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Can Digital Currencies Serve as Safe Havens in the Post-Covid Era?

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Abstract

The exponential growth of digital currencies in general and cryptocurrencies in particular has seemingly broken every record on the book. This has generated in the process a tremendous amount of interest in both developed and developing countries from scholars, academics, politicians, decision-makers and other stakeholders. Considering an applied methodology about asymmetric volatility with Exponential General Auto-regressive Conditional heteroscedasticity (EGARCH), this research work explores the fundamentals of the behavior of cryptocurrencies comparatively to a benchmark of key assets. To achieve its goal, this study uses two classes of assets. On the one hand, the first class (Class I) includes seven − *Bitcoin*, *Ethereum*, *Binance*, *Dogecoin*, *Tether*, *Ripple*, and *Cardano* − of the top 10 cryptocurrencies, which, as of July 2021, commanded more than $1.5 trillion in market capitalization. On the other hand, the second class (Class II) is comprised of three traditionally established, well-known and "safe" assets, namely, gold, the 3-month US treasury bill and the 30-year US treasury bond. Using thousands of datapoints, empirical findings regarding volatilities, returns, clustering and leverage effects of the two asset classes do not reveal any startling contrasts to warrant an outright dismissal of crypto-assets as viable repositories of purchasing power and value. However, the pace in the move towards a full "safe haven" status will hinge upon the introduction of a clear regulatory and legislative framework in the US and other major countries to instill more confidence and certainty about crypto assets in a post-Covid era.

Keywords: Digital assets; Crypto-currencies; EGARCH; Volatility; Returns; Leverage effect.

1. Introduction

In a breaking news on January 8, 2021, financial insiders reported on most major business outlets that the cryptocurrency *Bitcoin* had crossed the $40,000 mark for the first time since its inception in 2009. For argument's sake, let's imagine, in a not-so-distant future, that the average citizen could buy, among others, a house, a car, groceries, or repay a student loan, using a digital currency in general or a cryptocurrency in particular.

Have digital currencies earned the right to be incorporated by workers and other investors in their portfolios as investment vehicles? Would Main Street and Wall Street succumb to the newfound appeal of digital currencies as a hedge against inflation? Could digital currencies become the holy grail for workers trying to save for retirement? This series of questions has been gaining momentum in light of recent developments on financial markets as the world continues to grapple with the massive financial and economic disruptions caused by the coronavirus pandemic. Digital currencies still remain enigmatic for the average person. Simply defined, a digital currency is a form of currency available in digital or electronic form. It can either be regulated by a chief authority, such as a central bank, or unregulated. In the latter case, it is called a virtual currency or more commonly a cryptocurrency.

One may wonder at this juncture the reason why *Bitcoin*, for instance, should be introduced in a given investment portfolio. A two-fold response can be provided. First, it is increasingly becoming liquid; that is, it can very easily be converted into other assets like cash or gold. Second, and most importantly, it's been exhibiting a strong and steady performance over the years. Case in point, *Bitcoin* has risen by about 5,000 percent over the past five years.[1] More specifically, it was overall up by 160 percent from the beginning of 2020 to November of that year; and, it grew by 190 percent from March 2020 to November alone (Roberts, 2020). The specific reference to March 2020 is of importance, for it is the month that saw the Covid-19 pandemic alarmingly flare up in the US and the rest of the world. As of January 4, 2021, it was up by almost 300 percent from its level on March 2, 2020 (Business Insider, 2020). Is that upsurge a sheer coincidence or rather a sign of an asset acting as a safe haven for economic agents, such as workers and investors, in times of uncertainties? This research project draws its pertinence from pursuing answers to this question. Furthermore, digital currencies have recently gained widespread momentum. As a result, a long, perchance steep, learning curve still exists for financial experts, academics, decision-makers and the

[1] The actual figure is 4,992 percent, from July 2016 to July 2021.

general population both in the US and across the world. The spectrum of calculated reactions to this upsurge of cryptocurrencies ranges from the decision to accept or encourage the nationwide use of a cryptocurrency as legal tender – i.e., in El Salvador – to the implementation of an outright ban on its use, namely, in China.[2] Between the two ends of that spectrum, one denotes the majority of countries which advocates the introduction of a comprehensive regulatory framework for cryptocurrencies. The United States and the United Kingdom are part of this majority.

