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Towards a taxonomy for crypto assets

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Abstract: We explore the taxonomy of cryptocurrencies and integrate our analysis with traditional ways of understanding financial assets. We thus classify cryptocurrencies using the time series and distributional properties of returns. Cryptocurrencies appear inherently speculative in nature. The result is even more clear cut when time series measures of distance are used. Results tally with wider concerns raised regarding excessive volatility of stablecoins.

Subjects: Statistics & Probability; Economics; Finance

Keywords: Bitcoin; cryptocurrency; fin tech; probability distribution; statistics; time series

JEL Classification: C1; G1; G3

1. Introduction

Cryptocurrencies are a new type of financial instrument that have received much popular (Buterin, 2022) and acade mic (Kayal & Rohilla, 2021) attention. The first major cryptocurrency Bitocin was created by Satoshi Nahomoto in 2008 as a peer-to-peer electronic currency without needing financial institutions to act as intermediaries. Though originally conceived as an alternative to national currencies (Dowd, 2014), cryptocurrency markets are famed for their dramatic boom-bust patterns and the potential for a complete collapse in market prices (J. Fry, 2018). Relatedly, early work suggests Bitcoin and cryptocurrencies are more of a speculative asset than a genuine currency (Baur et al., 2018; Corbet, Meegan, et al., 2018).

The empirical classification of cryptocurrencies remains an interesting problem in its own right. Alongside an interesting technical discussion (see Section 2) the statistical properties of cryptocurrency returns are known to change over time (Jiang et al., 2018; Urquhart, 2016). There is also a vast literature on cryptocurrencies covering areas as diverse as speculative bubbles (Corbet, Lucey, et al., 2018), market efficiency (López-Martin et al., 2021), price discovery (Doan et al., 2022) and the market response to the pandemic (Corbet et al., 2020).

We thus seek to empirically determine the extent to which Bitcoin and cryptocurrencies are a purely speculative asset or a genuine currency. Here, a comparison is made with both major currency pairs and major tech stocks. There is long-standing interest in the stylized empirical facts of both cryptocurrency markets (Al-Yahyaee et al., 2018) and financial markets more generally (Cont, 2001). Moreover, it is natural to approach this question from both distributional and time series perspectives.

Firstly, from a distributional perspective, it is well known that crypto assets exhibit boom-bust patterns sometimes culminating in complete collapse. Speculative bubbles are also not a necessary requirement for these effects to occur (Fry, 2018). Moreover, this marked volatility has previously raised questions about how well Bitcoin and cryptocurrencies can serve as a unit of account (Fry & Cheah, 2016). Secondly, the time series properties of crypto assets are interesting and important in their own right (Gkillas et al., 2022; Katsiampa, 2017). The comparison with the time series data from other asset classes is also a natural one to make (Al-Yahyaee et al., 2018).

In this paper we develop four new methods to classify crypto assets based on either their distributional or time series properties. Cryptocurencies appear to be inherently speculative in nature. The result can be seen most clearly from a time series perspective though a distributional approach also leads to broadly the same conclusions. Results are consistent with previous concerns raised over the excessive volatility of stablecoins (Ante et al., 2023; Briola et al., 2023; Hoang & Baur, 2021).

The layout of this paper is as follows. Section 2 lays out the methodology used. Empirical results are given in Section 3. Robustness checks are conducted in Section 4. Section 5 concludes.

2. Methodology

In this section we propose four classification methods for asset price returns:

(1) A method based on the Kolmogorov-Smirnov distance.
(2) A method based on the Cramér-von Mises distance.
(3) A GARCH-based method based on the supremum norm.
(4) A GARCH-based method based on the Euclidean norm.

Methods 1–2 thus derive from a distributional comparison. Methods 3–4 derive from a time series comparison.

