Diversifier, Hedge and Safe Heaven Properties of Cryptocurrencies: The Case Against Asian Fiat Currencies

ABSTRACT

This paper adds evidence to the scant literature on the hedge and safe haven properties of cryptocurrencies against fiat currencies. These properties are examined using MGARCH-DCC method which is applied on daily data of 6 major cryptocurrencies against 10 Asian fiat currencies over the period from 30 December 2013 until 28 June 2019. The empirical results indicate that the role of a hedge is limited to the Hong Kong Dollar and Taiwan Dollar in the case of Bitcoin but prominent in Ripple, Monero and Stellar. Meanwhile, a safe haven is apparently a common property for all analysed cryptocurrencies. Overall, these major cryptocurrencies are potential gateways for a capital flight when Asian foreign exchange markets are under extreme distress.

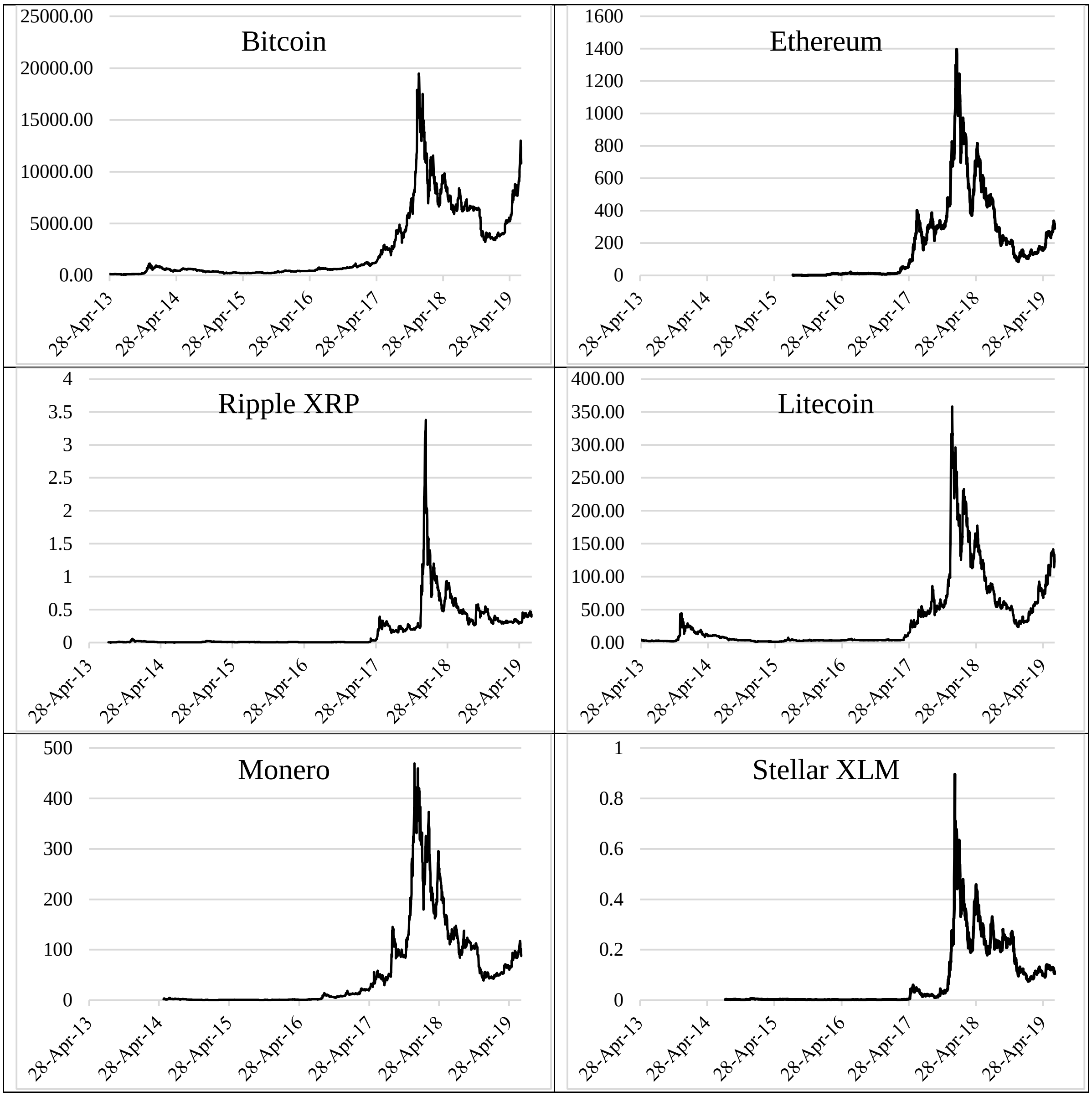
Keywords: Diversifier, hedge, safe haven, cryptocurrency, fiat currencies

Introduction

Modern portfolio theory posits that an efficient investment requires diversifying into a large number of assets of different classes and that maximizing the diversification effect can be accomplished by combining assets that are perfectly negatively correlated. The extent to which an asset contributes to reduce portfolio risk can be disintegrated into three levels; a diversifier, a hedge and a safe haven (Baur & Lucey 2010; Ratner & Chiu 2013). Conceptually, an asset is a diversifier as long as it has a weak positive correlation with another asset on average. The asset becomes a weak (strong) hedge factor if it is uncorrelated (negatively correlated) with another asset on average. Put differently, a hedge reduces portfolio risk significantly because the movements of the returns of negatively correlated assets offset each other. If the asset behaves as a hedge against another asset when the market is under extreme pressure, then it serves as a safe heaven. A safe haven is crucial in investment because it provides a means for shielding or growing the capital when it has to flight from the existing markets that are undergoing turbulence. While the properties of other financial assets have been well-researched, attention recently switches to cryptocurrency, one of the Fintech and blockchain application that has been disrupting the financial industry worldwide.