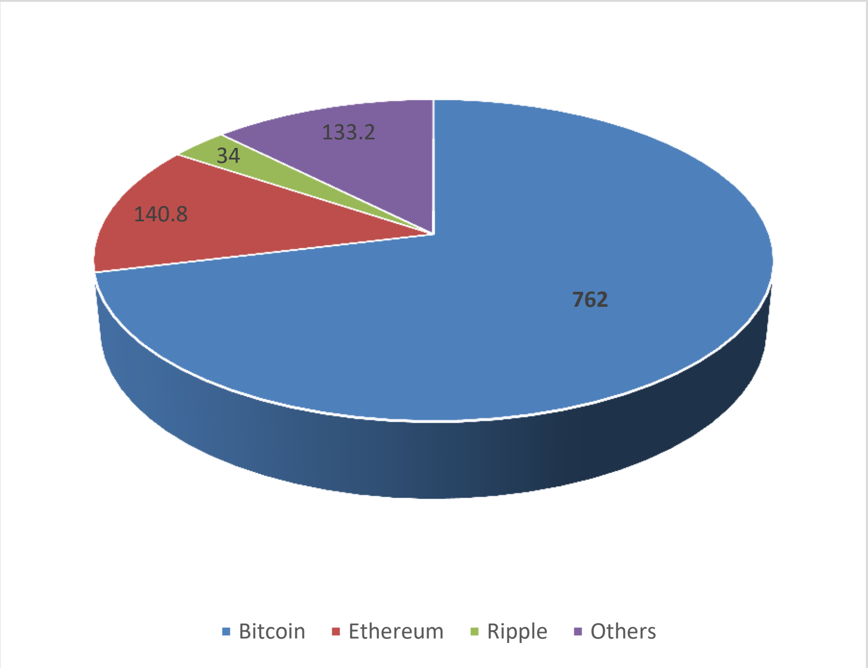
Conceptually, an asset fulfills the role of a safe haven when economic agents or decision-makers literally run towards it − and substantially increase their demand for it − to safeguard their income and wealth when the economy experiences headwinds or in times of turbulence. The primary research objective of this project is to specifically explore, with available data, whether the world of investors and other economic agents are ready for cryptocurrencies to serve as repositories of both purchasing power and value. In other words, we empirically analyze the safe haven status of digital currencies with a focus on cryptocurrencies. In practice, a comparative empirical assessment of fundamentals in two asset classes is performed. The first class (Class I) regroups seven of the most widely used cryptocurrencies: *Bitcoin, Ethereum, Binance, Dogecoin, Tether, Ripple, and Cardano*. The second class (Class II) comprises well-established and accepted safe haven assets such as gold and US securities – in particular, 3-month US treasury bills and 30-year US bonds.

As it pursues its objectives, the present paper is structured around five segments. The literature review is presented in the second segment, while the third articulates the methodology. Results and implications are discussed in the fourth segment, and a conclusion is provided in the fifth.

2. Literature Review

The market capitalization (market cap) of the entire cryptocurrency industry topped the trillion and half dollar threshold in July 2021.[3] This market cap soared by about half a trillion dollars from January to July of that year. Exhibit 1 displays the share of all cryptocurrencies in billions of US dollars out of the market cap, while Exhibit 2 gives a glimpse into the evolution of the price of *Bitcoin* − the most widely owned and used cryptocurrency in the world.

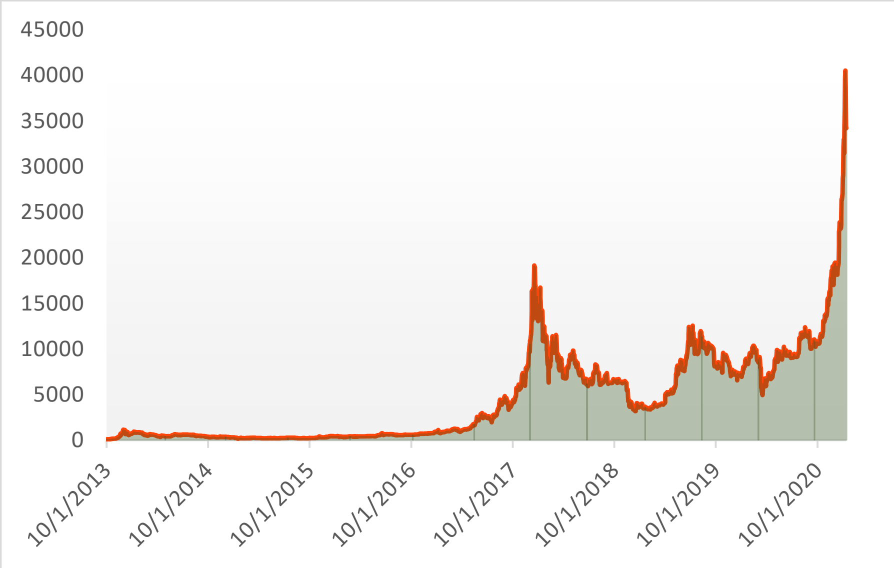
Exhibit-1. Share of cryptocurrencies out of total market cap, as of January 2021 (in billions of USD)



[2] On June 9, 2021, the Congress in El Salvador approved President Nayib Bukele’s proposal to make *Bitcoin* legal tender in the country. On May 18, 2021, China officially forbade all financial institutions and payment companies to use or facilitate the use of cryptocurrencies. Mass arrests of suspected violators took place in the following month. This crackdown forced de facto the closure of more than 90% of China’s mining capabilities, which were either shut down completely or moved to other Asian countries and the United States.

[3] As of July 2021, the total market cap was about $1.533 trillion for 6,095 publicly known cryptocurrencies. *(Source: investing.com)*

Exhibit-2. Evolution of price of Bitcoin, 2013-2021 (in USD)



To put into perspective the magnitude of cryptocurrencies total market cap in July 2021, it is almost 7% of the entire US economy or about 93% of the Canadian economy in 2020.

Owing to the fact that cryptocurrencies are part of a relatively new economic and financial theme, the literature is not replete with analyses and investigations, whether empirical or theoretical, pertaining to them. However, the literature includes a great deal of scholarly works focusing on assets and their resilience in acting as safe havens. Among other prominent studies, Brunnermeier and Haddad (2014) and Caballero *et al.* (2017) lay out what are considered to be the safest assets in the world. Their surveys and analytical investigations reveal that the top of the pyramid is dominated by debt instruments, or IOU's (I owe you's), sold by the most prominent OECD countries, such as the United States, Germany, the United Kingdom, Australia, to name a few.[4] These safe assets are followed by assets-backed securities (ABS), mortgage-backed securities (MBS) and gold. The process undergone by an asset as it reaches the global status of safe asset or haven has drawn as well significant interest among scholars. Habib *et al.* (2020) demonstrate that does not become a "safe asset" what wants. That is, not every asset winds up reaching safe asset status.