2.1. Measuring distributional distance

A measure of the difference in distribution between two variables X and Y can be constructed as follows. Define the empirical CDF $F_n(x)$ as

$$F_n(x) = \frac{\text{No of observations} \leq x}{\text{Length of } x}.$$

Given two samples $X_1, X_2, \ldots X_n \sim F$ and $Y_1, Y_2, \ldots Y_m \sim G$ the Kolmogorov-Smirnov distance between the two distributions can be calculated as

$$D = \sqrt{\frac{nm}{n+m}} \sup_x \left(G_m(x) - F_n(x)\right). \tag{1}$$

As a robustness check an alternative measure of distributional distance can be obtained from the Cramér-von Mises distance. This involves more observations in the sample and is often thought to be more powerful than the Kolmogorov-Smirnov test in empirical applications. If Z_k denotes the pooled sample the Cramér-von Mises distance can be calculated in terms of the Euclidean distance between the two empirical CDFs as

$$D = \sqrt{\frac{nm}{n+m} \sum_{k=1}^{n+m} \left(F_n(Z_k) - G_m(Z_k)\right)^2}. \tag{2}$$

2.2. Measuring time series distance

Given the apparent ubiquity of the GARCH(1, 1) in financial econometrics (Hansen & Lunde, 2005) we can define a notion of distance between two financial time series as follows.[1]. Suppose that using e.g. forward selection (Fry & Burke, 2022) two sets of ARCH and GARCH parameters are estimated:

ARCH parameters $(\alpha_{1,0}, \ldots, \alpha_{1,p_1})$ and $(\alpha_{2,0}, \ldots, \alpha_{2,p_2})$

GARCH parameters $(\beta_{1,1}, \ldots, \beta_{1,q_1})$ and $(\beta_{2,1}, \ldots, \beta_{2,q_2})$.

By analogy with the Kolmogorov-Smirnov distance defined in (1) a notion of time series distance can be constructed via the supremum norm. Under the conventions that

$$\alpha_{i,j} = 0 \text{ if } j > p_i; \text{ and } \beta_{i,j} = 0 \text{ if } j > q_i,$$

define

$$x = (\alpha_{1,0}, \ldots, \alpha_{1,\max(p_1,p_2)}, \beta_{1,1}, \ldots, \beta_{1,\max(q_1,q_2)})$$

$$y = (\alpha_{2,0}, \ldots, \alpha_{2,\max(p_1,p_2)}, \beta_{2,1}, \ldots, \beta_{2,\max(q_1,q_2)}).$$

A time series distance can then be constructed as

$$\text{Distance} = \sup_i \{|x_i - y_i|\}. \tag{3}$$

By analogy with the Cramér-von Mises distance in Equation (2) a second time series distance can also be constructed based around the Euclidean norm using

$$\text{Distance} = \sqrt{\sum_{j=0}^{\max(p_1,p_2)} (\alpha_{1,j} - \alpha_{2,j})^2 + \sum_{j=1}^{\max(q_1,q_2)} (\beta_{1,j} - \beta_{2,j})^2}. \tag{4}$$

3. Empirical results

In this paper we compare the top-ten most highly capitalised cryptocurrencies: (Cardano, Binance Token, Bitcoin, Binance USD, Doge, Ethereum, Solana, USD Coin, USD Tether, and Ripple) with top major dollar-denominated national currency prices (Australian Dollar, Canadian Dollar, Swiss Franc, Chinese Yuan, Euro, GB Sterling, Hong Kong Dollar, Japanese Yen, South Korean Won, and New Zealand Dollar) and with ten leading tech stocks (Apple, Adobe, AMD, Amazon, Cisco, Dell, Google, Meta, Microsoft, Netflix). Daily price data was collected from Jan 1st 2020 to Sept 28th 2022. Cryptocurrency data is collected from coinmarketcap.com. This is broadly in line with recommendations in Vidal-Tomás (2022) following concerns raised in Alexander and Dakos (2020). Stock price data is collected from Yahoo finance. All prices are denominated in US dollars. We then used the methods outlined in Section 2 to compare cryptocurrencies with tech stocks and national currencies. Summary statistics for this data are shown in Table 1.

3.1. Distributional results

Results based on distributional measures of distance are shown in Tables 2-3. Both sets of results confirm previous suggestions of cryptocurrencies being an inherently speculative asset (Baeck & Elbeck, 2015; Selgin, 2015). Results suggest that unless a cryptocurrency is explicitly pegged to the US Dollar they are inherently speculative in nature. Only the stable coins Binance USD, USD Coin and USD Tether more closely resemble a conventional currency. In contrast, a better comparison for crypto assets would appear to be tech stocks. Summary statistics shown in Table 1 also suggests a similar conclusion.

