THE
RISK
PROTOCOL

THE NATURE OF THE BEAST

A STUDY OF CRYPTO VOLATILITY - PART I

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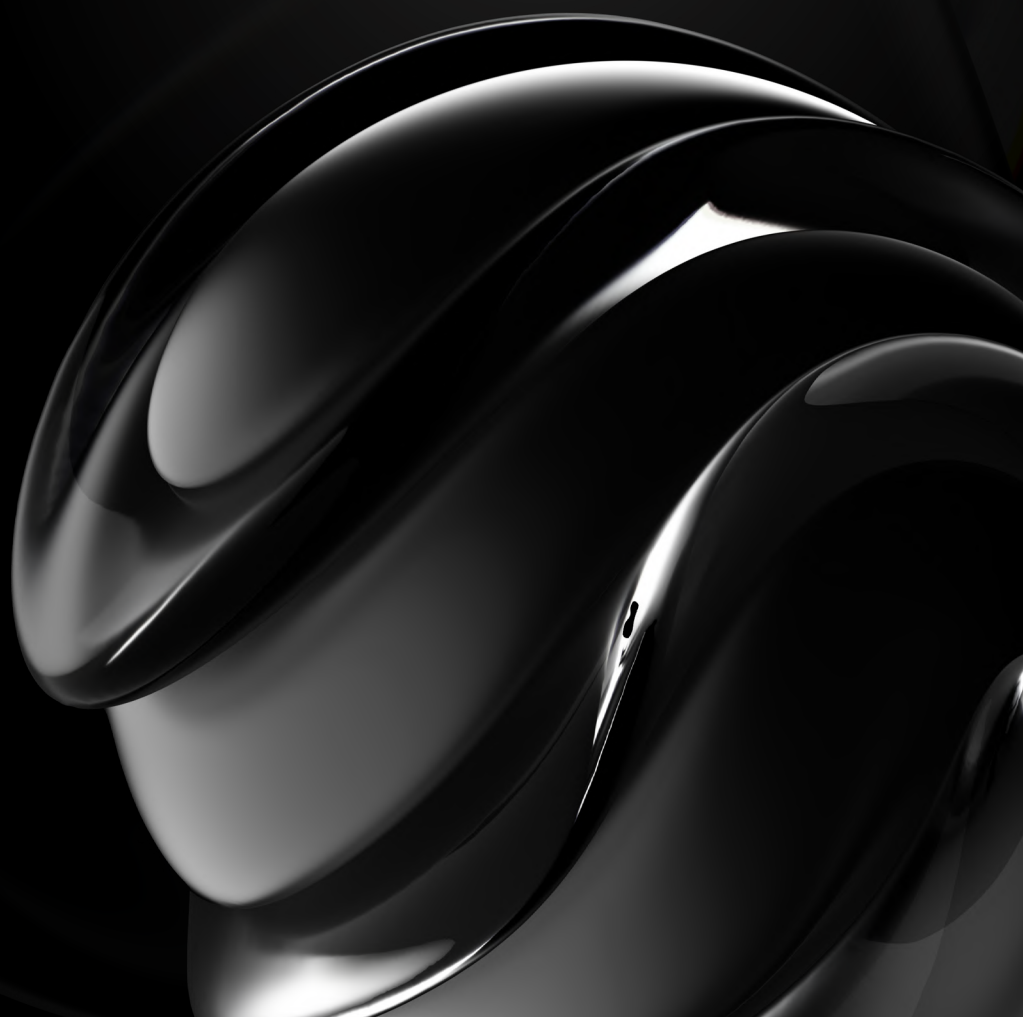


CONTENTS

Executive Summary

The Risk Protocol is a specialized investment platform that focuses on addressing some of the risks inherent in investing in cryptocurrencies. As we all know, there are many different types of investment risk including liquidity, volatility, interest rate, counterparty, operational, regulatory risk etc. Initially, at launch, our products shall be focused on the one risk that is most problematic for crypto – volatility. In this paper, we examine several aspects of volatility for the 50 largest cryptocurrencies. For instance, we study the standard deviation and variance of returns, the autocorrelation of absolute and squared returns, the beta of returns vis-à-vis Bitcoin, the leverage effect of cryptocurrency returns versus the standard deviation of returns and how calendar effects impact the magnitude of cryptocurrency price returns. As far as we know, this is the most exhaustive study done to date on cryptocurrency returns and volatility.

Using data and insights gleaned from this exercise, we have developed highly sophisticated statistical volatility models that have been empirically proven to provide more accurate forecasts of crypto volatility than either implied or realized volatility. Part II of this report, to be published in the near future, will focus on the design and development of these models and their initial results.

A primary motivation for undertaking this research is to be able to reliably forecast volatility. That is one of the critical inputs impacting pricing of certain very unique and sophisticated risk-managed investment products created by The Risk Protocol. Before one can forecast, one must first understand the properties and the attributes of the underlying returns distribution. However, we were surprised at how little is understood of crypto volatility. Industry participants are blindly applying known properties of equity market volatility to crypto. Not only that, popular lore has ascribed specific properties to crypto but precious little research has been done to date to either prove or disprove them. It is our hope that this research serves to better inform investors and advisors about this nascent sector and provides a solid foundation for further research initiatives.

Our study shows that most stylized facts associated with other financial returns are also exhibited in cryptocurrency returns. However, crypto's behavior is distinctly different in certain cases as illustrated in the summary findings below:

A. **Inconsistent Leverage Effect:** Equity markets exhibit a widely observed "leverage" effect, the phenomenon that an asset's volatility is negatively correlated to its returns. Typically, rising asset prices are accompanied by declining volatility, and vice versa. We did not observe such a consistent effect in our analysis of cryptocurrencies. We generally found that 1/3rd of our universe exhibited a leverage effect, 1/3rd exhibited an "anti-leverage" effect and 1/3rd was inconclusive. This has potentially significant implications. It means that one can't necessarily hedge long underlying crypto exposure by being long volatility. If the underlying crypto happens to be one that exhibits an anti-leverage effect, such a strategy would essentially double one's downside exposure instead of hedging it.

B. **Strong Persistent Calendar Effect:** We also found that cryptocurrencies exhibit significant calendar effects. Specifically, there are distinct and persistent "hour of the day" and "day of the week" patterns in cryptocurrency volatility. We found that intra-day volatility was persistently and significantly higher during hour 2 and hours 15 – 18 (UTC) each day. A similar analysis looking at daily returns across the week revealed that Saturdays and Sundays exhibited significantly lower volatility and volume relative

to weekdays. The lower volumes on weekends makes intuitive sense. However, one would ordinarily expect the lower volumes on weekends to lead to higher volatility -- our analysis indicates otherwise. We also found that US and Chinese holidays exhibited volatility patterns similar to weekends. These findings naturally have implications for crafting effective trading/investment strategies centered around optimal inter and intra-day periods for buying/selling volatility and entering or exiting trading positions.

C. **The Curious Case of LEO:** In looking at correlations among the top 50 cryptocurrencies, LEO (Unus Sed Leo) stands out as a confoundingly unique case. The average correlation among all the 50 currencies is 0.524 while Bitcoin and Ethereum have the highest correlation at 0.872. LEO has the lowest correlation with other cryptocurrencies across our universe. The average correlation between LEO and the 49 other cryptocurrencies is only 0.013, the maximum correlation is 0.03 and the minimum correlation is -0.014. So LEO is basically not correlated to any of the other cryptocurrencies in our universe. LEO, by way of quick background, is a utility token of centralized exchange Bitfinex and was issued through an IEO in 2019. Bitfinex is owned by iFinex, which is also the parent company of Tether. There have been reports in the past around inappropriate transfers between affiliated companies Bitfinex and Tether to cover losses at Bitfinex[1]. Tether of course has been the subject of consistent speculation regarding the adequacy and liquidity of its stablecoin reserves. Is it mere coincidence that LEO has the unique trading pattern it does? This issue bears further examination given the controversial past of both Bitfinex and Tether.

D. **Volatility is Predictable:** Our analysis reveals that while cryptocurrency returns themselves are not predictable using their own past, their magnitude, hence their volatility, is strongly predictable. Overall, the study shows that cryptocurrency volatility is similar to volatility patterns exhibited by other financial asset returns. However, they behave more like equities than currencies. The volatility has a long memory structure as shown by Ding, Granger and Engle in their 1993 paper for S&P 500 returns.