The emergence of cryptocurrencies has created what is known as the crypto economy, which has considerably gained in importance in the past decade or so. According to Merwe (2021), the crypto economy is characterized by four interdependent elements: (i) the distributed ledger or blockchain, (ii) the digital assets (for instance, *Bitcoin*), (iii) the active participants or "miners," and (iv) passive participants or users. In particular, a blockchain is a block or collection of cryptocurrency transactions. A typical transaction is a purchase and sale of a cryptocurrency. On another note, Merwe (2021) cautions potential investors in cryptocurrencies about the quantitative and qualitative risks considering the high volatility of their prices and the relatively novel blockchain technology, which poses its own and unique challenges.

Certain scholars have showed interest in understanding the existence of possible linkages between cryptocurrencies and the real economy. Among others, there are Yin *et al.* (2021) who explore whether oil market shocks impact volatility in cryptocurrencies. Using a generalized autoregressive conditional heteroscedasticity (GARCH) approach applied to three cryptocurrencies, they find evidence of such impacts. A noteworthy finding is that investors are drawn towards cryptocurrencies when there are oil shocks. Put otherwise, cryptocurrencies appear to serve as means for hedging in times of economic uncertainties.

Fasanya *et al.* (2021) have looked at the cryptocurrencies in the financial market from a different angle. They empirically pore over return and volatility spillovers among cryptocurrencies. Their study considers five cryptocurrencies − *Bitcoin*, *Ethereum*, *Litecoin*, *Ripple* and *Dogecoin* – and a methodological approach involving three spillover indexes, namely, the gross spillover index, the directional spillover index and the net spillover index. They use as well rolling-window analyses, which the authors argue are more "reliable and realistic." Overall, four pivotal results are derived: (i) existence of cross-market movements among the five cryptocurrencies indicating that there are return and volatility spillovers; (ii) substantial interdependence between returns and volatilities in the cryptocurrency market; (iii) increased integration among cryptocurrency portfolios with a high degree of volatility noted during severe crises; and, (iv) frequent inconsistencies in the behavior of cryptocurrencies as far as returns and volatilities are concerned.

In a parallel investigation, Kozlowski *et al.* (2021) focus on cryptocurrency returns using a large dataset of 200 cryptocurrencies from 2015 to 2019. They discover robust evidence that there are reversal effects in these returns as past losers regularly outperform past winners in the next period. These reversals remain prevalent even when subsamples are considered. Besides, they find that the entire cryptocurrency market is characterized by some predictability in returns, and they suggest that a deeper market is needed to help stabilize prices.

[4] The OECD, Organization for Economic Co-operation and Development, is a forum that regroups mostly advanced economies. As of April 2022, its membership was 38.

3. Methodology

The methodological approach in this study pursues an empirical assessment of volatility. In the literature, many models exist to assess volatility, including, among others, some well-known methods by Engle and Patton (2007), Katsiampa (2017), and Gamba-Santamaria *et al.* (2017). The most popular technique remains the generalized autoregressive conditional heteroskedasticity (GARCH) initially developed by Bollerslev (1986), as a variant of the seminal model introduced by Engle (1982). It is effective in estimating disturbances at a point in time as a function of previous disturbances and variances. This approach fits well the purpose of this research work.

The GARCH process starts with a straightforward mean equation capturing the return (Ret_t) of crypto-assets as follows:

$$Ret_t = c + \theta_t \quad (1)$$

Where c is a constant representing the expected value of Ret_t. θ_t is the normally distributed error term with zero mean and variance σ^2. That is, $\theta_t \sim N(0, \sigma^2)$. Equation (1) breaks down into:

$$\log(P_t/P_{t-1}) = c + \theta_t \quad (2)$$

Where P is the crypto price, while t and t-1 are time subscripts.[5] In the next step, the regression below is considered:

$$\sigma_t^2 = \tau_0 + \beta_1\theta_{t-1}^2 + \delta_1\sigma_{t-1}^2 \quad (3)$$

Equation (3) is the GARCH(1,1). It is the most utilized form of the broader GARCH (p,q) specification where p and q are respectively the orders of the GARCH and autoregressive conditional heteroscedasticity (ARCH) processes. GARCH(p,q) is defined as:

$$\sigma_t^2 = \tau_0 + \sum_{k=1}^{q}\beta_k\,\theta_{t-k}^2 + \sum_{v=1}^{p}\delta_v\sigma_{t-v}^2 \quad (4)$$

The presence of asymmetric effects in the real world when dealing with returns has led to formulations of GARCH models more robust than equation (4). In that regard, this study utilizes the Exponential GARCH (EGARCH). Equation (4) is thus augmented according to Nelson (1991) to obtain EGARCH(p,q):

$$log(\sigma_t^2) = \tau_0 + \sum_{k=1}^{p}\beta_k\left|\frac{\theta_{t-k}}{\sigma_{t-k}}\right| + \sum_{v=1}^{q}\delta_v\log(\sigma_{t-v}^2) + \sum_{h=1}^{l}\varphi_h\left(\frac{\theta_{t-h}}{\sigma_{t-h}}\right) \quad (5)$$

Where the parameters τ_0, β_k and δ_v are estimated using the maximum likelihood (ML) method. The ratio $\left(\frac{\theta_{t-h}}{\sigma_{t-h}}\right)$ is meant to capture the asymmetric effect of shocks (Dritsaki, 2017).[6] As explained by Dritsaki, there are at least two major benefits of using EGARCH comparatively to GARCH. On the one hand, its logarithmic form removes the positive constraint that must prevail with a GARCH model. On the other hand, an EGARCH model is engineered to account for asymmetric changes in volatility of returns. A standard GARCH model lacks this feature. Moreover, the existence of leverage effect as well as asymmetry is easily detected with the significance of φ_h coefficients.