The above notwithstanding concerns have been raised about the excessive volatility of stablecoins (Ante et al., 2023). A concern is that stablecoins may, unintentionally, increase speculative

Table 1. Summary statistics of collected data

Series	Mean	Max	Min	St. Dev	Kurtosis	Skewness	Jarque Bera
Cardano	0.003	0.279	−0.504	0.060	9.725	−0.327	1904.196
Binance Token	0.003	0.529	−0.543	0.058	22.291	−0.261	15532.37
Bitcoin	0.001	0.172	−0.465	0.040	23.095	−1.626	17282.50
Binance USD	−0.000	0.053	−0.058	0.000	126.871	−0.547	640019.0
Doge	0.003	1.516	−0.515	0.090	91.462	5.573	331570.7
Ethereum	0.002	0.231	−0.551	0.053	1.739	−1.378	8958.178
Solana	0.004	0.387	−0.465	0.079	6.535	−0.081	470.198
USD Coin	−0.000	0.042	−0.037	0.003	60.344	1.395	137475.6
USD Tether	0.000	0.053	−0.053	0.003	125.944	0.435	630464.2
Ripple	0.001	0.445	−0.551	0.064	17.232	−0.152	8451.637
Aus Dollar	−0.000	0.029	−0.032	0.007	4.585	−0.150	77.471
Can Dollar	−0.000	0.032	−0.030	0.004	7.592	−0.129	630.321
Swiss Franc	−0.000	0.028	−0.012	0.004	7.111	0.981	225.744
Chinese Yuan	−0.000	0.014	−0.012	0.003	6.726	−0.415	434.176
Euro	−0.000	0.016	−0.028	0.005	5.298	−0.429	179.321
GB Sterling	−0.000	0.029	−0.042	0.006	10.385	−0.927	1727.413
HK Dollar	−0.000	0.002	−0.001	0.000	9.755	6.287	1406.437
Japenese Yen	−0.000	0.022	−0.027	0.005	6.567	−0.334	392.390
Korean Won	−0.000	0.027	−0.021	0.005	5.129	0.104	136.377
NZ Dollar	−0.000	0.028	−0.037	0.007	4.591	−0.249	82.778
Apple	0.001	0.113	−0.138	0.023	7.519	−0.229	592.190
Adobe	−0.000	0.163	−0.184	0.027	11.024	−0.779	1917.892
AMD	0.000	0.153	−0.158	0.035	4.766	−0.015	89.529
Amazon	0.000	0.127	−0.151	0.024	7.306	−0.264	540.331
Cisco	−0.000	0.126	−0.148	0.020	14.514	−0.768	3873.939
Dell	0.000	0.135	−0.145	0.026	8.944	−2.125	1019.521
Google	0.000	0.090	−0.117	0.021	6.230	−0.179	303.234
Meta	−0.000	0.162	−0.306	0.030	21.531	−1.605	10154.05
Microsoft	0.001	0.133	−0.159	0.022	10.607	−0.348	1675.163
Netflix	−0.001	0.156	−0.433	0.034	46.692	−3.480	56194.85

trading in Bitcoin (Hoang & Baur, 2021). Stablecoins may also share the same vulnerabilities as other crypto assets. These include a propensity to crash, concerns over their practical usage as a medium of exchange and their ultimate vulnerability to self-fulfilling perceptions of intrinsic worth (Briola et al., 2023).