E. **Returns have Leptokurtic Distribution:** Unsurprisingly, cryptocurrency returns have a non-normal distribution and are fat-tailed with greater likelihood of extreme events occurring. As with most other financial asset returns, they exhibit the so-called leptokurtic property with fat tails. Out of the 50 cryptocurrencies analyzed, 40% have a negative skewness number. The standard deviations over the sample period are also very different for different cryptocurrencies. LEO has the lowest annualized standard deviation at 76% while MANA (Decentraland) has the highest at 338%. As a reference point, the annualized standard deviation over the past two decades is 20% for the S&P 500 and 25% for Nasdaq.

F. **Magnified Gain/Loss Asymmetry:** Cryptocurrencies exhibit gain/loss asymmetry, which refers to the observation that it usually takes less time for a financial instrument to drop a certain amount than it takes to move up by the same amount. This attribute of crypto is similar to broader equity markets and in contrast to FX exchange rates which exhibit greater symmetry in up/down moves.

G. **Increasingly Correlated with Broader Equity Markets:** In comparing returns against other asset classes, it is observed that prior to 2019, there was no significant correlation between BTC returns and broader stock market returns. However, for the past three years from 2020 to 2022, the return correlation has become very significantly positive, especially between BTC and Nasdaq.

1. See Section 3.2 for further details.

H. **Evidence of Negative Correlation to USD:** While there is little correlation between BTC and the Dollar Index for daily frequencies, the correlation gradually becomes significantly negative as one goes from daily to monthly data, and from monthly to annual. The annual return correlation between BTC and the Dollar Index reached a very significant -0.75 level. This lends credence to the popular narrative that over a longer horizon, if the US dollar weakens, one would expect BTC returns to be stronger with negative correlation to the dollar.

I. **One-way Volatility Spillover:** Finally, we found significant volatility spillover from the broader US stock market to crypto, especially in recent years. This is more pronounced for some of the more mature cryptocurrencies. Our hypothesis is that the spillover currently is unidirectional i.e. while volatility in traditional financial markets has an impact on crypto markets, volatility in crypto is self-contained and does not flow into traditional finance ("TradFi"). However, we could not statistically establish that there was no spillover from crypto to broader markets.

These findings have profound implications for risk managers, portfolio allocators, investors and traders as far as investing in cryptocurrencies is concerned.

For instance, the study suggests that constructing "diversified portfolios" of various crypto assets is harder to accomplish given the higher average correlations between crypto assets and their universally high correlation with Bitcoin. There is always the possibility that there are other tokens like LEO or CVX with little or no correlation with the broader universe of cryptocurrencies, but a broader analysis needs to be conducted to prove/disprove that hypothesis. Risk managers shall be similarly challenged to construct hedges by being long volatility. In TradFi, higher volatility is synonymous with market declines. However, this phenomenon, called leverage effect, is inconsistent within the crypto universe. It is applicable for some cryptocurrencies, the opposite is true for others and for the remainder, there is no statistically significant relationship. We also found that the volatility of crypto volatility is significantly higher than the "vol of vol" of other asset classes. That makes it more difficult to forecast, compounding the woes of risk managers.

From a trader's perspective, taking into account the calendar effects of crypto volatility would be a key data point in timing of trades. Our study reveals that there are specific times during the day and certain days in the week when volatility is markedly lower. A trader trying to build a large position would want to do it in a period of low volatility. Similarly a trader selling options would want to do so when volatility is observed to be higher and buy options in periods of low volatility.

Finally, from an allocator's perspective, the increasing correlation between cryptocurrencies and the broader equity markets presents a sticky problem. How much should they allocate to a category that adds volatility to the portfolio without getting much in the way of diversification benefits?

01 Introduction

When we first launched this research initiative at the end of April 2022, the crypto world looked very different. Bitcoin traded at $39,469 and Ethereum was at $2,922, both having come off highs of $69,000 and $4,815 just a few short months earlier in November, 2021. Terra was a top 10 token with a market cap of $32 billion. FTX was the darling of VCs and seemingly everywhere one looked.

And then volatility struck….

This report has its origins in our seemingly quixotic quest to tame crypto volatility. Recognizing the potentially radical impact of digital assets principles and technology on the financial services sector, we assembled a core team that is a unique balance of senior investments experience and crypto native talent. The team came together with a singular objective -- to build a sophisticated and enduring investments platform focused on a "risk-managed" approach to investing in digital assets. Each of us brings a very specific skillset to the equation and our reservoir of specialized expertise runs deep including deep investments industry knowledge, crypto native credentials, derivatives structuring and valuation, risk management, quantitative factor modeling and research, advanced econometrics, volatility analysis and forecasting, portfolio management and market microstructure & trading systems. Uniting us is the focus on risk management and quiet conviction in the sea change of opportunities heralded by digital assets.

As much as crypto natives revel in the untamable ethos of crypto, one of the primary factors holding back more mainstream adoption (and by extension growth of the sector) is the gut wrenching volatility. As we set about devising investment solutions that “managed” directional market risk and volatility, we were struck by how little was understood of crypto volatility. When examined at all, it was through the lens of traditional finance, making the grand assumption that the underlying nature of crypto returns was similar to traditional equity market returns. That assumption can have dangerous consequences, including if one tries to hedge crypto market downside by relying on known behavior of volatility vis-à-vis returns in equity markets (It turns out that not all cryptocurrencies have an inverse relationship with volatility. See “leverage effect” in Section 5).

Crypto, as we all know, is a very different beast. The initial step in developing any sophisticated risk-managed investment solution in crypto, must be to first examine the properties of crypto returns and volatility – we must first understand *the nature of the beast*.

02 Report Structure

This is the first half of a body of research that focuses on forecasting crypto volatility. Volatility forecasts are integral to the reliable pricing of derivative instruments. However, before one can forecast, one must first understand the properties and the attributes of the underlying distribution. This report focuses on the statistical properties of cryptocurrency returns. Part II expands on this work to build sophisticated statistical models for forecasting crypto volatility. In Part II, we also compare the effectiveness of our volatility forecasting vs. implied volatility and realized volatility, and convincingly demonstrate the superior performance of our volatility models. Part II will be published separately in a subsequent report.

Our universe, for this white paper, was the top 50 cryptocurrencies based on their market cap as of the end of April 2022[2]. All market data was sourced from Coin Metrics, a reputable crypto data vendor. Studies of other financial time series data have found at least the following "stylized facts" which seem to be common to a wide variety of markets and instruments (see Cont 2001):

A. **Fat Tails:** the (unconditional) distribution of returns exhibit large leptokurtosis. This represents a greater likelihood of extreme returns occurring than that implied by a normal distribution.

B. **Volatility Clustering:** the observation that large changes in price tend to be followed by large changes and small changes tend to be followed by small changes.

C. **Gain/Loss Asymmetry:** one observes large drawdowns in stock prices and stock index values but not equally large upward movements. This property is not true for currency exchange rates where there is a higher symmetry in up/down moves.

D. **Absence of Autocorrelations:** (linear) autocorrelations of asset returns are often insignificant, except for very small intraday time scales (~20 minutes) for which microstructure effects come into play. This implies that asset returns are usually not predictable using their own past.

E. **Slow Decay of Autocorrelation in Absolute or Squared Returns:** the autocorrelation function of absolute returns decays slowly as a function of the time lag. This is sometimes interpreted as a sign of long-range dependence which implies that asset return volatility is predictable even though the returns themselves might not be.

F. **Leverage Effect:** most measures of volatility of an asset are negatively correlated with the returns of that asset.

2. The top 50 cryptocurrencies were picked on the basis of a ranking of the largest cryptocurrencies on “Coinmarketcap.com” as of April, 2022. Stablecoins were excluded from the list.