With that knowledge, the specification of equation (5) for EGARCH(1,1) is reduced to:

$$log(\sigma_t^2) = \tau_0 + \beta_1\left|\frac{\theta_{t-1}}{\sigma_{t-1}}\right| + \delta_1 log\sigma_{t-1}^2 + \varphi_1\left(\frac{\theta_{t-1}}{\sigma_{t-1}}\right) \quad (6)$$

For robustness and reliability of results, $|\delta_1|<1$ is expected for each asset.[7]

4. Data and Results

This research work uses two sets of data. The first set (Class I) consists of prices of seven top 10 cryptocurrencies:[8] Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), Cardano (ADA), Ripple (XRP), and Dogecoin (DOGE). The second set (Class II) includes data on prices of gold (XAU),[9] and yields on 3-month (3USTB) and 30-year US (30USB) treasury securities. All sets are sourced from three outlets, namely, *coinmetrics.io/data-downloads/*, the US Treasury Department, and The Federal Reserve Bank of St Louis. Data are reported daily based on availability. Ranges are not uniform across the board, as cryptocurrencies in particular entered circulation at varied dates.

The descriptive statistics of time series are presented in Table 1. A quick glance at prices of cryptocurrencies over their respective ranges shows that BTC for instance crossed the $63,000 bar from a level of five cents sometime in 2010. As far as ETH is concerned, it leaped over $4,100 from a low of 42 cents. Another striking point is that standard deviations across assets vary substantially. Among others, one encounters a standard deviation of $10,333.19 for BTC, whereas it reaches a moderate 6 cents and 0.8 cents for DOGE and USDT, respectively.

It should be noted however that the latter is known as a stablecoin. It is a cryptocurrency whose intrinsic value is pegged to another valuable assets, such as the US dollar, gold or a government-backed security. As a result of this unique characteristic, it is stable in value and experiences low volatility.

Before proceeding any further into the discussion of empirical results, a necessary step is to check for the stationarity of assets' series, as it is required for both GARCH and EGARCH methodologies. Table 2 indicates that return series of all cryptocurrencies and gold are stationary in level. However, 3USTB and 30USB return series are stationary in first difference.

[5] In practice, when deriving $\hat{\theta}_t$, first differences are used to ensure stationarity of time-series.
[6] Dritsaki (2017) provides an extensive discussion of EGARCH process with empirical applications.
[7] This expectation also ensures convergence (and stability) of the empirical process described by Equation (6).
[8] Together, they commanded a market cap of more than $1.2 trillion as of August 3, 2021 according to *CoinMarketCap.com*.
[9] Dollar price per oz of gold.

Table-1. Descriptive statistics

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	XAU	3USTB	30USB
Frequency	Daily	Daily	Daily	Daily	Daily	Daily	Daily	Daily	Daily	Daily
Range	2010-2021	2015-2021	2019-2021	2014-2021	2017-2021	2014-2021	2017-2021	2010-2021	2010-2021	2010-2021
Mean	5133.293	3.97E+02	80.11494	0.015226	0.999566	0.266847	0.279663	1407.473	0.530753	2.996507
Median	589.199	2.00E+02	24.03609	0.001905	1.000244	0.216923	0.092413	1318.7	0.11	2.99
Maximum	6.34E+04	4.16E+03	673.6189	0.685335	1.112537	2.745794	2.261626	2061.5	2.49	4.85
Minimum	0.050541	0.42	9.373772	8.09E-05	0.950334	0.004074	0.024106	1050.6	0	0.99
Std. Dev.	10331.19	6.18E+02	142.5505	0.064754	0.00813	0.336412	0.428731	229.1137	0.76495	0.764787
Skewness	3.392002	2.799616	2.533516	5.791477	1.687419	2.592826	2.149955	0.732925	1.415929	0.081645
Kurtosis	15.3509	11.48776	8.479574	39.72288	42.64895	13.07418	6.518524	2.367302	3.461866	3.135756
Jarque-Bera	33309.7	9387.266	1833.476	169340.6	88144.22	13570.85	1714.53	310.8747	992.7306	5.437532
Probability	0	0	0	0	0	0	0	0	0	0.065956
Observations	4026	2179	790	2741	1336	2537	1333	2927	2894	2894