The development of the cryptocurrency market began with the advent of Bitcoin in 2009 following the publication of a white paper by Nakamoto (2008). When Bitcoin was first listed on coinmarketcap.com in April 2013, it was worth USD1.5 billion. In only a decade after its debut, Bitcoin's worth leaps by more than 11,000% to around USD175 billion. That does not account the time when Bitcoin was trading at nearly USD20 grams per BTC during the bubble (Figure 1) period in the cryptocurrency market. By September 2019, there are around 2,400 cryptocurrencies listed on the coinmarketcap.com platform, with a total market capitalization of around USD260 billion. The tremendous development explains the growing interest in the economics and finance implications of Bitcoin. It was initiated as a digital currency (Demir et al., 2018) but its applications quickly evolve to include crowdsourcing and peer-to-peer (P2P) networking. The fast and widespread acceptance of Bitcoin and the other cryptocurrencies can be attributed to it being decentralized from the central authority (Phillip et al., 2018) such that they are not subject to any financial system. Cryptocurrency also offers better security and faster settlement because it is developed from the blockchain technology, which operates as an open distributed ledger that records all transactions (Lee et al., 2018). The cryptographic nature of cryptocurrency offers few other advantages such as high liquidity, lower transaction costs and anonymity (Chan et al, 2017). Urquhart (2016) attributed the great attention and popularity of Bitcoin to the innovative structures, simplicity and transparency characteristics.

FIGURE 1. Prices of the sample cryptocurrencies (in USD)



The listing of cryptocurrencies on the global trading platforms such as tradingeconomics.com (lists Bitcoin, Ethereum and Ripple XRP) and finance.yahoo.com (lists all) are evidence that this innovative digital currency has been accepted and acknowledged as an investment instrument. With that development, it is only natural that a group of studies examines the potentials of cryptocurrencies for investment by examining the efficiency of the Bitcoin market. Urquhart (2016) is among the first to establish evidence that the Bitcoin market is not efficient but is moving towards being more efficient in the later period. Similar findings are reported by Bariviera (2017) where the author finds the Bitcoin is gradually moving towards efficiency after 2014. Contrary to Urquhart (2016) and Bariviera (2017), Nadarajah and Chu (2017) discover that Bitcoin returns are efficient when the return data are transformed into odd integers which are capable of preventing information loss in the returns. The increasing efficiency of Bitcoin in the later periods is again reported by Kurihara and Fukushima (2017) who predict that Bitcoin prices will become efficient and random in the future. Tiwari et al. (2018) also find that Bitcoin is informationally efficient except between April and August 2013 and between August and November 2016. By focusing on USD and CNY Bitcoin market, Kristoufek (2018) finds that the Bitcoin markets in both currencies still exhibit inefficient characteristics and remain predictable during the study period from 2010 until 2017 except in few sub-periods especially during the cooling-downs periods after bubble-like price surges.

The efficiency of cryptocurrencies is important to investors because it reveals the predictability of the asset prices and the speed at which new information is reflected in the prices. Another stream of studies examines the relationship between cryptocurrencies and other assets, which directly addresses the viability of an asset as a portfolio component. Dyhrberg (2016a, 2016b) examines the volatility of Bitcoin relative to gold, US dollar and the stock market. The author finds that Bitcoin is not much different from gold and the US dollar and it is not affected by the stock market. The results also show that Bitcoin is significant on the federal funds rate and other assets that are similar to gold. Bouri et al. (2018) discover evidence on the positive return spillover from World, Emerging and China markets to Bitcoin in a bull market and negative return spillover in a bear market except for China. Corbet et al. (2018) discover that cryptocurrencies possess little evidence of volatility spillover effects to other assets in short horizon and they are relatively isolated from other assets such as bond, commodities and equity in other markets. This isolation behaviour indicates that cryptocurrency is capable of creating diversification advantages in the short-term. Ji et al. (2018) also report the isolation of Bitcoin as they find no other assets could influence the Bitcoin market. Selmi et al. (2018) report that Bitcoin behaves similar to gold during the financial stress period but vice versa during stable times. The authors then argue that Bitcoin is an attractive investment alternative during a market meltdown because it is free of authority control, not influenced by the volatility of the stock market, unaffected by inflationary pressures, and has a fixed supply as well as transparency. Although many claim the similarity between Bitcoin and precious metal (gold and silver), Klein et al. (2018) prove that Bitcoin responses differently from gold, especially during market distress. However, it has no hedge function in equity markets. The results are supported by Gajardo et al. (2018) who find Bitcoin to be influenced more by gold than stock indices.

Among all the uses of cryptocurrencies, its application as a speculation tool is clearly driven by the high volatility and bubbles (Cheah and Fry, 2015; Dyhrberg, 2016a). Kristoufek (2018) explains that institutional and retail investors are attracted to cryptocurrencies because of the exceptional price movement which could be exploited for easy profit. However, a cryptocurrency also offers characteristics that are different from other financial assets (Corbet et al. 2018; Lee et al. 2018). Its relationship with various classes of financial assets has attracted the interest of researchers. For instance, Demir et al. (2018) suggest that Bitcoin is an effective tool for hedging especially in a bullish market, while it shows diversification advantage during a bearish market. Dyhrberg (2016a) suggests that Bitcoin is advantageous for portfolio and risk management as it is isolated from the other financial assets. Briere et al. (2015), Corbet et al. (2018) and Lee et al. (2018) also report that Bitcoin offers diversification benefit since it is weakly correlated with other traditional assets. The disadvantage of cryptocurrency, as explained by Kristoufek (2018), is the low liquidity of the cryptocurrency market compared to equity or foreign exchange market.

In a nutshell, the evidence from the previous studies (eg., Ji et al. 2018; Klein et al. 2018; Selmi et al. 2018) support the argument of this study that cryptocurrencies can perform more than just a diversifier, but also a hedge and a safe haven that are critical in generating an efficient investment portfolio. Bouri et al. (2016) are first to address the lack of emphasis on the role of bitcoin as a safe haven in those prior research. Bouri et al. (2016) examine whether Bitcoin has the properties that suit it as a diversifier, hedge and safe heaven against major asset classes including bond, equity, gold, oil and other commodities indexes. This study contributes to the literature by expanding the scope of cryptocurrencies in Bouri et al.'s (2016) study to include five other major cryptocurrencies, namely Ethereum, Ripple, Litecoin, Monero, and Stellar. The diversifier, hedging and safe haven properties of these cryptocurrencies are determined against a sample of conventional currencies. Motivated by Corelli's (2018) argument on the presence of "Asian Effect" in the cryptocurrency market, this study focusses on 10 currencies of the Asian region as the base assets. In the study, Corelli (2018) finds evidence that cryptocurrencies are correlated with Asian conventional currencies but not with major currencies of Commonwealth countries like Australian Dollar, South African Rand and New Zealand Dollar. Asian effect is also documented by Bouri et al. (2017) as they find that Bitcoin shows hedging and safe haven properties only against Asian stock markets (Nikkie225, Shanghai A-share and MSCI Asia-Pacific), but not against non-Asian stock markets like S&P500, FTSE100, DAX30, MSCI World and MSCI Europe.