These stylized facts are crucial for understanding the nature of cryptocurrency volatility and vital when managing cryptocurrency exposure and modeling or forecasting volatility. They also have practical implications for investors. The fact that crypto currency returns have fat tails means that large one-day price moves will happen with greater frequency. This can have significant implications for hedging and risk management. Knowledge of volatility clustering is important for traders -- a higher volatility trading day today will likely lead to higher-than-normal volatility over the near term. An understanding of the leverage effect is vital if the investor is hedging their crypto portfolio using volatility derivatives. As we shall show later in this report, cryptocurrencies do not universally exhibit the leverage effect; some exhibit it, others are inconclusive and yet others exhibit an anti-leverage effect. This has potentially significant implications. It implies that one can't necessarily hedge long underlying crypto exposure by being long volatility. If the underlying crypto happens to be one that exhibits an anti-leverage effect, such a strategy would essentially double one's downside exposure instead of hedging it.

In this paper, we systematically examine whether the above stylized facts, prevalent in traditional financial markets, are also exhibited in cryptocurrency returns. We study the above properties for the top 50 cryptocurrencies, but look at the two largest, BTC and ETH, in greater detail when comparing crypto with other asset classes. The findings in this report will inform us on the form of the statistical models we should use in predicting cryptocurrency volatility[3]. The remainder of this paper is organized as follows: Section 3 studies the return distributional properties related to stylized facts A to C; Section 4 studies the term structure of autocorrelations for BTC and ETH and compares those with that of other financial assets (stylized facts D and E); Section 5 studies the leverage effect (stylized fact F) in cryptocurrency volatility; Section 6 studies the calendar effect in cryptocurrency volatility, including hour of the day and day of the week effects as well as the impact of US and Chinese holidays on crypto volatility; Section 7 studies the impact of broader US stock market volatility on crypto volatility; and finally, Section 8 concludes the paper with the primary takeaways.

03 Cryptocurrency Returns Properties

In this section, we study the statistical properties of cryptocurrency returns and their cross-sectional correlation structure. We first look at the distributional properties of each cryptocurrency and the impact of outliers. We then do a cross-sectional correlation analysis to see the statistical grouping based on clustering analysis.

3. A separate subsequent Part II of this report examines the various models best suited for forecasting crypto volatility.

3.1 Universe and summary statistics

Table 1A shows the universe of 50 currencies in alphabetic order and each currency's inception time and data end time. We use Real-Time Reference Rates constructed by Coin Metrics[4] and extract data on an hourly cadence. Each currency's log returns is calculated as follows:

$$r_t = \ln(P_t / P_{t-1})$$

where P_t is the reference rate at hour *t*. Table 1A also shows the total number of observations (count), the mean, standard deviation, min, max, skewness and kurtosis of the log returns for each crypto currency. For purposes of this presentation, the mean and standard deviation numbers are annualized (We first calculate the hourly mean and standard deviation of the log return, then multiply each 24×365 = 8760 and then take $\sqrt{8760}$ = 93.59 to get the annualized mean and standard deviation. The minimum return can be less than -1 since we use log returns).

Table 1A. Summary Statistics – Raw Data

(All the return related data are in decimals. For example, AAVE has an annualized mean log return of 77.1%, an annualized standard deviation of 158.4%, an hourly minimum return of -41.5%, and an hourly maximum return of 19.8%.)

Asset	Inception Time	End Time	Count	Annualized Mean	Annualized Std. Dev.	Hourly Min	Hourly Max	Skewness	Kurtosis
AAVE	10/10/2020 9:00	4/28/2022 0:00	13551	0.771	1.584	-0.415	0.198	-1.21	38.89
ADA	12/1/2017 1:00	4/27/2022 23:00	38614	0.447	1.433	-0.659	0.655	0.19	191.59
ALGO	6/22/2019 1:00	4/27/2022 22:00	24981	-0.525	1.497	-0.217	0.206	-0.11	15.16
ATOM	4/23/2019 1:00	4/28/2022 0:00	26423	0.545	1.422	-0.361	0.254	-0.48	27.98
AVAX	9/23/2020 2:00	4/27/2022 23:00	13965	1.682	1.687	-0.285	0.196	0.03	13.19
AXS	11/5/2020 2:00	4/27/2022 23:00	12933	3.783	2.083	-0.374	0.435	1.06	29.02
BCH	7/28/2017 1:00	4/28/2022 0:00	41639	-0.204	1.626	-0.955	0.500	-5.21	339.08
BNB	7/15/2017 1:00	4/27/2022 22:00	41949	1.759	1.422	-0.585	0.265	-0.92	82.16
BSV	11/9/2018 1:00	4/28/2022 1:00	30384	-0.050	1.493	-0.473	0.395	-0.06	92.91
BTC	7/18/2010 4:00	4/27/2022 22:00	103242	1.137	1.402	-0.690	0.699	-0.06	265.74
CAKE	2/19/2021 2:00	4/28/2022 0:00	10390	-0.827	1.530	-0.296	0.144	-1.26	30.00
CRO	3/20/2019 1:00	4/27/2022 23:00	27238	0.577	1.268	-0.189	0.379	2.29	76.13
CVX	6/3/2021 2:00	4/28/2022 1:00	7895	0.699	2.606	-0.395	0.513	1.46	40.14
DOGE	1/23/2014 21:00	4/27/2022 23:00	72386	0.545	2.460	-0.845	0.807	0.15	84.51
DOT	8/20/2020 2:00	4/27/2022 23:00	14781	1.042	1.451	-0.385	0.180	-1.12	36.09
EGLD	9/4/2020 2:00	4/27/2022 23:00	14406	1.300	1.505	-0.279	0.146	-0.71	18.50
EOS	6/29/2017 1:00	4/28/2022 0:00	42335	0.229	1.517	-0.317	0.466	0.77	64.93
ETC	7/25/2016 1:00	4/27/2022 22:00	50469	0.611	1.593	-0.320	0.329	0.22	39.25
ETH	8/8/2015 7:00	4/27/2022 22:00	58911	1.022	1.941	-1.917	2.079	3.23	3348.56
FIL	10/16/2020 1:00	4/27/2022 23:00	13399	-0.924	1.322	-0.273	0.155	-1.03	30.67
FLOW	2/10/2021 6:00	4/28/2022 1:00	10603	-1.693	1.843	-0.280	0.182	-6.33	274.78
FTM	6/18/2019 1:00	4/27/2022 23:00	25078	1.258	1.957	-0.345	0.405	0.20	18.54

4. Coin Metrics produces the Coin Metrics Real-Time Reference Rates (the "Real-Time Reference Rates"), a collection of reference rates quoted in U.S. dollars and other currencies, published once per second, for a set of cryptocurrencies and fiat currencies. The Real-Time Reference Rates are calculated using a robust and resilient methodology that is resistant to manipulation and applies international best practices for financial benchmarks, including the International Organization of Securities Commissions' (IOSCO) Principles for Financial Benchmarks. See link for further details: https://docs.coinmetrics.io/market-data/methodologies/real-time-reference-rates-methodology