Table-2. Unit roots tests *(H_o: Series has unit root)*

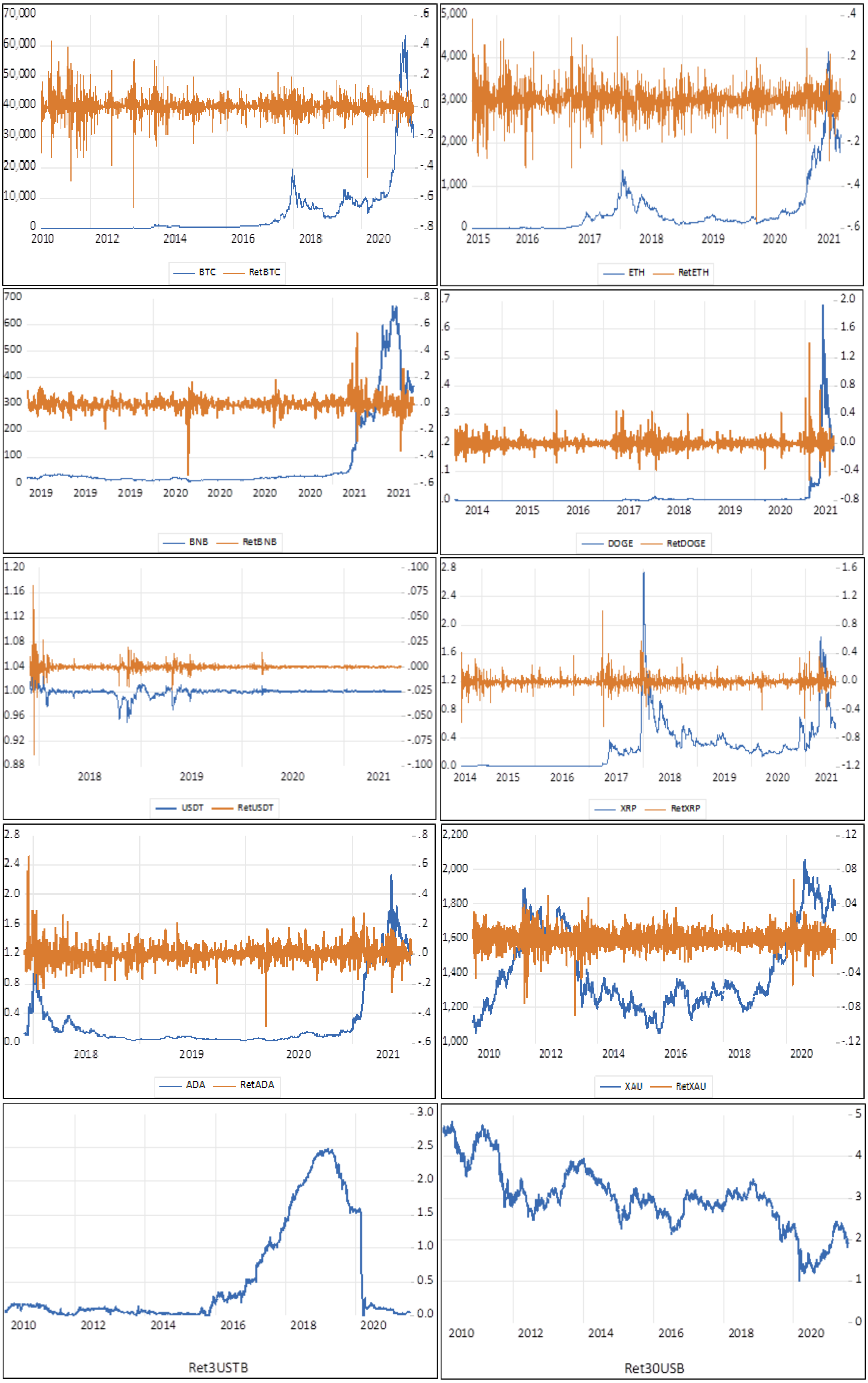
		BTC	ETH	BNB	DOGE	USDT	XRP	ADA	XAU	3USTB	30USB
	ADF	-23.1185	-48.446	-18.09	-28.438	-12.637	-53.855	-38.055	-53.817	-1.212	-3.000
Level	Probability	0	0	0	0	0	0	0	0	0.671	0.1323
	PP	-62.062	-48.46	-30.449	-51.813	-69.219	-54.186	-38.174	-53.844	-0.561	-2.839
	Probability	0	0	0	0	0.0001	0	0	0	0.981	0.183
	ADF	-	-	-	-	-	-	-	-	-12.111	-54.716
First Difference	Probability	-	-	-	-	-	-	-	-	0	0
	PP	-	-	-	-	-	-	-	-	-52.592	-55.019
	Probability	-	-	-	-	-	-	-	-	0	0

Exhibit 3 highlights the movements of prices and returns of all assets in this analysis. There is a noticeable upward trend in prices of gold and cryptocurrencies, except for USDT, which rather evinces some stability over the period of investigation. This behavior is consistent with expectations for a stablecoin. Considering returns, patterns of zigzags capturing persistent ups and downs are observed across the board. However, in the cases of 3USTB and 30USB, patterns are more distinct. An upward trend is mostly noted for the former, whereas a downward trend is in order for the latter.

A scrutiny of EGARCH-based results in Table 3 regarding the volatility of asset returns brings to light some interesting elements that deserve attention. One element found pertains to the existence of leverage effect in both classes of assets. In Class I, out of seven major cryptocurrencies in circulation, six − namely, BTC, BNB, DOGE, USDT, XRP, and ADA − feature evidence of leverage effect. ETH remains the exception, as evidence of leverage effect has so far not been detected since its inception.[10] Specifically, wherever leverage effects are found, they appear negative. In other words, negative shocks to returns beget more instability or volatility as compared to positive shocks of similar magnitude. This finding substantiates the fact that asymmetry prevails in crypto markets as far as volatilities of returns are concerned. This outcome could find ground in the fact that investors would overreact to negative shocks due in part to the newness of these relatively “unknown” and unproven assets along with considerable uncertainties about their long-term prospects. For instance, investors would disproportionally reduce their holdings of cryptocurrencies to limit their losses or make a quick profit when sensing or observing the slightest downturns. These actions would impact prices which in turn jitter returns.

[10] It was first released in July 2015. In this study, the dataset for ETH runs from August 8, 2015 through July 25, 2021.

Exhibit-3. Movements of prices and returns[11]



[11] Only returns are available and provided for 3USTB and 30USB.

The flight away from cryptocurrencies is additionally compounded by the stylized fact that retail investors, not institutional investors, have largely constituted the most active participants in crypto markets. Indeed, the latter group of investors has for years stayed clear of these new types of asset – crypto assets – which are literally branded as highly speculative. In the same line of arguments, renowned trading platforms such as *Ameritrade, Fidelity, E*Trade, Interactive Brokers*, *Trade Station*, and *Schwab*, among others, either (i) drastically reduce availability and trading in and with cryptocurrencies, or (ii) do not offer them at all. This timidity of traditional and popular trading platforms has given rise to new major players in the industry with, for instance, the likes of *Coinbase, Binance, Crypto.com*, and *Robinhood*.