The merit of the Asian effect may be justified by their leadership in cryptocurrency market. As reported by the Ibinex.com and Development Asia, Asia could soon become the "cryptocurrency hub" given the highest ownership, trading volumes, investments, payments and also home of some major exchanges like Binance, Bithumb, and Huobi. Ibinex's Global Cryptocurrency Report (2018) also reports that Korea and Japan are the two countries with highest cryptocurrency awareness and knowledge. Japan and South Korea also contribute around 50% and 12% of the global trading values, respectively. Drawing from the arguments about the uses of cryptocurrencies in investment and the significance of Asian countries to the cryptocurrency market, this study aims to examine the diversifier, hedge, and safe haven properties of the major cryptocurrencies against the conventional currencies of Asian markets. While five of these markets are known for being the major players in the cryptocurrency market, ASEAN-5 countries (Malaysia, Indonesia, Singapore, Thailand, and Philippines) are included because their foreign exchange markets and economies are also prone to a financial crisis that is not necessarily happening within close proximity. It was expected that the currencies of ASEAN-5 were badly affected by the 1997/1998 Asian Financial Crisis. However, these currencies were apparently not insulated because they were also experiencing spillover from the 2008 Global Subprime Crisis and 2015 Chinese Stock Market Crisis. This justifies the motivation to identify an asset that can serve as a safe haven for these vulnerable currencies.

The remainder of this paper is organized as follows. The next section describes the data and methodology used in this study. This is followed by a section reporting and discussing the results and a final section that concludes and discusses the implications of the study.

RESEARCH METHODOLOGY

Data

The data for this study are collected from coinmarketcap.com which as of August 6th, 2019 lists 2,426 cryptocurrencies with a total market capitalization of USD317.40 billion. At that point, the three largest cryptocurrencies are Bitcoin (USD217.46b), Ethereum (USD25.12b) and Ripple (USD13.86b) which collectively account for approximately 80% of the total market capitalization. In this study, a total of six cryptocurrencies are used to examine their hedge and safe heaven properties against the conventional currencies of 10 Asian markets. These six cryptocurrencies are Bitcoin, Ethereum, Ripple, Litecoin, Monero and Stellar which collectively account for 84% of the total market capitalization. Table 1 presents the profiles of the sample cryptocurrencies including their prices and market capitalization (in USD), whether they are minable, and the number of exchanges in which they are currently traded. The sample of conventional currencies is selected from among markets that have been the cryptocurrency leaders in Asia such Japan, China, Taiwan, South Korea and Hong Kong (reported in many including Development Asia) and other increasingly active cryptocurrency players namely Indonesia, Malaysia, Singapore, Thailand, and the Philippines which are collectively known as the ASEAN-5 countries.

TABLE 1. Profiles of sample cryptocurrencies

Characteristics	Bitcoin	Ethereum	Ripple	Litecoin	Monero	Stellar
Unit	BTC	ETH	XRP	LTC	XMR	XLM
Minable	Yes	Yes	No	Yes	Yes	No
Max supply	21mill	none	100bill	84mill	none	100.8bill
Circltg supply	18mill	108mill	43bill	63mill	17mill	20.1bill
No of exchanges	1,000	1,000	319	514	91	191
Mean Price	2846.66	206.15	0.19	37.69	55.00	0.06
Min Price	178.10	0.43	0.003	1.16	0.22	0.001
Max Price	19497.40	1396.42	3.38	358.34	469.20	0.90
Mean MktCap	4.79E+10	2.03E+10	7.60E+09	2.06E+09	8.68E+08	9.6E+08
Min MktCap	2.44E+09	3.22E+07	2.20E+07	4.12E+07	1.28E+06	767679
Max MktCap	3.27E+11	1.35E+11	1.31E+11	1.95E+10	7.27E+09	1.60E+10

The data on the cryptocurrencies that are collected from coinmarketcap.com are daily closing prices in USD for sample cryptocurrencies from the date the data are available until the end of June 2019. Meanwhile, the daily foreign exchange rates of the sample currencies over USD are downloaded from Thomson Reuter's DataStream starting with the earliest date the cryptocurrency data is available (i.e., 28 April 2013 which is for Bitcoin) until end of June 2019. However, due to analytical issues, the sample period only covers from 31 December 2013 until 28 June 2019. Note that trading of cryptocurrencies during the weekend are omitted to synchronize the data with the closing prices of the sample currencies. Returns on cryptocurrencies and currencies are calculated as $R_t = [(P_t - P_{t-1})/P_{t-1}]$, where R_t

represents the daily returns of the cryptocurrencies and conventional currencies at day *t*, P_t and P_{t-1}represent the closing prices or exchange rates of the cryptocurrencies and conventional currencies at time *t* and *t*-1, respectively. Table 2 reports the descriptive statistics of returns on the currencies.

TABLE 2. Descriptive statistics

Currency	Mean	Min	Max	Std.Dev.	Skew.	Kurt.	Obs.
Panel A. Price returns of cryptocurrencies							
Bitcoin	0.2961	-23.3713	42.9680	4.6337	0.5705	12.9066	1610
Ethereum	0.6398	-25.3035	51.0344	7.1862	1.2425	9.5679	1015
Ripple	0.6237	-46.0047	83.4708	8.1457	2.3904	21.7691	1540
Litecoin	0.3513	-40.1857	129.0954	8.1457	2.3904	65.8201	1610
Monero	0.2992	-31.4917	57.0866	7.6301	1.1395	10.4162	1332
Stellar	0.5339	-30.6745	94.7952	8.5728	2.8831	25.8575	1278
Panel B. Price returns of conventional currencies							
CNY	0.0069	-1.1432	1.8262	0.1926	0.4130	13.1220	1610
HKD	0.0004	-0.4788	0.3002	0.0336	-2.7880	56.2806	1610
JPY	0.0077	-3.3488	0.3242	0.5702	-0.0993	7.1393	1610
KRW	0.0035	-1.7657	2.4995	0.4898	0.0379	3.7166	1610
TWD	0.0032	-1.0408	1.2404	0.2291	-0.0810	6.1156	1610
IDR	0.0240	-3.2270	1.9266	0.3851	-0.6879	11.1802	1610
MYR	0.0201	-3.5318	1.9690	0.4313	-0.6307	9.7182	1610
PHP	0.0139	-1.2052	1.3420	0.2649	0.1763	5.2913	1610
SGD	0.0061	-2.3104	1.7121	0.3226	-0.3168	7.4915	1610
THB	0.0031	-2.2412	1.4833	0.2902	-0.1728	7.0322	1610

Notes: The currency abbreviations CNY refers to Chinese Yuen, JPY refers to Japanese Yen, KRW refers to South Korean Won, TWD refers to Taiwan Dollar, HKD refers to Hong Kong Dollar, SGD refers to Singaporean Dollar, MYR refers to Malaysian Ringgit, IDR refers to Indonesian Rupiah, PHP refers to Philippines Peso, and THB refers to Thailand Baht. Mean, min and max are stated in percentage.