Asset	Inception Time	End Time	Count	Annualized Mean	Annualized Std. Dev.	Hourly Min	Hourly Max	Skewness	Kurtosis
FTT	7/30/2019 1:00	4/27/2022 21:00	24068	1.149	0.958	-0.158	0.226	0.25	26.13
GRT	12/18/2020 2:00	4/28/2022 1:00	11903	0.722	1.804	-0.316	0.259	0.47	20.30
HBAR	9/18/2019 1:00	4/27/2022 23:00	22870	0.190	1.771	-0.500	0.526	1.36	100.34
HNT	8/19/2020 2:00	4/28/2022 0:00	14806	1.373	1.737	-0.254	0.238	0.27	14.92
ICP	5/11/2021 1:00	4/27/2022 23:00	8317	-3.557	1.619	-0.254	0.270	0.04	21.22
LEO	5/21/2019 1:00	4/27/2022 22:00	25749	0.577	0.760	-0.211	0.191	2.83	152.93
LINK	9/29/2017 1:00	4/28/2022 0:00	40127	0.863	1.668	-0.306	0.637	0.62	24.20
LTC	4/1/2013 7:00	4/28/2022 0:00	79529	0.518	2.530	-0.133	0.340	0.26	3354.02
LUNA	2/25/2020 1:00	4/27/2022 22:00	19029	2.714	1.765	-0.271	0.438	0.16	29.45
MANA	8/25/2017 3:00	4/27/2022 23:00	40964	0.834	3.383	-2.384	2.365	-0.02	2949.12
MATIC	4/27/2019 1:00	4/27/2022 23:00	26326	1.811	1.808	-0.373	0.299	-1.13	74.67
MIOTA	6/13/2017 1:00	4/28/2022 1:00	42720	0.062	1.636	-2.958	2.826	-0.17	27.10
MKR	12/26/2017 12:00	4/28/2022 1:00	38005	-0.282	1.825	-0.680	0.304	-11.89	1034.76
NEAR	10/15/2020 2:00	4/27/2022 23:00	13437	1.549	1.693	-0.336	0.243	-0.04	12.01
RUNE	7/20/2020 9:00	4/27/2022 23:00	15518	1.518	1.909	-0.368	0.365	-0.04	6.27
SAND	8/15/2020 1:00	4/27/2022 23:00	14773	2.191	2.000	-0.299	0.168	2.62	94.65
SHIB	5/11/2021 1:00	4/27/2022 23:00	8446	-0.359	1.869	-0.219	0.193	-0.01	31.43
SOL	4/11/2020 2:00	4/27/2022 22:00	17924	2.256	1.717	-0.367	0.707	0.30	13.73
THETA	1/17/2018 1:00	4/27/2022 23:00	37486	0.657	1.687	-0.356	0.223	1.57	78.52
TRX	10/7/2017 1:00	4/27/2022 21:00	39932	0.639	1.728	-0.229	0.268	0.56	82.84
UNI	9/18/2020 1:00	4/28/2022 0:00	14072	0.541	1.496	-0.327	0.710	-0.14	16.25
VET	7/14/2018 2:00	4/27/2022 23:00	33213	0.202	1.520	-0.576	0.497	0.33	25.41
WAVES	11/16/2016 1:00	4/28/2022 0:00	47735	0.693	2.787	-0.274	0.187	0.31	94.63
XLM	8/12/2014 1:00	4/27/2022 22:00	67581	0.493	1.749	-0.265	0.412	0.38	62.30
XMR	5/20/2014 1:00	4/27/2022 22:00	69597	0.588	1.605	-0.673	0.947	0.16	26.75
XRP	8/15/2014 17:00	4/27/2022 22:00	67493	0.558	1.935	-0.174	0.235	2.83	3368.04
XTZ	6/24/2017 1:00	4/28/2022 0:00	42455	-0.076	2.345	-0.594	0.641	-3.00	208.01
ZEC	10/29/2016 0:00	4/28/2022 0:00	48168	-0.808	1.661	-0.367	0.335	2.39	176.43

Unsurprisingly, the cryptocurrencies studied were found to have non-normal distributions with fat tails.

For a standard normal distribution, the skewness is zero and the kurtosis is 3. The huge kurtosis numbers in Table 1A show, not surprisingly, that cryptocurrency returns are not normal. As most other financial asset returns, they exhibit the so-called leptokurtic property with fat tails (stylized fact A). Out of 50 currencies, 21 of them have a negative skewness number. The sample standard deviations are also very different for different currencies. LEO has the lowest standard deviation at 76% while MANA has the highest at 338%. While these statistics are calculated from different samples, they can still give us a sense as to the magnitude of the volatility.

The min and max columns reveal that the maximum hourly gain and loss can be substantially different. For some currencies, such as BCH, MATIC, BNB, AAVE and DOT, the maximum hourly losses experienced are much larger than the maximum hourly gains they experienced. Yet for some other currencies, such as THETA, SAND, KLAY, ZEC, WAVES and LEO, the maximum hourly gains experienced are much larger than their maximum hourly losses.

Figures 1A and 1B show the log prices and log returns for Bitcoin and Ethereum, the two cryptocurrencies most synonymous with crypto. We can see that the prices steadily grow over time, but the returns can be very random in nature. It can be seen that large (small) returns are more likely to be followed by large (small) returns of either sign, i.e., volatility tends to cluster (stylized fact B).

Figure 1A. Log Prices for Bitcoin and Ethereum

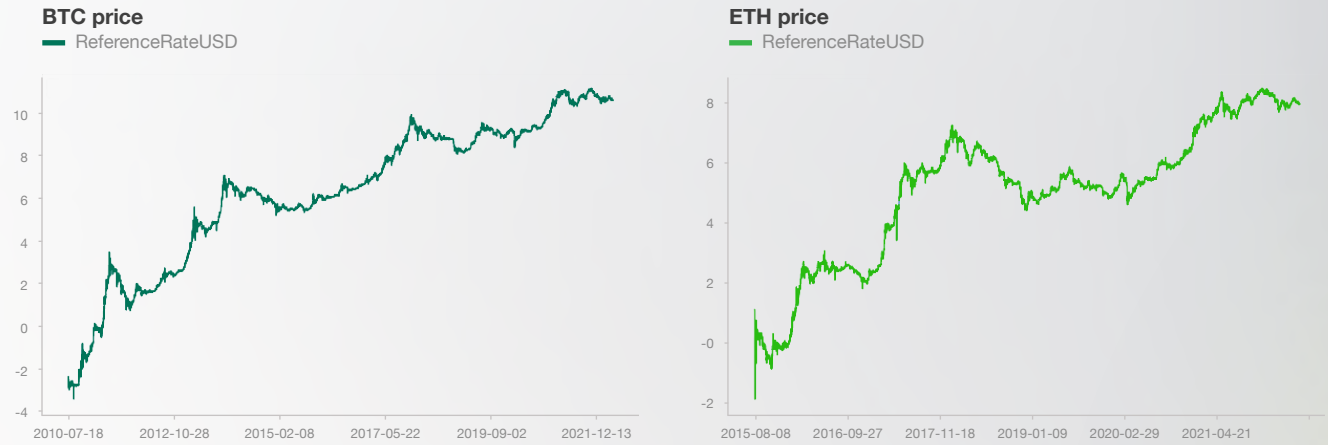
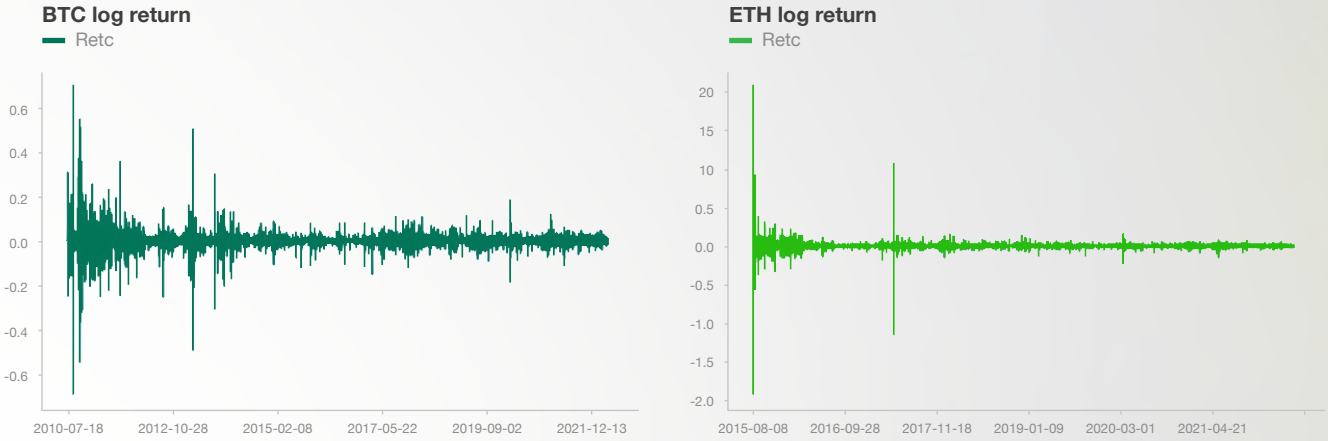


Figure 1B. Log Returns for Bitcoin and Ethereum



It can be seen from the return plots that the early days of existence can be quite erratic, possibly due to thin trading volumes, price manipulation or data errors. Those days at the beginning cannot be considered as indicative of the future return path, which is our main interest. As a result, data for those early days must be cleaned before we can do any meaningful statistical analysis and modelling. In our analysis, we exclude some early day outliers for certain currencies where we determined that these early days were likely not representative of subsequent days. The adjusted starting date for returns data we used in our analysis can be found in Table 1C.