3.2. Time series results

The time series measures of distance examined in Section 3.2 require the order of the GARCH model to be estimated via forward selection (see e.g. Fry & Burke, 2022). Results are summarised in Table 4. Results for the time series measures of distance constructed are shown in Tables 5-6. When viewed from a time series perspective volatility fluctuations suggest only Bitcoin can be

Table 2. Suggested categorisation of cryptocurrencies based on Kolmogorov-Smirnov distance

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	AMD	0.104	Speculative asset
Binance Token	AMD	0.085	Speculative asset
Bitcoin	AMD	0.043	Speculative asset
Binance USD	Chinese Yuan	0.154	Currency
Doge	AMD	0.078	Speculative asset
Ethereum	AMD	0.100	Speculative asset
Solana	AMD	0.172	Speculative asset
USD Coin	HK dollar	0.184	Currency
USD Tether	HK dollar	0.180	Currency
Ripple	AMD	0.074	Speculative asset

Table 3. Suggested categorisation of cryptocurrencies based on Cramér-von Mises distance

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	AMD	1.327	Speculative asset
Binance Token	AMD	0.935	Speculative asset
Bitcoin	AMD	0.374	Speculative asset
Binance USD	Chinese Yuan	1.708	Currency
Doge	AMD	0.813	Speculative asset
Ethereum	AMD	1.106	Speculative asset
Solana	AMD	2.280	Speculative asset
USD Coin	Chinese Yuan	2.368	Currency
USD Tether	Chinese Yuan	2.244	Currency
Ripple	AMD	0.815	Speculative asset

Table 4. Order of the fitted GARCH models chosen using forward selection

Series	GARCH model chosen	Series	GARCH model chosen	Series	GARCH model chosen
Cardano	(1, 2)	Aus Dollar	(1, 1)	Apple	(1, 1)
Binance	(1, 1)	Can Dollar	(1, 1)	Adobe	(2, 1)
Bitcoin	(1, 1)	Swiss France	(0, 0)	AMD	(1, 1)
BUSD	(1, 0)	Chinese Yuan	(1, 0)	Amazon	(1, 1)
DOGE	(1, 1)	Euro	(1, 1)	Cisco	(1, 1)
Ethereum	(1, 1)	Sterling	(1, 1)	Dell	(1, 1)
Solana	(1, 1)	HK Dollar	(0, 0)	Google	(1, 1)
USDC	(1, 0)	Japanese Yen	(0, 0)	Meta	(1, 1)
USDT	(1, 0)	Korean Wong	(1, 1)	Microsoft	(1, 1)
Ripple	(1, 2)	NZ Dollar	(1, 1)	Netflix	(1, 1)

viewed as a genuine currency. Results thus reinforce wider concerns raised regarding the excessive volatility of stablecoins (Ante et al., 2023; Briola et al., 2023; Hoang & Baur, 2021).

Table 5. Suggested categorisation of cryptocurrencies based on the GARCH distance measure shown in Equation (3)

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	Cisco	0.3053	Speculative asset
Binance Token	Microsoft	0.025	Speculative asset
Bitcoin	Aus Dollar	0.024	Currency
Binance USD	Cisco	3.226	Speculative asset
Doge	Cisco	1.034	Speculative asset
Ethereum	AMD	0.004	Speculative asset
Solana	Meta	0.014	Speculative asset
USD Coin	Cisco	1.821	Speculative asset
USD Tether	Cisco	3.207	Speculative asset
Ripple	Cisco	0.185	Speculative asset

Table 6. Suggested categorisation of cryptocurrencies based on the GARCH distance measure shown in Equation (4)

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	Meta	0.437	Speculative asset
Binance Token	Microsoft	0.032	Speculative asset
Bitcoin	Aus Dollar	0.033	Currency
Binance USD	Cisco	3.239	Speculative asset
Doge	Cisco	1.062	Speculative asset
Ethereum	AMD	0.005	Speculative asset
Solana	Meta	0.015	Speculative asset
USD Coin	Cisco	1.845	Speculative asset
USD Tether	Cisco	3.220	Speculative asset
Ripple	Cisco	0.216	Speculative asset

4. Robustness checks

As a robustness check we repeat the same analysis but replaced the ten Fin Tech stocks with ten major stock indices. In particular the stock indices we analyse are the S&P 500, DJIA, Nasdaq, DAX, CAC 40,

Table 7. Suggested categorisation of cryptocurrencies based on Kolmogorov-Smirnov distance