Table-3. EGARCH-based results

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	XAU	3USTB	30USB
c	0.003001	0.00285	0.003346	0.00087	-2.88E-05	-0.00212	0.000626	0.000184	0.000293	-0.00128
	(0.0000))	(0.0101)	(0.0516)	(0.2333)	(1.29E-01)	(0.0066)	(0.6894)	(0.254)	(0.1484)	(0.1237)
τ_0	-0.66244	-0.6108	-0.53444	-1.03665	-0.3182	-1.26054	-0.4882	-0.36308	-0.45876	-0.21401
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_1	0.349607	0.287325	0.369773	0.599202	0.350912	0.577889	0.250798	0.185098	0.258552	0.124525
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ_1	0.931057	0.92861	0.954413	0.883602	0.994896	0.847044	0.944065	0.976181	0.966818	0.980922
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
φ_1	-0.008686	-0.00132	-0.02819	-0.04834	-0.09003	0.08967	-0.01511	0.005146	-0.02477	-0.03652
	(0.0488)	(0.8612)	(0.0094)	(0.0000)	(0.0000)	(0.0000)	(0.093)	(0.4308)	(0.0002)	(0.0000)
Obs*	4025	2178	789	2740	1335	2536	1332	2926	2893	2893

*: Observations after adjustments. Probabilities are in parenthesis.

In Class II, leverage effects are found for 3USTB and 30USB only. The effects are both negative. XAU manifests positive leverage effects, but they come out insignificant. In a nutshell, some similarities do exist between both classes of assets regarding the presence as well as the nature of leverage effects.

We carry on the analysis by taking a closer look at volatilities of asset returns reported in Table 4 and Exhibit 4. Not surprisingly, USDT showcases the highest degree of stability as revealed in Table 4. In the first category of assets, it is followed, in that order, by BTC, BNB, ETH, and ADA. DOGE displays the most instability and closely queued by XRP. On the other hand, XAU boasts the most stability followed by 3USTB. Although 30USB can be singled out as the most unstable in the second class of assets, it appears more stable than BTC and ETH, which are the two largest crypto assets in terms of market cap.[12] It's worth pointing out as well that USDT outpaces XAU in terms of stability in returns. Overall, the gap in standard deviations between the most unstable and stable assets is about 0.07 for cryptocurrencies, while hovering around 0.04 for commonly known and traditional "safe" assets. Considering that the first class includes seven assets compared to three in the second, one may argue that the spread is relatively limited between classes. Furthermore, Exhibit 4 unveils that volatility clustering exists for all assets as similarly found by Yin *et al.* (2021) and Fasanya *et al.* (2021). As a matter of fact, it is apparent that periods of high volatility in returns are succeeded by periods of relative lull with low volatility. This is a typical characteristic for many financial assets.