One big shock to the cryptocurrency market occurred on May 19, 2021. Market pundits hypothesized that one of the main factors driving the selloff was the Chinese government banning financial and payment institutions from providing cryptocurrency services. Bitcoin and Ethereum posted their largest one-day drop in more than a year, with losses in the market capitalization for the entire cryptocurrency sector approaching $1 trillion. The returns data for May 19, 2021, at 1:00PM first posted a big drop from the previous hour and then recovered about a third of the losses by 2:00PM. This caused a large first order negative return autocorrelation for most cryptocurrencies if one carries out an ACF analysis. However, the negative autocorrelation drops substantially or becomes negligible after these two data points are excluded.

Table 1B in Appendix A shows the actual returns during these two hours for each cryptocurrency. For instance, it can be seen that BSV and XTZ initially dropped 47.3% and 43% respectively at 1pm. They subsequently recovered 14.5% and 30.4% respectively in the next hour. So exogenous shocks such as government regulation can cause price (volatility) spikes up and down with no warnings. Since this is a one-time unpredictable shock, we set the returns for all assets to zero for these two hours for our preliminary analysis, in order to study the return behavior of non-intervened data. Later, when we do volatility modelling & forecasting (in Part II of this report), we will add these two return numbers back in.

In addition, the price for ETH dropped from 94.43 at hour 22:00 on May 7, 2017 to 30 at hour 23:00, and then recovered to 87.4 on May 8, 2017 at hour 00:00. This is very likely a data error or manipulation. The same thing happened to LTC on October 6, 2014. The price dropped from 3.8199 at hour 13:00 to 0.6497 at hour 14:00 and then recovered to 3.9272 at hour 15:00. We set the returns for these two events to zero as well, to exclude the abnormal impact for these two cryptocurrencies. Finally, we trimmed hourly returns that are outside a band of -30% to +30%in order to reduce the impact of a few large but legitimate return outliers. This only impacts 19 out of the 50 cryptocurrencies we studied with a total of 40 such observations (the last column in Table 1B in Appendix A shows the count for the number of instances when the absolute hourly return is larger than 30% for each currency).

Table 1C shows the summary statistics for the final cleansed data. It can be seen that the large kurtosis numbers in Table 1A are all gone. So, the extreme leptokutic phenomenon is mostly owing to some extreme events or possible data errors. After we cleanse the data, we can see that the kurtosis numbers are more comparable across cryptocurrencies even though they are still very much non-normal. We will use the cleansed data as described in Table 1C for the analysis that follows in this white paper.

Table 1C. Summary Statistics – Cleansed Data

Asset	Inception Time	End Time	Count	Mean	Std. Dev.	Skewness	Kurtosis
AAVE	10/20/2020 0:00	4/28/2022 0:00	13321	1.130	1.515	0.02	6.03
ADA	1/11/2018 0:00	4/27/2022 23:00	37632	0.039	1.251	-0.01	13.49
ALGO	6/22/2019 2:00	4/27/2022 22:00	24981	-0.510	1.488	-0.07	13.91
ATOM	5/1/2019 0:00	4/28/2022 0:00	26233	0.611	1.383	-0.20	13.80
AVAX	9/23/2020 3:00	4/27/2022 23:00	13965	1.770	1.668	0.28	8.96
AXS	11/5/2020 3:00	4/27/2022 23:00	12933	3.763	2.032	0.97	14.07
BCH	9/1/2017 0:00	4/28/2022 0:00	40801	-0.102	1.302	-0.02	26.47
BNB	4/1/2019 0:00	4/27/2022 22:00	26951	1.044	1.040	-0.86	27.88

Asset	Inception Time	End Time	Count	Mean	Std. Dev.	Skewness	Kurtosis
BSV	1/1/2019 0:00	4/28/2022 1:00	29114	0.023	1.268	0.56	50.27
BTC	11/1/2014 0:00	4/27/2022 22:00	65639	0.643	0.803	-0.51	30.81
CAKE	2/19/2021 3:00	4/28/2022 0:00	10390	-0.748	1.525	-1.23	30.02
CRO	3/20/2019 2:00	4/27/2022 23:00	27238	0.565	1.256	1.71	56.96
CVX	6/3/2021 3:00	4/28/2022 1:00	7895	0.395	2.529	0.69	18.98
DOGE	1/1/2015 0:00	4/27/2022 23:00	64176	0.861	2.139	0.34	12.04
DOT	8/20/2020 3:00	4/27/2022 23:00	14781	1.240	1.419	-0.09	11.52
EGLD	9/4/2020 3:00	4/27/2022 23:00	14406	1.381	1.485	-0.41	12.53
EOS	8/1/2017 0:00	4/28/2022 0:00	41545	0.095	1.340	-0.19	18.00
ETC	9/1/2016 0:00	4/27/2022 22:00	49559	0.588	1.513	0.10	29.33
ETH	7/1/2016 0:00	4/27/2022 22:00	51047	0.961	1.071	-0.30	20.82
FIL	10/16/2020 2:00	4/27/2022 23:00	13399	-0.786	1.303	-0.52	21.69
FLOW	3/1/2021 0:00	4/28/2022 1:00	10154	-1.020	1.440	0.66	13.87
FTM	6/18/2019 2:00	4/27/2022 23:00	25078	1.319	1.940	0.22	12.21
FTT	7/30/2019 2:00	4/27/2022 21:00	24068	1.188	0.953	0.40	24.51
GRT	12/18/2020 3:00	4/28/2022 1:00	11903	0.763	1.769	0.68	12.68
HBAR	11/1/2019 0:00	4/27/2022 23:00	21816	0.606	1.558	1.03	28.47
HNT	8/19/2020 3:00	4/28/2022 0:00	14806	1.458	1.724	0.43	12.93
ICP	8/1/2021 0:00	4/27/2022 23:00	6480	-1.395	1.342	-0.36	13.96
LEO	5/21/2019 2:00	4/27/2022 22:00	25749	0.573	0.754	1.98	108.86
LINK	9/29/2017 2:00	4/28/2022 0:00	40127	0.859	1.655	0.45	16.20
LTC	4/1/2014 0:00	4/28/2022 0:00	70777	0.273	1.141	0.14	24.78
LUNA	2/25/2020 2:00	4/27/2022 22:00	19029	2.817	1.751	0.46	24.44
MANA	8/1/2018 0:00	4/27/2022 23:00	32784	0.777	1.505	0.94	22.89
MATIC	4/27/2019 2:00	4/27/2022 23:00	26326	1.987	1.769	0.45	19.76
MIOTA	6/13/2017 2:00	4/28/2022 1:00	42720	0.090	1.626	-0.04	24.16
MKR	4/1/2018 0:00	4/28/2022 1:00	35714	0.303	1.498	0.30	33.25
NEAR	10/15/2020 3:00	4/27/2022 23:00	13437	1.709	1.675	0.30	6.84
RUNE	7/20/2020 10:00	4/27/2022 23:00	15518	1.533	1.896	-0.01	5.10
SAND	8/15/2020 2:00	4/27/2022 23:00	14773	2.043	1.910	0.73	12.29
SHIB	5/11/2021 2:00	4/27/2022 23:00	8446	-0.158	1.826	0.64	21.04
SOL	4/11/2020 3:00	4/27/2022 22:00	17924	2.284	1.706	0.36	12.55
THETA	1/17/2018 2:00	4/27/2022 23:00	37486	0.603	1.649	0.23	14.95
TRX	4/1/2018 0:00	4/27/2022 21:00	35710	0.186	1.130	0.04	25.83
UNI	9/18/2020 2:00	4/28/2022 0:00	14072	0.604	1.474	0.13	9.86
VET	7/14/2018 3:00	4/27/2022 23:00	33213	0.202	1.505	0.13	14.82
WAVES	4/1/2018 0:00	4/28/2022 0:00	35713	0.414	1.359	0.71	20.79
XLM	8/12/2014 2:00	4/27/2022 22:00	67581	0.505	1.720	0.36	28.16
XMR	8/1/2014 0:00	4/27/2022 22:00	67847	0.593	1.434	0.17	15.84
XRP	1/1/2015 0:00	4/27/2022 22:00	64175	0.399	1.392	0.67	43.92
XTZ	8/1/2017 0:00	4/28/2022 0:00	41545	0.197	1.850	-0.41	19.34
ZEC	1/1/2018 0:00	4/28/2022 0:00	37873	-0.227	1.240	-0.17	22.65

Gain/loss asymmetry (stylized fact C) refers to the observation that it usually takes less time for a financial instrument to drop a certain amount than it takes to move up by the same amount. See, for example, Cont (2001) and Jensen et al. (2018) for context. Table 1D shows the gain/loss asymmetry phenomenon for BTC and ETH. We set the drawdown threshold value to be 80%. It can be seen that from 2011 to the present, BTC prices dropped by more than 80% from the previous peak 3 times. Each time it took twice as long for the price to get back to the previous peak (relative to the time it took to drop from the previous peak to the previous trough). The same holds true for ETH which has dropped by more than 80% from the previous peak once.