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	Nasdaq	0.240	Speculative asset
Binance Token	Nasdaq	0.230	Speculative asset
Bitcoin	Nasdaq	0.157	Speculative asset
Binance USD	Chinese Yuan	0.154	Currency
Doge	Nasdaq	0.186	Speculative asset
Ethereum	Nasdaq	0.241	Speculative asset
Solana	Nasdaq	0.299	Speculative asset
USD Coin	HK dollar	0.184	Currency
USD Tether	HK dollar	0.180	Currency
Ripple	Nasdaq	0.193	Speculative asset

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Table 8. Suggested categorisation of cryptocurrencies based on Cramér-von Mises distance

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	Nasdaq	3.108	Speculative asset
Binance Token	Nasdaq	2.731	Speculative asset
Bitcoin	Nasdaq	1.920	Speculative asset
Binance USD	Chinese Yuan	1.708	Currency
Doge	Nasdaq	2.547	Speculative asset
Ethereum	Nasdaq	2.950	Speculative asset
Solana	Swiss Franc	2.950	Currency
USD Coin	Chinese Yuan	2.368	Currency
USD Tether	Chinese Yuan	2.244	Currency
Ripple	Nasdaq	2.606	Speculative asset

Table 9. Suggested categorisation of cryptocurrencies based on the GARCH distance measure shown in Equation (3)

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	Nasdaq	0.040	Speculative asset
Binance Token	Bel 20	0.031	Speculative asset
Bitcoin	Aus Dollar	0.024	Currency
Binance USD	CAC 40	3.453	Speculative asset
Doge	CAC 40	1.261	Speculative asset
Ethereum	Hang Seng	0.006	Speculative asset
Solana	NZ Dollar	0.044	Currency
USD Coin	CAC 40	2.048	Speculative asset
USD Tether	CAC 40	3.434	Speculative asset
Ripple	SSE	0.269	Speculative asset

Table 10. Suggested categorisation of cryptocurrencies based on the GARCH distance measure shown in Equation (4)

Cryptocurrency	Closest to	Distance	Most resembles
Cardano	Nasdaq	0.045	Speculative asset
Binance Token	Bel 20	0.033	Speculative asset
Bitcoin	Aus Dollar	0.033	Currency
Binance USD	CAC 40	3.495	Speculative asset
Doge	CAC 40	1.367	Speculative asset
Ethereum	Hang Seng	0.007	Speculative asset
Solana	NZ Dollar	0.045	Currency
USD Coin	CAC 40	3.476	Speculative asset
USD Tether	CAC 40	3.476	Speculative asset
Ripple	Nasdaq	0.321	Speculative asset

Nikkei, Hang Seng, SSE Composite Index, Shenzhen Index and Bel 20. Results for the distributional measures of distance are shown in Tables 7-8. Results for the time series measures of distance are shown in Tables 9-10. Results lead to broadly the same conclusions as Section 4 if the tech stocks are replaced by stock indices. Results again classify cryptocurrencies as primarily speculative assets with only Bitcoin and Solana seen as genuine currencies if time series measures of distance are used.

5. Conclusions

This paper undertakes a taxonomic analysis of leading cryptocurrencies based on traditional ways of analysing financial asset returns. We develop four new methods to classify cryptocurrencies based on either their distributional or their time series properties. From a distributional perspective unless pegged to the US Dollar cryptocurrencies more closely resemble a tech stock. However, time series measures more clearly classify cryptos as primarily speculative assets. The only exceptions are Bitcoin and possibly Solana. Results reinforce wider concerns raised in the literature regarding the excessive volatility of stablecoins (Ante et al., 2023; Briola et al., 2023; Hoang & Baur, 2021).

The implications of this study are that despite economic motivations to the contrary (Dowd, 2014) cryptocurrencies continue to be more of a speculative asset than a genuine currency (Baeck & Elbeck, 2015; Selgin, 2015). Stablecoins seem to share many of the vulnerabilities associated with other crypto assets (Briola et al., 2023). Results suggest that although Bitcoin seems to have achieved a degree of traction crypto investors should tread carefully.

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Note

1. Evidence of the sufficiency of low-order GARCH models for the data collected for this study is presented below in Table 4.

Disclosure statement

No potential conflict of interest was reported by the authors.

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