**SPX**	**FROM**
BTC	93.1	1.3	0.1	5.5	6.9
GOLD	0.1	99.6	0.2	0.2	0.4
OIL	0.2	0.2	86.5	13.2	13.5
SPX	1.5	0.4	2.3	95.8	4.2
TO	1.7	1.90	2.50	18.80	
NET	**-5.2**	**1.50**	**-11.00**	**14.60**	**6.20%**

Note: TSI: Total Spillover Index. Column From sums up all spill overs from other assets to an asset j (named in the head of respective row). Row To sums up all spill overs from an asset k to other assets (named in the head of respective column).

Figure 6. Dynamic Spillover Index for the System



The results of Table 8 indicate that the total spillover index is 6.6% for the bull market period (2016-2017) and 6.2% for the bear market period (2018-2019). As observed, there is no significant difference between those two numbers, which suggests that the spillover between Bitcoin and other financial markets are similar during two sub-periods. In addition, from the two dynamic spillover index plots, we can see that the values of total spillover indices range consistently from 5% to 45% in both periods. That means the TSI is relatively stable in both the bull market and bear market period. This provides further support that our conclusions based on the Table 6 and 7 are reliable.

5. Conclusion and Implications

Within a decade of its emergence as a decentralized cryptocurrency, Bitcoin has seen dramatic growth in its acceptance by the financial industry. The increasing speculative demand places Bitcoin among other investment assets, and its clear divergence from the traditional money market has prompted investors to label it as a panacea to the global economic system. In this research report, we use the volatility spillover index proposed by Diebold and Yilmaz (2012) to examine the connectedness between Bitcoin and other financial assets. Using the realised volatility of Bitcoin that is readily observable and the conditional volatility of other commodities derived using their prices, we find that Bitcoin neither exerts nor receives any spillover effects from other markets and commodities. Their forecast error variance is predominantly driven by their own shocks whereas asset classes such as gold and the S&P500 are largely dependent on shocks from other financial markets and commodities. Hence, we conclude that cryptocurrencies exhibit very weak and insignificant integration with the global financial market and that they can be interpreted as independent financial instruments that pose little to no systematic risk.

Our findings reveal several important implications for regulators and investors. Firstly, the lack of linkage between Bitcoin and other financial instruments suggests that Bitcoin is essentially invulnerable to shocks generated in other financial markets. During turbulent market conditions, investors could switch their portfolio holdings to Bitcoin to effectively mitigate their investment risks. Moreover, the trivial and insignificant impact of Bitcoin on other financial assets indicate that it does not threaten the financial stability of the market as a whole. Policymakers need not be concerned about the volatility spillover of Bitcoin and restrict its usage since there appears to be no tangible impact of Bitcoin on the real economy.

Nevertheless, our research report has left some limitations which can be improved upon in future research. Firstly, although we include a large variety of the stock market indexes, only gold and oil are included as the commodity counterparts in comparison with Bitcoin. These two assets do capture a significant portion of the commodities market, yet however they fail to paint the full picture. Financial derivatives such as options and futures can also be incorporated in the future to contribute to a more comprehensive analysis. Secondly, due to the unavailability of data, we were limited to use both realised volatility and conditional volatility derived from price data in our estimation. A uniform usage of realised volatility should provide more precise estimation results. The third problem arises due to the fact that Bitcoin is trading on several exchanges simultaneously. This means several different Bitcoin prices, and hence volatilities, are observed simultaneously in time. In this sense, the use of Bitcoin volatility from individual exchanges could alter some of our findings. Lastly, although the results from the spillover index appears to be promising, the lack of significance testing on those spillover estimates makes it vulnerable to estimation errors. Future studies can include p-values of the estimates to enhance the accuracy of results.