Table 1D. Gain/Loss Asymmetry for BTC and ETH

	Peak Day	Peak Price	Trough Day	Trough Price	Recover Day	Recover Price	Draw -down	Peak Trough Duration	Recover Duration
BTC									
1	6/8/2011 18:00	31.6	11/19/2012:00	2.02	2/28/2013 1:00	32.76	-0.936	3920	11207
2	11/30/2013 4:00	1161	11/14/2015 23:00	175	2/23/2017 19:00	1166.3	-0.849	9859	18500
3	12/17/2017 23:00	19690	12/14/2018 22:00	3157.06	12/1/2020 0:00	19714	-0.840	8687	17210
ETH									
1	1/13/2018 21:00	1418.61	12/15/2018 16:00	81.27	1/25/2021 1:00	1457.6	-0.943	8059	18513

3.2 Cryptocurrency returns correlations and clustering analysis

In order to study how correlated the 50 cryptocurrencies are, we calculate the cross-correlations of all pairs of cryptocurrencies and further conduct a clustering analysis. The common sample size we use is from 8/1/2021 0:00 to 4/27/2022 23:00[5] with a total of 6480 hourly observations. Among all the currencies, Bitcoin and Ethereum have the largest correlation at 0.872. On the other hand, LEO has the lowest correlations with other cryptocurrencies across the universe. The average correlation between LEO and 49 other currencies is only 0.013, the maximum correlation is 0.03 and the minimum correlation is -0.014. So LEO is basically not correlated to other currencies in our universe. The average correlation among all the 50 currencies is 0.524.

As a comparison, we randomly picked 40 US stocks from different sectors/industries and calculated return correlations among them. The maximum correlation is only 0.78, the minimum correlation is -0.126, and the average correlation is 0.346. So in general, and not surprisingly, cryptocurrencies have higher correlations with other cryptocurrencies than US equities have amongst each other.

5. 8/1/2021 0:00 to 4/27/2022 23:00 is the longest common sample that includes all 50 cryptocurrencies.

Figure 2A shows the correlations between Bitcoin, Ethereum, LEO and other cryptocurrencies. Since Bitcoin and Ethereum are highly correlated, the correlation structure of these two cryptocurrencies with other cryptocurrencies is very similar. On the other extreme, LEO has almost no correlation with any of the other top 50 cryptocurrencies in our universe. The currency that has the next lowest correlation with other currencies is CVX. Its correlation with Bitcoin is only 0.26 and the average correlation with the other 49 cryptocurrencies is only 0.21. Why that is the case for LEO and CVX bears further examination. However, it appears that with their exceptionally low correlations with the other cryptocurrencies, LEO and CVX can potentially add some diversification benefit when constructing cryptocurrency portfolios.

Figure 2A. Correlations Between Bitcoin, Ethereum, LEO and Other Currencies

(The correlation calculated in this chart uses the longest common sample available for the 50 cryptocurrencies. The data sample starts from 8/1/2021 0:00 and ends at 4/27/2022 21:00 with 6480 total observations)

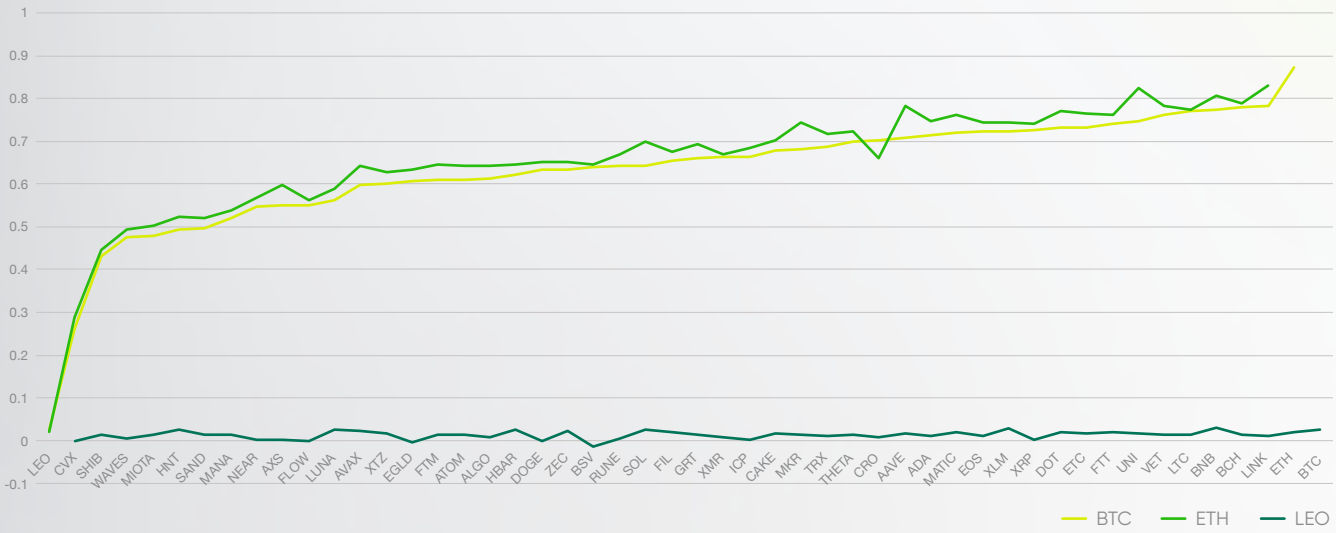
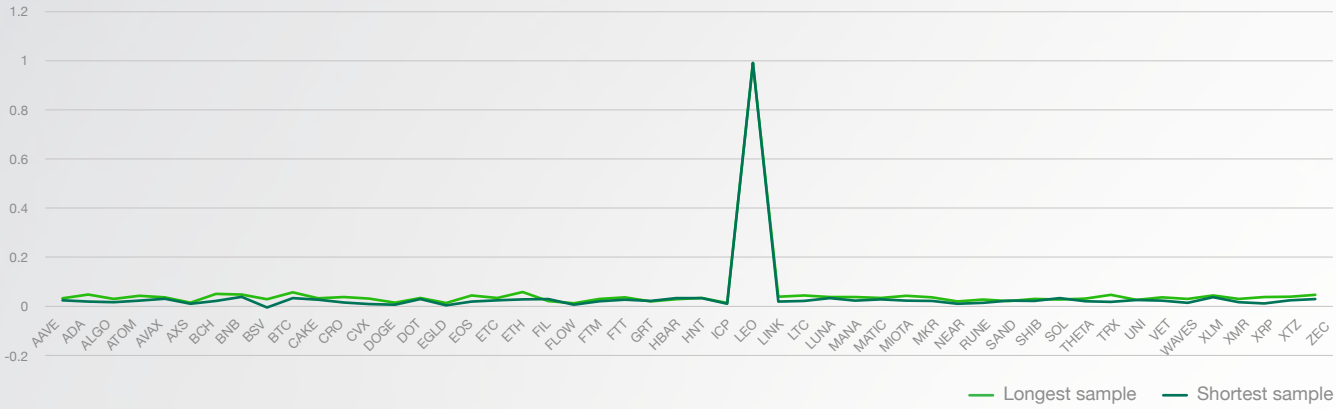


Figure 2B. Correlations Between LEO and Other Currencies Using Different Samples

(The shortest sample correlation is the same as in Figure 2A. For the longest sample correlation, the sample starts from either LEO's start date in Table 1C which is 5/21/2019 2:00, or the correlated currency's start date in Table 1C, whichever is later. The samples end at 4/27/2022 22:00.)