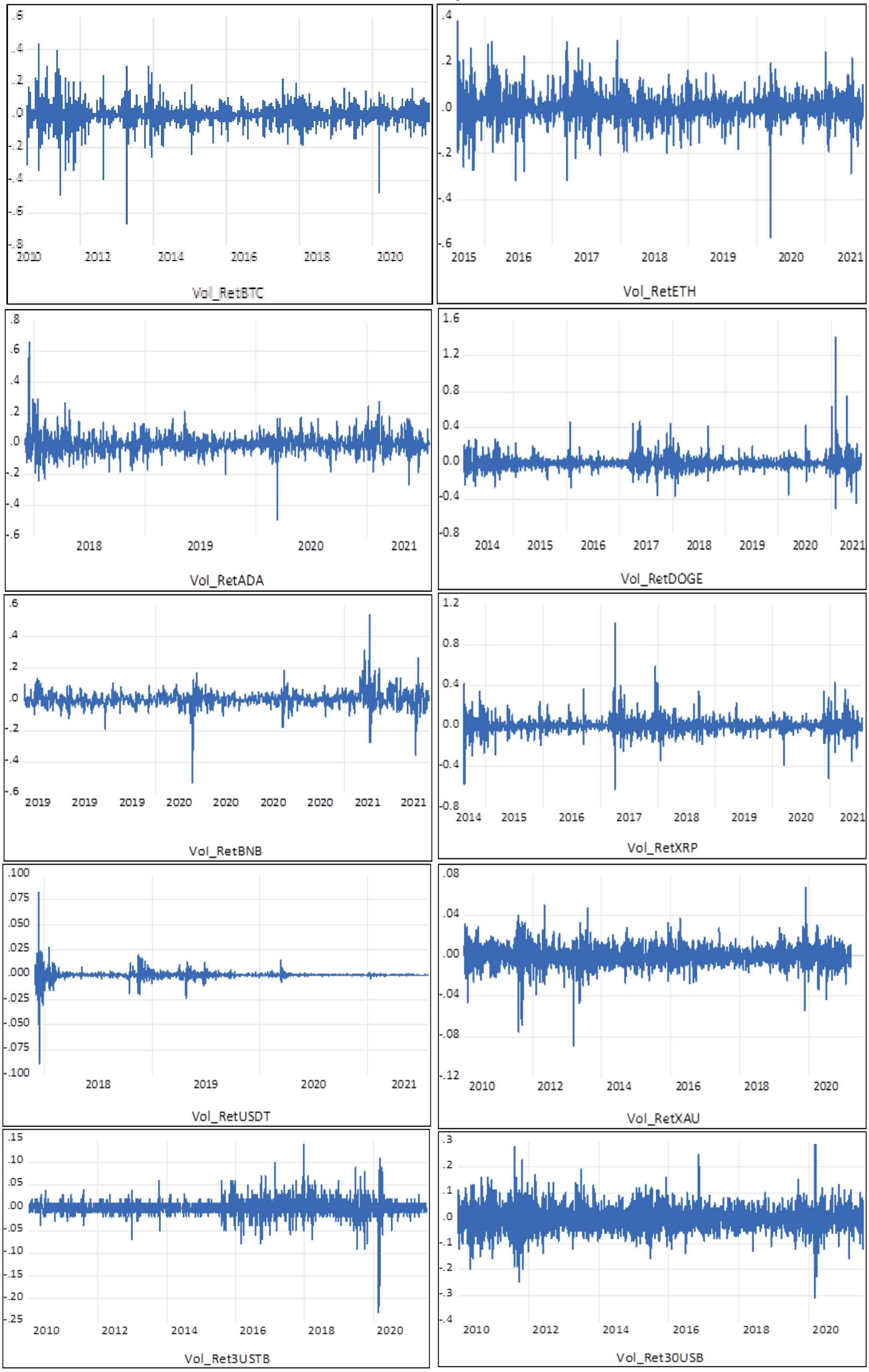
Table-4. Volatility of return series

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	XAU	3USTB	30USB
Mean	0.000209	0.000597	0.000226	0.000901	2.55E-05	0.003969	0.001058	-4.98E-05	-0.0003	0.000343
Median	-0.00093	-0.002225	-0.00161	-0.00221	2.33E-06	0.000592	-0.00011	1.12E-05	-0.00029	0.001283
Maximum	0.433654	0.377881	0.537392	1.40619	0.083141	1.010868	0.663354	0.067715	0.139707	0.291283
Minimum	-0.66795	-0.568465	-0.53513	-0.51452	-0.08893	-0.63437	-0.49304	-0.08931	-0.23029	-0.30872
Std. Dev.	0.053187	0.063752	0.060784	0.076391	0.004981	0.072841	0.06833	0.009849	0.018469	0.050204
Skewness	-0.75904	-0.177875	0.086355	3.382812	-0.85623	1.44159	1.042777	-0.48808	-1.88608	0.022019
Kurtosis	21.10371	9.636647	21.2653	55.39433	141.1107	29.26599	16.02292	9.900428	27.9143	6.034577
Jarque-Bera	55351.96	4008.577	10968.78	318632.3	1061187	73778.04	9653.997	5731.116	76538.14	1110.26
Probability	0	0	0	0	0	0	0	0	0	0
Obs*	4025	2178	789	2740	1335	2536	1332	2832	2893	2893

*: Number of observations after adjustments.

[12] As of July 2021.

Exhibit-4. Volatility of Return Series



In order to further understand the dynamics in this comparative approach, the interdependence of returns and volatility of assets is surveyed. To that end, this research work provides the reader with spillover indexes in tables 5, 6, 7, 8, 9, and 10.[13] The spillover index is a well-known and effective tool popularized in the literature by Diebold and Yilmaz (2009). It is helpful when exploring the behavior of assets and their connections. The Diebold-Yilmaz (DY) spillover index of returns is 5% for all assets. This figure indicates a low level of connectedness. We take

[13] All series in the vector auto-regression (VAR) used to derive DY spillover indexes are stationary.

another look at the index by deriving it for each class of assets to check if additional insights could be gained. Thus, it is found that the spillover index for Class I is very low at 4.5%. For Class II, this figure stands even lower at 0.7%. In essence, it comes out that there is a lack of interdependence within each class of assets. When volatility is considered, there is a slight departure from previous findings. Case in point, the DY spillover index of volatility series for all assets is 7.4%. The figures are respectively 6.6% and 1.1% for cryptocurrencies and "safe" assets.

Table-5. Spillover index of return series (Class I +Class II)

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	XAU	3USTB	30USB	From Others
BTC	96.6	0.4	1.1	0.4	0.4	0.2	0.1	0.3	0	0.5	3.4
ETH	0.4	93.6	0.9	0.7	1.7	0.7	0.7	0.4	0.3	0.6	6.4
BNB	1.6	0.2	97	0.2	0.2	0.1	0.1	0.1	0.2	0.5	3
DOGE	0.3	0.3	0.3	96.6	0.6	0.6	0.6	0.3	0.1	0.4	3.4
USDT	0.2	0.4	0.4	1.4	86	1.1	8.2	1.2	0.5	0.4	14
XRP	0.7	0.3	0.7	0.2	0.8	95.7	0.6	0.8	0.1	0.2	4.3
ADA	1.2	0.1	0.4	0.8	0.9	0.4	95.5	0.3	0.2	0.2	4.5
XAU	0.2	0.3	0.3	0.4	0.3	0.3	0.4	96.6	0.6	0.6	3.4
3USTB	0.5	0.8	0.2	0.8	0.4	0.1	1.1	0.4	94.7	0.9	5.3
30USB	0.4	0	0.3	0.5	0.1	0.2	0.1	0.3	0.2	97.8	2.2
Contribution to others	5.4	2.8	4.8	5.5	5.3	3.7	12	4	2.3	4.2	50
Contribution including own	102	96.4	101.7	102	91.4	99.3	107.5	100.6	97	102.1	5.00%

Table-6. Spillover index of return series (Class I)