Panel A of Table 2 shows that Ethereum records the highest average daily returns (0.6398%), followed by Ripple (0.6237%) and then Stellar (0.5339%). It is interesting to find that Bitcoin turns out to be the crypto with lowest return-lowest risk combination as it records the average daily returns of 0.2961% and standard deviation of 0.46337%. This finding suggests that Bitcoin has reached a certain level of stability, essentially because it is the earliest cryptocurrency being traded. Despite being the lowest among the cryptocurrencies, bitcoin's mean return is still 12 times higher than the highest mean return recorded by Indonesian Rupiah among the conventional currencies (Panel B). A similar result has been documented earlier by Feng et al. (2018) and Trabelsi (2018). It is also interesting to note that with the exception of Singaporean Dollar and Thai Baht, the ASEAN-5 currencies record higher average daily mean than the other Asian currencies when their standard deviations are not much difference. Hong Kong Dollar appears to be an exceptional case as it records very low mean return and standard deviation. Overall, the results suggest that ASEAN-5 currencies stand as a profitable investment choice as they are able to provide a higher return at least extra risk than the currencies of Asian more developed markets. Meanwhile, all returns on cryptocurrencies are positively skewed, as also documented earlier by Trabelsi (2018). However, these returns show negative skewness in other studies (Feng et al. 2018; Huynh 2019). The positive skewness suggests that cryptocurrencies tend to exhibit more extreme returns in their right tails (Feng et al. 2018). In contrast, returns on the conventional currencies (Panel B) have negative skewness.

All cryptocurrencies series are leptokurtic as higher kurtosis is recorded except for Ethereum which records a slightly lower kurtosis value (9.5679). Feng et al. (2018) and Trabelsi (2018) also find the leptokurtic behaviour in their sample cryptocurrencies especially in Ethereum and Bitcoin which record the lowest kurtosis values.

Econometric Model

The multivariate-GARCH dynamic conditional correlation (MGARCH-DCC) is applied to test the conditional correlation between two series by considering the time-varying and also their dynamic relationships. Engle (2002) explains that DCC is flexible like univariate GARCH and it also could parameterize the conditional correlation directly. Saiti and Noordin (2018) explain that MGARCH-DCC is capable of estimating the conditional volatility and time-varying correlation as well as determining the directions and magnitude of the conditional correlations. Saiti, Bacha and Masih (2014) and Abdullah, Saiti and Masih (2015) explain that extreme movements of volatilities indicate whether the assets are complementary or substitute and investors can use the information in their investment consideration. In general, the estimation of MGARCH-DCC involves two steps. In the first step, the univariate GARCH model will be estimated to get the standardized residuals that will be used to estimate the time-varying conditional correlation matrix in the second step. The followings are models to estimate the MGARCH-DCC including the univariate GARCH (Eq. (1) and (2)) and the conditional correlation (Eq. (3)).

$$r_t = \mu_t + \omega r_{t-1} + \varepsilon_t \tag{1}$$

$$h_t = c + \alpha\varepsilon_{t-1}^2 + bh_{t-1} \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

where r_t represents the returns of cryptocurrency and conventional currencies; μ_t represents the conditional mean for r_t , ε_t represents the standardized residuals, h_t represents the conditional variance, c represents the constant, a represents the parameter of short-run persistence (ARCH effect), and b represents the long-run persistence of the volatility (GARCH effect). In Eq. (3), H_t represents the multivariate conditional covariance matrix, $D_t$represents the diagonal matrix of conditional time-varying standardized residuals (ε_t) from equation (1) and $R_t$represents the time-varying correlation matrix (off-diagonal elements).

The dynamic conditional correlation (DCC) between cryptocurrencies (i^{th}) and conventional currencies (j^{th}) is estimated using the following equation:

$$DCC_{i,j,t} = p_{ij,t} = \frac{q_{ij,t}}{(\sqrt{q_{ii,t}}\sqrt{q_{jj,t}})} \tag{4}$$

where q_{ij} represents the elements of the i^{th} and j^{th} column on the matrix Q_t;

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\ \varepsilon_{t\_1}\acute{\varepsilon}_{t-1} + \beta Q_{t-1} \tag{5}$$

where Q_t represents the time-varying conditional correlation matrix of standardized residuals and $\bar{Q}$ represents the unconditional correlation of $\varepsilon_{t_1}\acute{\varepsilon}_{t-1}$and a and β represent the non-negative parameters with $a + \beta < 1$.

After obtaining the pairwise DCC between cryptocurrencies (i^{th}) and conventional currencies (j^{th}) from the MGARCH-DCC, Eq. (6) is used to estimate the properties of cryptocurrencies as a diversifier, hedge and safe haven against conventional currencies.

$$DCC_t = c_0 + c_1 D(r_{FX} q_{10}) + c_2 D(r_{FX} q_5) + c_3 D(r_{FX} q_1) + \varepsilon_t. \quad (6)$$