LEO's extremely low correlations with the other cryptocurrencies stands out as a very unique case. Since the correlations calculated in the above analysis use common samples for all the pairs, the sample size is by definition constrained to be the shortest sample available from the universe. In order to see if our observation reflects reality across longer time periods, we recalculated the correlations using the longest available pairwise samples (as opposed to common samples for all 50 cryptocurrencies). The result is shown in Figure 2B. It is evident that the general conclusion does not change. LEO appears to be a very unique cryptocurrency that has almost no correlation with the other currencies in our research universe. To provide some background, LEO is a utility token of centralized crypto exchange, Bitfinex. Bitfinex is owned by iFinex, which is also the parent company of Tether, the largest stablecoin issuer in crypto. There have been reports in the past about Bitfinex potentially using Tether's reserves to cover $850 million in losses at Bitfinex[6]. LEO was launched in 2019 via an IEO (Initial Exchange Offering) and reportedly raised $1 billion. It offered holders discounts on transaction fees at Bitfinex and also promised token buybacks equivalent to 27% of revenues on a quarterly basis[7]. The LEO whitepaper further mentions "repayment of indebtedness and other recapitalization activities" as a potential use of proceeds, making it likely that a decent portion of the $1 billion raised could go towards covering lost funds. The token also offered investors the ability to participate in the recovery of certain funds. Given the rather colorful past of Bitfinex and its association with Tether, which has had recurring concerns regarding 1:1 backing of the Tether issued, it is certainly curious that LEO should display the trading patterns it does. While beyond the scope of this report, further inquiry into the curious case of LEO might yield interesting results.

Why LEO has almost no correlation with any of the other cryptocurrencies bears further examination.

Figure 3A lists a dendrogram illustrating cryptocurrency clustering analysis using the longest available common sample data (common across all 50 cryptocurrencies) from 8/1/2021 0:00 to 4/27/2022 21:00, with 6480 total observations. A dendrogram is a branching diagram that represents the degree of similarity among a group of entities. Each branch is called a clade. The terminal end of each clade is called a leaf. The arrangement of the clades tells us which leaves are most similar to each other. The length of the branch points indicates how similar or different they are from each other: the greater the length, the greater the difference. Here we use a dendrogram to represent the relationships between any two cryptocurrencies, using the return correlation to measure their similarity to each other.

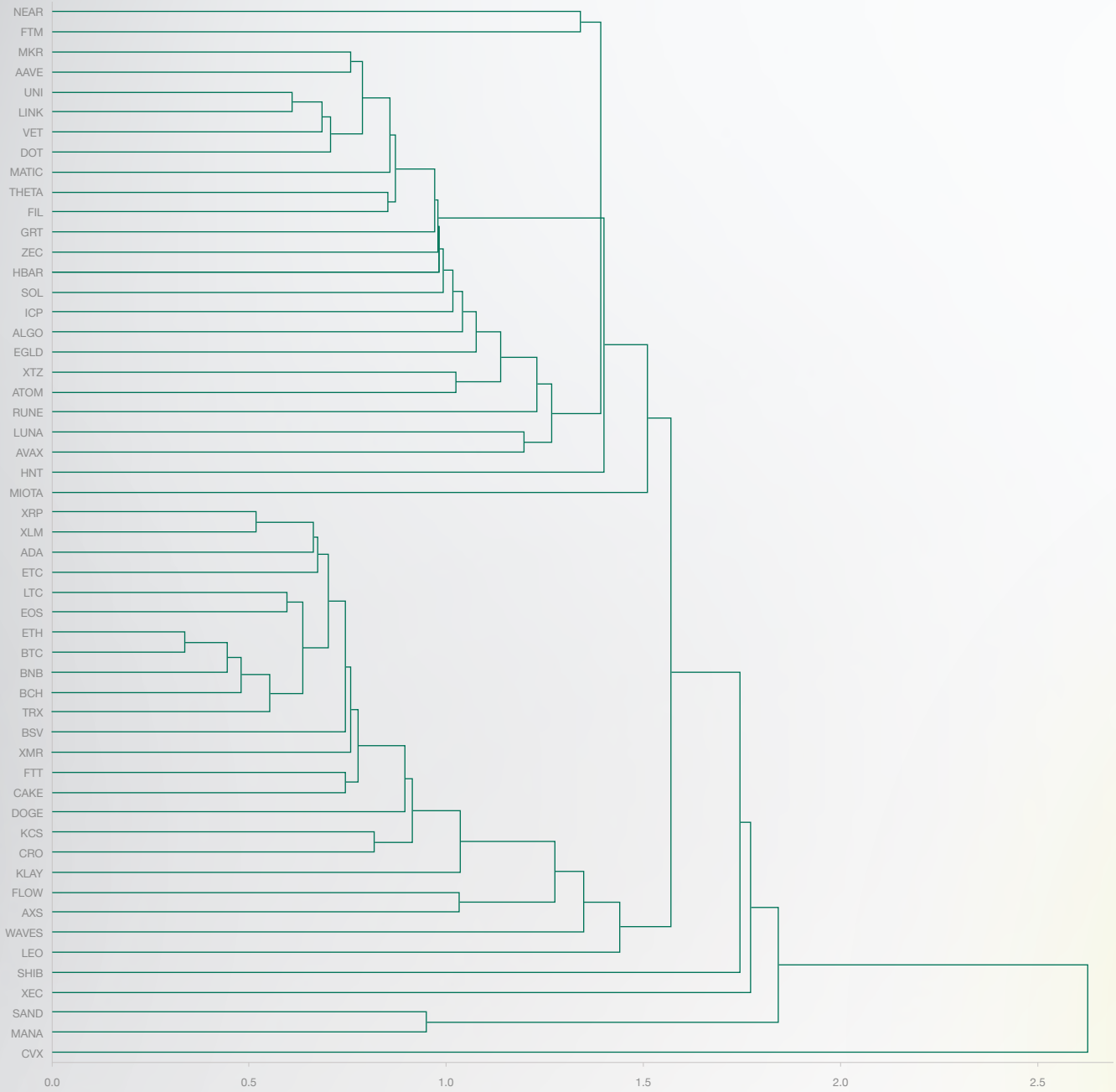
It can be seen that CVX, MANA, SAND, SHIB and LEO are located at the lower part of the dendrograms and are a distinct group, very different from other cryptocurrencies. It can also be seen that (BTC, ETH, BNB, BCH, TRX, LTC, EOS) are clustered in another group and (XRP, XLM, ADA, ETC), (FLOW, AXS), (MKR, AAVE, UNI, LINK, VET, DOT), (THETA, FIL) are the other clustered groups.

6. https://www.wsj.com/articles/bitfinex-used-tether-reserves-to-mask-missing-850-million-probe-finds-11556227031 & https://en.wikipedia.org/wiki/Bitfinex
7. https://messari.io/report/bitfinex-s-leo

Figure 3A. Clustering Analysis of 50 Cryptocurrencies

(The common sample return data used for this analysis is from 8/1/2021 0:00 to 4/27/2022 21:00 with 6480 total observations)