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	From Others
BTC	97.2	0.5	1.1	0.5	0.4	0.2	0.1	2.8
ETH	0.4	94.7	0.9	0.8	1.8	0.8	0.6	5.3
BNB	1.5	0.2	97.8	0.2	0.1	0	0.1	2.2
DOGE	0.2	0.4	0.3	97.5	0.6	0.5	0.5	2.5
USDT	0.2	0.4	0.5	1.5	88	1	8.4	12
XRP	0.6	0.2	0.6	0.2	0.7	97	0.7	3
ADA	1.1	0.1	0.4	0.9	0.9	0.4	96.2	3.8
Contribution to others	4	1.7	3.9	4.2	4.4	3	10.4	31.6
Contribution including own	101.2	96.4	101.7	101.6	92.5	100	106.6	4.50%

Table-7. Spillover index of return series (Class II)

	XAU	3USTB	30USB	From Others
XAU	99.8	0	0.2	0.2
3USTB	0.1	98.6	1.4	1.4
30USB	0	0.5	99.4	0.6
Contribution to others	0.1	0.6	1.5	2.2
Contribution including own	99.9	99.2	100.9	0.70%

Table-8. Spillover index of volatility series (Class I + Class II)

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	XAU	3USTB	30USB	From Others
BTC	92.4	0.3	1.4	0.3	0.4	1.3	1	0.3	1.8	0.8	7.6
ETH	0.2	94	0.5	1.9	1.3	0.3	0.6	0.7	0.4	0.1	6
BNB	2.2	0.3	94.2	0.1	0.3	0.4	0.1	1.6	0.7	0.2	5.8
DOGE	0.1	1.2	0.2	95.2	0.1	0.4	0.6	1.1	0.5	0.6	4.8
USDT	0.4	1.1	0.2	2.3	79.9	1.8	13.1	0.3	0.5	0.5	20.1
XRP	0.5	2.4	1.4	0.5	0.7	91.9	1.2	0.5	0.3	0.5	8.1
ADA	1.3	0.2	0.4	1.9	0.6	0.3	93.9	0.4	0.8	0.3	6.1
XAU	0.3	0.3	0.5	1.1	0.4	0.5	0.6	93.5	0.8	2	6.5
3USTB	0.2	0.3	0.5	0.9	0.8	1	0.1	0.4	95	0.8	5
30USB	0.6	0.2	0.1	0.7	1	0.6	0.4	0.4	0.2	95.7	4.3
Contribution to others	5.8	6.3	5.3	9.8	5.6	6.5	17.8	5.7	5.8	5.7	74.5
Contribution including own	98.2	100.3	99.5	105	85.5	98.4	111.7	99.1	100.8	101.4	7.40%

Table-9. Spillover index of volatility series (Class I)

	BTC	ETH	BNB	DOGE	USDT	XRP	ADA	From Others
BTC	95.1	0.2	1.5	0.3	0.5	1.4	1	4.9
ETH	0.2	95.2	0.5	1.9	1.4	0.3	0.6	4.8
BNB	2.6	0.3	96.4	0.1	0.2	0.4	0.1	3.6
DOGE	0.1	1.1	0.3	97.5	0.1	0.4	0.5	2.5
USDT	0.5	1.1	0.2	2.2	81.1	1.8	13	18.9
XRP	0.6	2.5	1.3	0.5	0.6	93.5	1.1	6.5
ADA	1.6	0.2	0.5	2	0.5	0.3	95	5
Contribution to others	5.4	5.5	4.3	6.9	3.4	4.6	16.3	46.3
Contribution including own	100.5	100.6	100.7	104.4	84.5	98	111.3	6.60%

Table-10. Spillover index of volatility series (Class II)

	XAU	3USTB	30USB	From Others
XAU	98.8	0.5	0.7	1.2
3USTB	0.1	98.2	1.7	1.8
30USB	0.1	0.2	99.7	0.3
Contribution to others	0.2	0.8	2.4	3.3
Contribution including own	99	99	102.1	1.10%

The implications of all findings are revealing about the two classes of assets. Traditionally considered “safe” assets in financial markets are not unambiguously and consistently outperforming the new wave of assets known as cryptocurrencies. In particular, when leverage effects exist they remain negative and do not greatly diverge between classes. Similarly, volatilities of returns do not indicate large-scale departures from those experienced by “safe” assets. Behind this backdrop, it could be posited that crypto assets deserve a closer and second look from both retail and institutional investors in their medium and long term strategies of portfolio diversification. It is true that the lack of clear regulations continues to this day to be an impediment in easing fears from investors. However, all signals from politicians, decision-makers and stakeholders in Washington, DC., New York City, Tokyo, and London, for instance, signal that these hurdles will be overcome sooner rather than later. Plus, a variety of cryptocurrencies possess intrinsic economic value as they contribute in drastically reducing transactions costs and facilitating transactions between economic agents both domestically and internationally. They act as global economic facilitators on countless levels with applications in virtually all industries. On a simple notecard, it would not be a far-fetched idea to write: “Crypto-assets have earned a seat at the table.”

5. Conclusion

Digital currencies have gained importance in the financial and economic debate as of late thanks to the impressive growth realized by *Bitcoin* and *Ethereum*, among others. This study has attempted to understand the behavior of some major cryptocurrencies using a comparative approach in search of any clues or patterns to examine their safe haven status. Empirical findings regarding volatilities, returns, clustering and leverage effects of two categories of assets − namely, seven crypto-assets and three traditionally well-known and “safe” assets − do not reveal any startling contrasts among these classes. One could argue, at the minimum, that the absence of strong evidence against cryptocurrencies up to this point in time gives them a fighting chance in being considered in portfolios of mainstream investors, both retail and institutional. However, the pace of this role in portfolios will hinge upon the introduction of a clear regulatory framework in the US and other major countries to engender more confidence and certainty about these crypto assets in a post-Covid era.

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