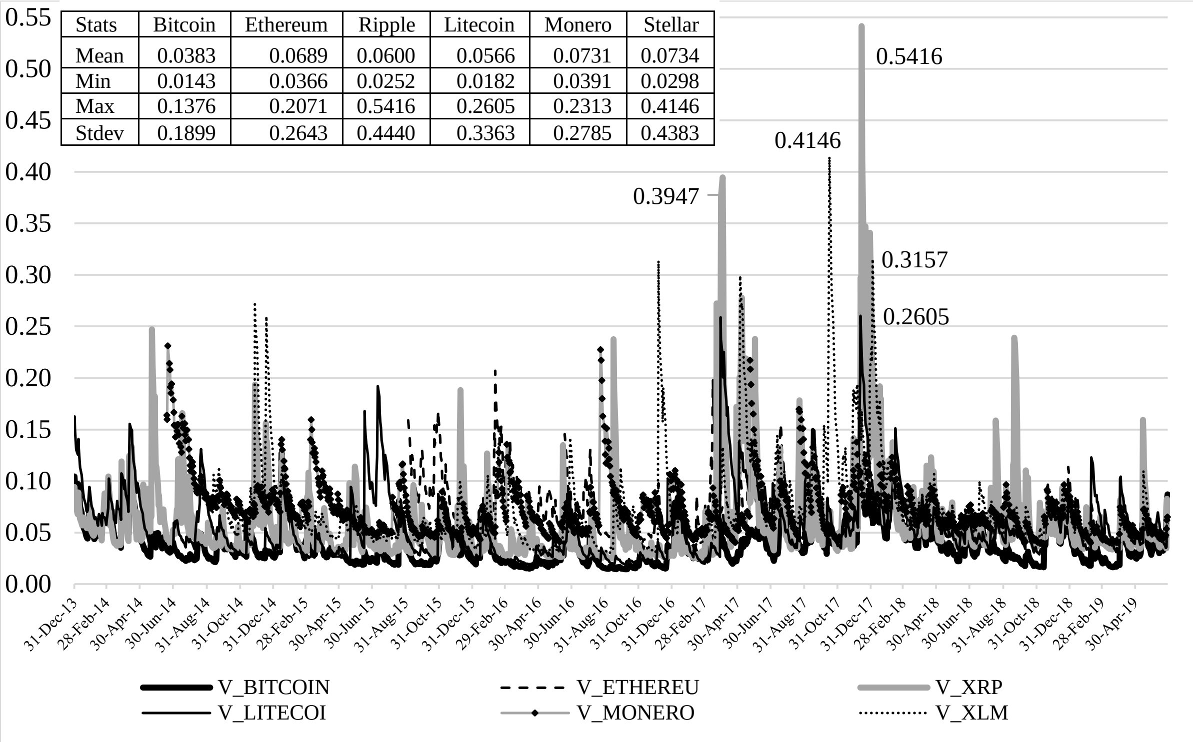
where DCC represents the dynamic conditional correlation between cryptocurrency and conventional currencies, r_{FX} represents the return on conventional currency exchange rate, and ε_t represents the error term. In Eq. (6), dummy variable (D) represents the extreme movement in the 10^{th} (q_{10}), 5^{th} (q_5) and 1^{st} (q_1) percentile of negative returns distribution for a particular conventional currency. If c_0 is significantly positive, the i^{th} cryptocurrency is said to be a diversifier whereas if it is significantly negative, the cryptocurrency is a strong hedge tool. An i^{th} cryptocurrency is a strong safe haven for a j^{th} conventional currency if c_1, c_2 and c_3 are significantly negative. It is a weak safe haven if the parameters are insignificantly different from zero. The DCC model has been used earlier by Ratner and Chiu (2013), Bouri et al. (2017) and Stensas et al. (2019).

RESULT AND DISCUSSION

Before examining the properties of the sample cryptocurrencies as a hedge, diversifier and safe haven against the currencies of the sample Asian markets, this section presents the resulting dynamic conditional volatilities of all sample currency returns that are estimated using the MGARCH-DCC model. The dynamic conditional volatility or time-varying conditional volatilities are illustrated in Figures 1 and 2. In general, Figure 1 shows that the cryptocurrency volatilities are picking up in August 2016 until the end of 2017, which coincides with the "bubble" period in the cryptocurrencies market (Ferreira & Pereira 2019). Comparatively among the individual cryptocurrencies, Ripple's XRP is the most volatile altcoin and it also records the highest spike of 54.16% that occurs in December 2017. Ripple also has several other notable spikes such as those in September 2018, March 2017, May 2014, and December 2015. The next most volatile altcoin is Stellar's XLM which records its most volatile day in October 2017, followed by Litecoin. The volatilities of Ethereum and Monero are subtler whereas Bitcoin turns out to be the least volatile among the sample cryptocurrencies.

The patterns in Panels A and B of Figure 2 suggest that the conditional volatilities for the fiat or conventional currencies of Asian main cryptocurrency leaders are more settled than the other five currencies but consistently high. In particular, the conditional volatilities of the Japanese Yen and South Korean Won series support the earlier findings in that both currencies report with the highest standard deviation and unconditional volatilities among all 5 Asian major cryptocurrency players. In the meantime, the pattern of Hong Kong Dollar appears steadiest and constantly at the lowest volatility during the study periods, except for a few minor fluctuations like in early 2016 and September 2018. This pattern confirms the currency's profile noted earlier in Table 2. Meanwhile, the conditional volatilities of cryptocurrencies of ASEAN-5 countries record lower mean values but with apparently more erratic movements. The most obvious instances are those shown by the Indonesian Rupiah and Malaysian Ringgit, particularly during the final quarter of 2015 when the currencies were experiencing quite a major depreciation.