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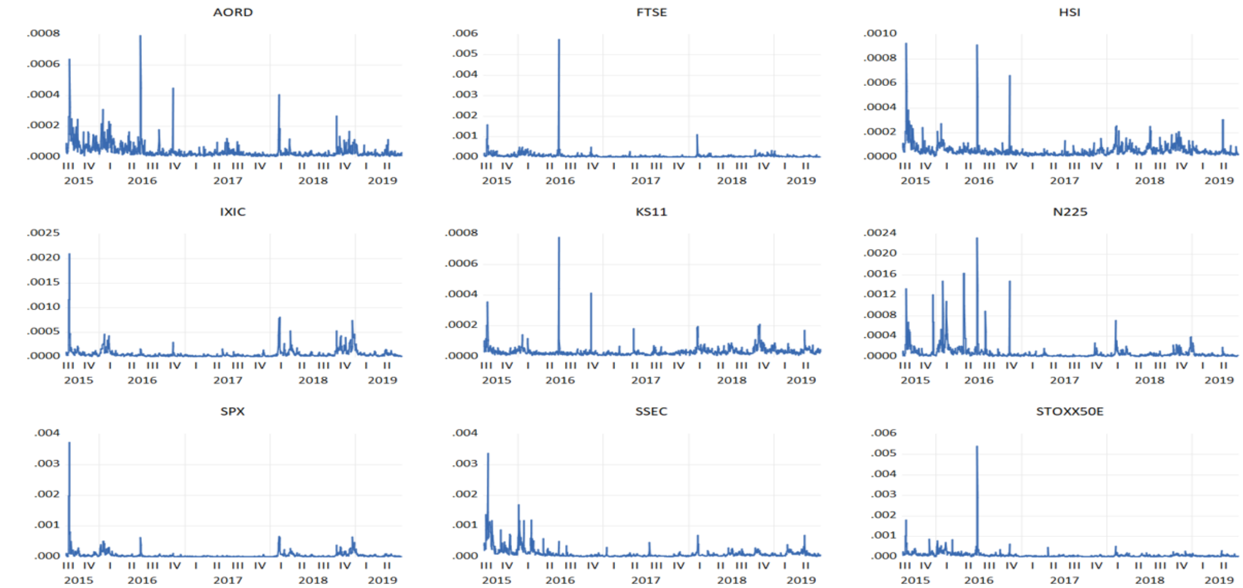
Appendix

Appendix-1. Plots of realized volatilities



Appendix-2. Plots of Price series of Bitcoin Gold and Oil

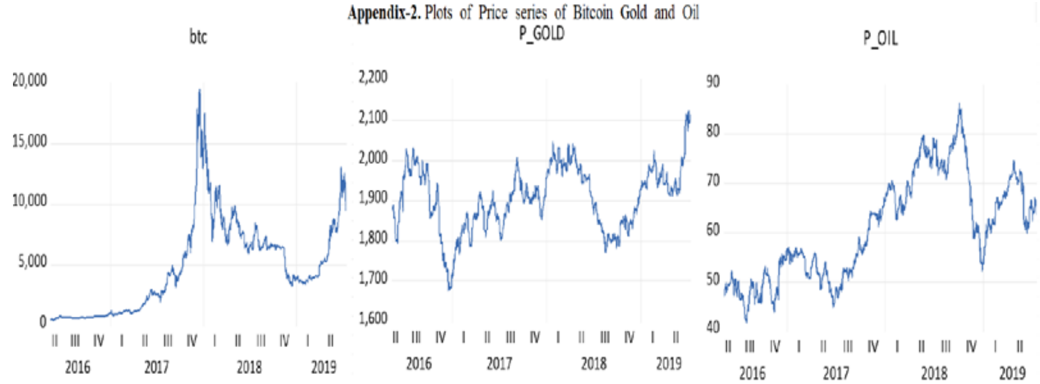


Table 2. Summary statistics of daily prices of three assets

	BTC	GOLD	OIL
Mean	4797.98	1906.15	60.81
Median	4031.68	1911.08	60.60
Maximum	19497.40	2131.15	86.29
Minimum	438.71	1677.69	41.77
Std. Dev.	3825.02	81.00	10.44
Skewness	0.91	-0.15	0.26
Kurtosis	3.66	2.96	1.93
J-B	182.53*	4.22*	68.53*
Obs.	1,162	1,162	1,162

Note: J-B: Jarque–Bera statistic. *, ** denotes the rejection of the null hypothesis at the 1 and 5% significance levels, respectively.