FIGURE 1. Conditional volatilities for sample cryptocurrencies

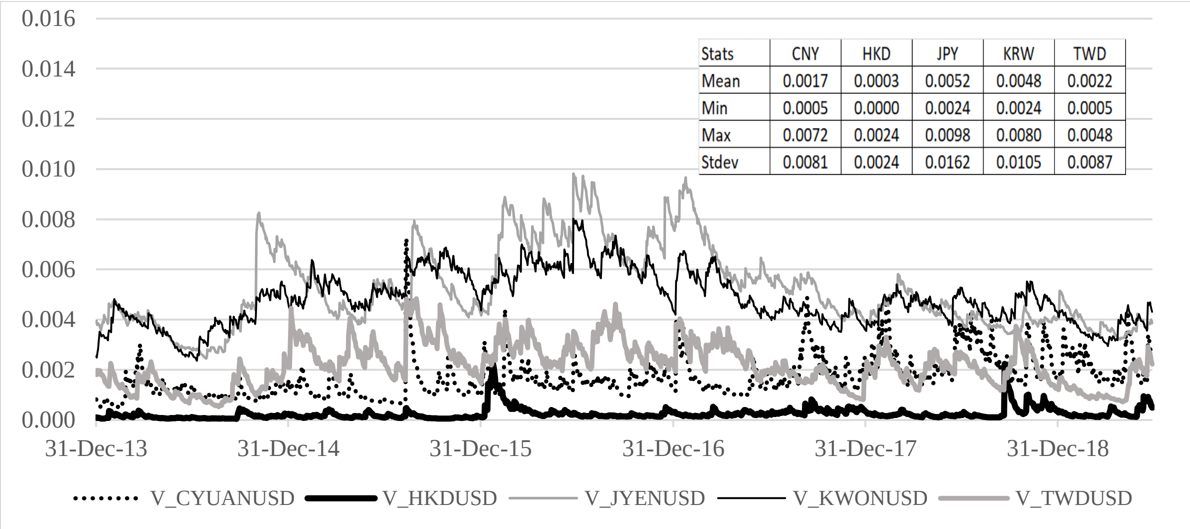


Stats	Bitcoin	Ethereum	Ripple	Litecoin	Monero	Stellar
Mean	0.0383	0.0689	0.0600	0.0566	0.0731	0.0734
Min	0.0143	0.0366	0.0252	0.0182	0.0391	0.0298
Max	0.1376	0.2071	0.5416	0.2605	0.2313	0.4146
Stdev	0.1899	0.2643	0.4440	0.3363	0.2785	0.4383

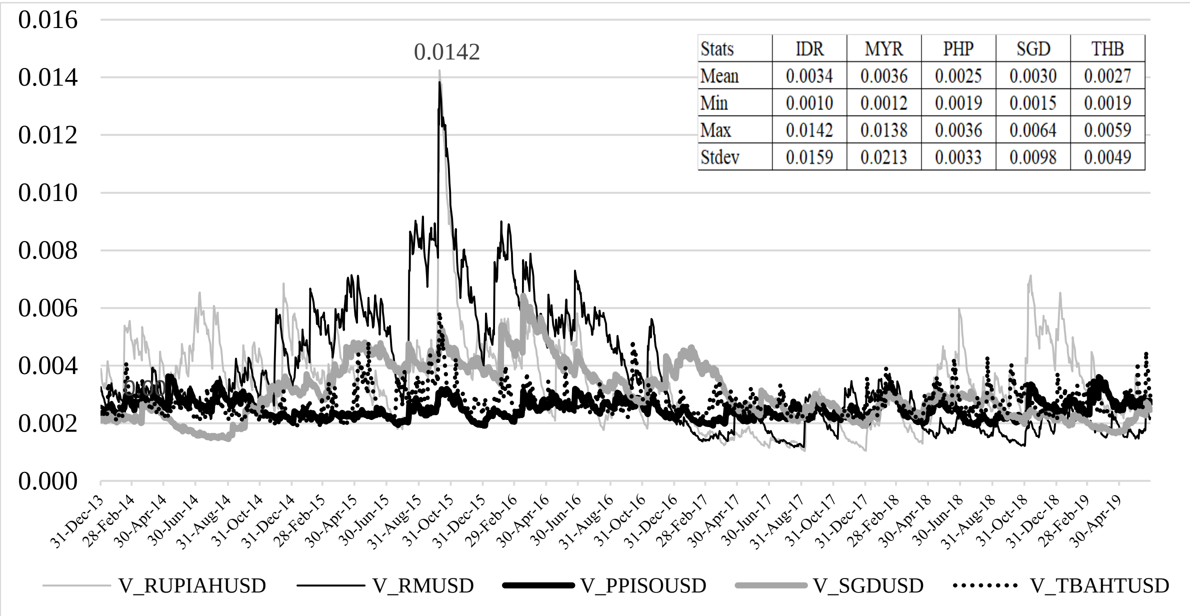
In general, the patterns in Figures 1 and 2 concur with the increasingly acknowledged stylized facts that cryptocurrencies are much more volatile than the conventional or fiat currencies. Compared based on the mean conditional volatility, Stellar is 14 times more volatile than Japanese Yen (the most conditional volatile currency) and 292 more volatile than the Hong Kong Dollar (the least volatile currency). Even Bitcoin, which is noted earlier as the least volatile cryptocurrency, is 7 times more volatile than Japanese Yen and 150 times more volatile than the Hong Kong Dollar. These explain the reason that the top use of cryptocurrencies is for speculation. Second, the patterns in Figures 1 and 2 also show that the time frame when cryptocurrencies are most volatile is different from the time for conventional currencies, there is a great potential that these assets can work as a hedge or safe haven for each other.

FIGURE 2. Conditional volatilities of the currencies of Asian region

Panel A. Volatility of Asian major players in the cryptocurrency market



Panel B. Volatilities of 5 other Asian currencies



After examining the conditional volatilities of the return series using the MGARCH-DCC model, the dynamic conditional correlation (DCC) of the crypto-conventional currencies pairwise are estimated using Eq. (6) and the results are reported in Table 3. The results in Table 3 are then evaluated against several criteria as presented in Table 4. These criteria represent the usefulness of the cryptocurrencies in investment decision with respect to their hedge and safe haven properties. Recall the interpretations of Eq. (6) which state that if the c_0 in the DCC equation is significantly positive, the i^{th} cryptocurrency is said to be a diversifier whereas if it is significantly negative, the cryptocurrency is a strong hedge tool. An i^{th} cryptocurrency is a strong safe haven for a j^{th} conventional currency if c_1, $c_2$and c_3 are significantly negative. It is a weak safe haven if the parameters are insignificantly different from zero.

TABLE 3. Estimation results of hedge and safe haven properties of cryptocurrencies against conventional currencies

CRYPTO	Coeff.	CNY	JPY	SKW	HKD	TWD	SGD	IDR	MYR	PHP	THB
Bicoin	C_0	0.0222***	0.0106***	0.0210***	-0.0204***	-0.0124***	0.0319***	0.0074***	0.0058***	0.0304***	-0.0002
	C_1	-0.0087	-0.0133*	0.0139**	-0.0163*	0.0239***	-0.0094	0.0019	0.0007	-0.0111*	0.0051
	C_2	0.0087	0.0032	0.0117	0.0224*	-0.0013	-0.0029	-0.0004	-0.0000	0.0205**	-0.0005
	C_3	-0.0083	-0.0419**	-0.0189	-0.0208	0.0026	-0.0097	-0.0416***	-0.0021	-0.0154	-0.0288
Ethereum	C_0	0.0974***	-0.0308***	0.0135***	-0.0258***	0.0069***	-0.0031	-0.0031*	0.0231***	0.0627***	-0.0201***
	C_1	-0.0181	-0.0237***	0.0194	0.0024	0.0127	0.009	0.0028	0.0105	-0.0116	-0.0121*
	C_2	-0.0114	0.0184	-0.0034	0.0321**	-0.0129	0.0025	0.0194*	0.0199*	0.0208	0.0075
	C_3	-0.0112	-0.0360*	0.0258	-0.0121	-0.0128	0.0434	-0.0031	-0.021	-0.0212	0.0044
Ripple	C_0	-0.0281***	-0.0006	-0.0183***	-0.0594***	-0.0126***	0.0162***	-0.0648***	-0.0396***	0.0173***	-0.0204***
	C_1	-0.0102	-0.0030	-0.0045	-0.0198**	0.0062	-0.0025	0.0072	0.0035	-0.0097	-0.0232***
	C_2	0.0038	0.0002	0.0011	0.0306***	-0.0119	-0.0034	0.0073	-0.0189**	0.0170**	0.0223**
	C_3	0.0062	-0.0076	-0.0071	-0.0274*	-0.0164	-0.0048	-0.0301**	-0.0180	-0.0039	-0.0087
Litecoin	C_0	0.0127***	0.0145***	0.0403***	-0.0290***	-0.0008	0.0352***	0.0276***	-0.0029***	0.0332***	0.0222***
	C_1	0.0032	-0.0125*	0.0170**	-0.0216**	0.0217***	-0.0076	0.0035	0.005	-0.0116*	0.0009
	C_2	0.0089	0.0066	0.0155	0.0221*	0.00004	0.0033	0.0048	-0.0024	0.0178**	-0.0045
	C_3	-0.0108	-0.0259	-0.0159	-0.0316*	-0.0145	-0.0059	-0.0408***	-0.0121	-0.0044	-0.0176*
Monero	C_0	-0.0111***	-0.0017	0.0092***	-0.0389***	-0.0021	-0.0381***	0.0399***	0.0143***	-0.0198***	-0.0008
	C_1	-0.0048	-0.0038	0.0150*	-0.0033	0.0215***	0.0041	0.0101*	0.0004	0.0054	-0.0050
	C_2	-0.0021	0.0155*	-0.0052	0.0040	-0.0236**	0.0020	0.0073	0.0140*	-0.0015	0.0022
	C_3	-0.0060	-0.0141	-0.0063	-0.0117	0.0044	0.0065	-0.0201	0.0054	-0.0251**	-0.0257***
Stellar	C_0	0.0213***	0.0003	-0.0105***	-0.0237***	-0.0132***	0.0140***	-0.0447***	-0.0340***	0.0135***	-0.0180***
	C_1	-0.0240***	0.0053	0.0041	-0.0100	0.0022	-0.0020	0.0073	-0.0095*	-0.0174***	-0.0092
	C_2	-0.0054	-0.0069	0.0038	0.0261**	0.0091	0.0155*	-0.0009	0.0053	0.0268***	0.0030
	C_3	-0.0157	0.0027	-0.0012	-0.0261	-0.0296	-0.0014	-0.0204*	-0.0169	-0.0259	-0.0017

Notes: The currency abbreviations CNY refers to Chinese Yuen, JPY refers to Japanese Yen, KRW refers to South Korean Won, TWD refers to Taiwanese Dollar, HKD refers to Hong Kong Dollar, SGD refers to Singaporean Dollar, MYR refers to Malaysian Ringgit, IDR refers to Indonesian Rupiah, PHP refers to Philippines Peso, and THB refers to Thailand Baht. Asterisks *, **, and *** indicate significant at 10%, 5%, and 1% levels, respectively. The C_0 to C_3 coefficients are from Eq. (6).

The results from Table 4 show that the most popular cryptocurrency, Bitcoin, apparently only qualifies as a hedging tool against 3 conventional currencies of which Bitcoin is a strong hedge against Hong Kong Dollar and Taiwan Dollar. The result so far supports Bouri et al.'s (2016) conclusion that Bitcoin does not serve more than just an effective diversifier. However, the remaining results seem to suggest that Bitcoin still has a more positive role for the Asian currencies. The coefficients on the dummy variables representing extreme distress in the 10th, 5th and 1st percentile indicate that Bitcoin is a safe haven for all sample currencies. Of those currencies, Bitcoin's safe heaven property is strong in Japanese Yen, Hong Kong Dollar and Indonesian Rupiah. In the most extreme distress condition of 1% percentile (C_3), Bitcoin remains a safe haven for all sample currencies except for Taiwan Dollar. The more positive results found in this study could be associated with Corelli's (2018) claim of the presence of the Asian effect. That said, the results are not strong enough to justify the attention that investors put on Bitcoin. Thus, it justifies the need to analyse the potentials of the altcoins (other cryptocurrencies) to serve the hedge and safe haven purposes for their portfolios. The summary in Table 4 proves that based on several criteria, Bitcoin is trailing behind three other altcoins namely Ripple, Stellar and Altcoin.

TABLE 4. Summary of the hedge and safe heaven analyses

Hedge/safe heaven criteria	Bitcoin	Ethereum	Ripple	Litecoin	Monero	Stellar
Hedge ($-C_0$)	3	5	8	3	7	6
Strong hedge ($-C_0$)*	2	4	7	2	4	6
Safe heaven ($-C_1$,$-C_2$, $-C_3$)	10	9	10	10	8	10
Strong safe heaven ($-C_1$,$-C_2$, $-C_3$)* against (#) currencies	3	2	4	5	3	4
Consistent safe heaven ($-C_1$,$-C_2$ & $-C_3$) against:	SGD	CNY	SGD	None	CNY	CNY
Safe haven in extreme market distress ($-C_3$)*	9	7	9	10	7	9
Overall ranking	4	6	1	3	4	2

Notes: Abbreviations SGD is Singaporean Dollar and CNY is Chinese Yuen. Parameters $C_{0\ \mathrm{until}}$ C_3 are from

The results for Ripple show that this altcoin, which falls short of Bitcoin in various aspects including market capitalization, analyst coverage and investment attractiveness, has greater potentials for the purposes of investment. Ripple behaves as a hedge against all sample currencies with the exception of Singaporean Dollar and Philippines Peso. Furthermore, in all sample currencies which Ripple can serve as a hedge tool, the effect is significant (strong) except for the Japanese Yen. The results also show that this altcoin has a safe haven property against all sample currencies and in four of them (Hong Kong Dollar, Indonesian Rupiah, Malaysian Ringgit, and Thailand Baht), it prevails as a strong safe haven. All of the sample currencies can turn to Ripple when they are under extreme pressure. Except for Chinese Yuen, the same recommendation applies when the currencies are under the most turbulence condition. Applying the same evaluation process leads to the overall ranking in Table 4 which places Stellar in the second place, Litecoin in the third place and Bitcoin in the fourth place.

From the conventional currency perspective, major cryptocurrency players in Asia seem to have more use of cryptocurrencies as a hedging tool than the other markets. The results from Table 3 indicate that Chinese Yuen can use Monero and Ripple as a strong hedge tool.

Both cryptocurrencies are also useful as a hedge against the Japanese Yen but their effect is not strong as in the case of Ethereum. For the Korean Won, its strong hedge tool is the Ripple and Stellar. Among currencies of these major players, Hong Kong Dollar and Taiwan Dollar have greater benefits from the sample cryptocurrencies. All of the sample cryptocurrencies are strong hedge candidates for Hong Kong Dollar whereas Ethereum is the only exception in the case of the Taiwan Dollar. For currencies of the ASEAN-5 countries, Singaporean Dollar can be hedged with Ethereum and Stellar but only the latter would give a strong effect. Both Indonesian Rupiah and Malaysian Ringgit have 3 hedge tools and all three are a strong hedge. Ripple and Stellar are the common hedge tool for both currencies while Ethereum and Litecoin are the unique hedge for Indonesian Rupiah and Malaysian Ringgit, respectively. Philippines Peso can only be hedged with Monero but the effect is strong. Among the five currencies, Thailand Baht seems to have the greatest hedging benefits from the cryptocurrencies. Except for Litecoin, the Baht can use any of the sample cryptocurrencies to hedge its downward movement. Like Indonesian Rupiah, the strong hedge candidates for Thai Baht are Ethereum, Ripple and Stellar. These results indicate that while the hedge property of Bitcoin is somewhat limited, those of other cryptocurrencies in particular Stellar and Ripple suggest that they can play a role more important than just diversifier in an investment.

The results in Table 4 pertaining to the safe haven property of the cryptocurrencies lead us to several conclusions. Prior to that, note that an asset which can serve as a safe haven for the base asset is crucial to investors because it compensates for the losses that investors incur in the base assets their markets are under extreme pressure. For the Japanese Yen, the investors should seriously consider cryptocurrency as a safe haven because the results prove that it is the currency that has the most indications of a strong safe haven. Specifically, Bitcoin, Ethereum and Litecoin are found to have strong safe haven property against the currency. Bitcoin is also potentially useful as a safe haven for Chinese Yuen but the currency could be shielded from distress more reliably with Ethereum, Monero and Stellar. Comparatively, South Korean Won, Taiwan Dollar and Singaporean Dollar appear to be the least to benefit from the safe haven of cryptocurrencies since none of their three dummy coefficients is significant. The difference is the Singaporean Dollar has Bitcoin and Ripple that consistently behave as weak safe havens. Other than the Japanese Yen, another currency that can benefit from cryptocurrency is the Hong Kong Dollar. For this currency, it can strongly rely on Bitcoin, Ripple and Litecoin when its market is in distress. For the remaining four currencies (Indonesian Rupiah, Malaysian Ringgit, Philippines Peso and Thailand Baht), they also can find safe haven in several of the sample cryptocurrencies. Overall, the results suggest that cryptocurrencies can be of great value to the currencies of Asian markets when they are in market turmoil.

CONCLUSION AND IMPLICATION

Taking the spirit of Corelli's (2018) Asian effect, this paper examines the hedge and safe haven properties of a sample of major cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Monero and Stellar) against 10 currencies of the Asian region. These include several major players in the cryptocurrency market such as Japan, China, Hong Kong, South Korea and Taiwan while five others the ASEAN-5 countries. The tests are done using MGARCH-DCC model on daily returns data over a period that spans from 30 December 2013 to 28 June 2019. The results suggest that although Bitcoin has a limited function as a hedge against the currencies, other cryptocurrencies show promising evidence that they can be more than just a diversifier. In particular Ripple, Stellar and Monero show that they have great potential as effective hedging instruments for the currencies. The results also suggest that these cryptocurrencies can do more than just hedging tool. In general, all sample cryptocurrencies can function effectively as a safe haven for the sample currencies. In particular, Litecoin, Ripple and Stellar acquire ample evidence to prove that they can be the safe haven for these currencies including during the time when these currencies are stricken with the most extreme condition.

The results of this study lend support for the proposition that bitcoin and particularly Ripple, Stellar, Monero and Litecoin have the properties that make them more useful than just a diversifier in an investment portfolio. Having an asset with a hedging property is crucial to maximizing the diversification effect of a portfolio because the negative correlation effectively reduces portfolio risk. The results which show that the cryptocurrencies remain a hedging mechanism when the conventional currencies are under extreme stress suggest that these digital assets have properties that other financial assets have failed to offer. This safe haven property is critical from an investment perspective because a new avenue is necessary to preserve or grow the wealth once it is liquidated from the base asset that is in distress. The results suggest that all of the sample cryptocurrencies have safe haven properties against conventional currencies. However, of the five major cryptocurrencies players in Asia, Japanese Yen and Hong Kong Dollar appear to be the ones that will benefit the most from the safe haven properties of the sample cryptocurrencies

For the ASEAN-5 countries, a safe haven can make a significant difference because they have always been treated like a bowl of economies that reacts to and is affected by the same market shocks. The 1997/98 Asian Financial Crisis is a great example on the region’s economy was almost obliterated as a result of problematic currency of one of the member countries. Having a safe haven for the currencies enables the economy to avoid being so adversely affected when the currencies are weakened. Since cryptocurrencies are not subject to any central authority or country, its value is insulated from country-specific or region-specific shocks. Put differently, they do not react to the same shock that is affecting the conventional currency such that their values remain strong or unaffected when the conventional currency weakens. When the financial market of the base currency is under extreme pressure, investors holding a depreciating currency can shift their capital to a certain cryptocurrency to protect or even grow their wealth. However, investors must take this recommendation with great cautions not only because cryptocurrencies are extremely volatile, but also because in most markets the laws and regulations governing cryptocurrencies have yet to be put in place.

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