Dendrogram

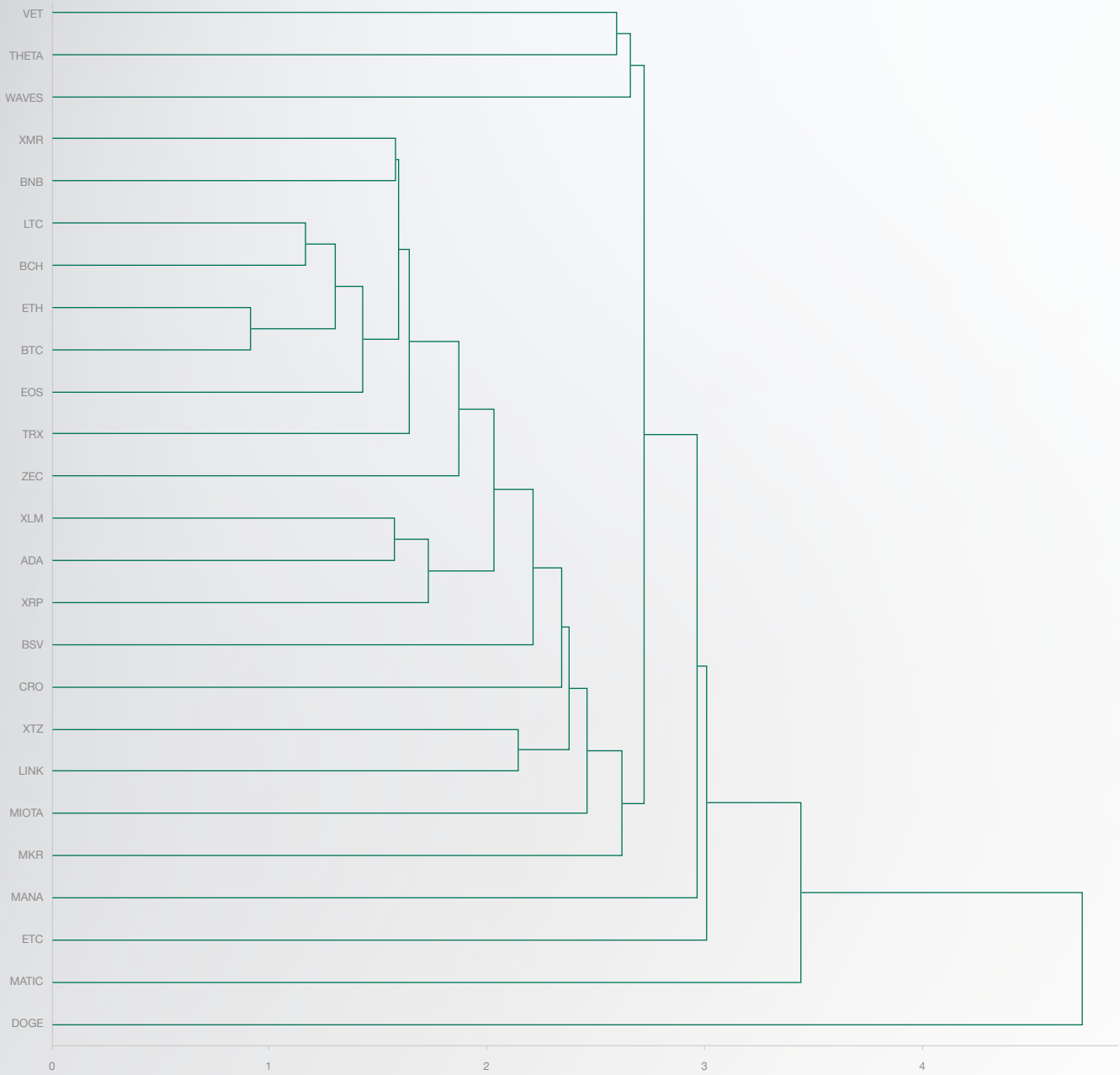


The small sample size might not give us a reliable picture. To run a more robust analysis, we conducted a similar clustering analysis using a sub-universe of 25 currencies with the longest histories. The result is shown in Figure 3B. It can be seen that the major clusters did not change. However, currencies like DOGE, MATIC and ETC do have some changes in clustering pattern with a longer sample. Overall, the clustering properties are quite similar across the different samples.

Figure 3B. Clustering Analysis of 25 Longest Sample Cryptocurrencies

(The common sample return data used for this analysis is from 4/27/2019 2:00:00 to 4/27/2022 21:00 with 26,324 total observations)

Dendrogram

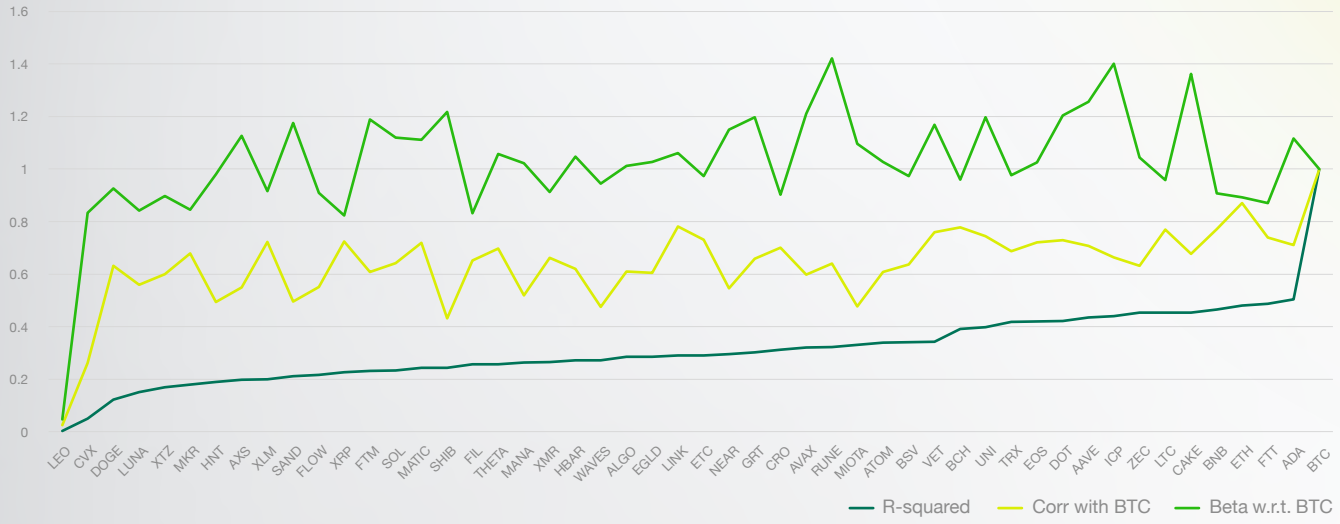


Finally, we ran a CAPM type regression of each individual cryptocurrency's returns on BTC returns to study the dependence structure of individual currencies on Bitcoin, the oldest and most prominent cryptocurrency. Figure 3C shows the regression beta, R-squared and the correlation for each cryptocurrency. The regression beta tells us the systematic risk of the currency relative to BTC; a beta higher than 1.0 indicates that the corresponding cryptocurrency is more volatile than BTC. Mathematically, a cryptocurrency's beta with respect to BTC equals its correlation with BTC times its volatility, divided by BTC's volatility. Not surprisingly, LEO has the lowest beta among all the currencies since it has the lowest volatility and the lowest correlation with BTC. The betas for other currencies range from 0.82 to 1.42 and are all higher than the correlations with BTC. This implies that all the other cryptocurrencies have higher volatility than BTC, a fact corroborated by Table 1C.

The regression R-squared are relatively small which means only a small portion of each cryptocurrency's return variance can be explained by BTC. The R-squared for the cryptocurrencies on the right-hand side of the graph are higher than those on the left side of the graph indicating that knowing BTC returns gives more information about the returns of the cryptocurrencies on the right-hand side than on the left.

Figure 3C. Cryptocurrency Betas with Respect to Bitcoin[8]

(The correlation numbers here are the same as in Figure 2A's yellow line. The sample used for the beta calculation starts from the inception time for each currency as listed in Table 1C and ends at 4/27/2022 21:00)



3.3 A Comparison with other financial assets

In order to get a sense of the similarities and differences between cryptocurrency returns and returns of other financial assets, we calculated the daily log return distributional parameters for BTC, ETH, S&P 500, NASDAQ, GLD (SPDR Gold ETF) and U.S. Dollar Index (presented in Table 2A). The sample period is from 9/17/2014 to 8/31/2022, with a total of 2003 days of observations. The only exception is ETH, which is from 11/9/2017 to 8/31/2022 with 1209 days of observations.

Tables 2A shows the basic statistics of daily log returns for BTC, ETH, S&P 500, NASDAQ, Gold (GLD) and U.S. Dollar Index. The following observations can be made from the table:

1) The cryptocurrency returns (BTC and ETH) are closer to Nasdaq returns than to S&P 500 returns, with similar skewness and kurtosis numbers.

2) The daily minimum returns are larger than the daily maximum returns (in absolute magnitude) across all the asset classes, confirming the "gain/loss asymmetry" stylized fact we had discussed earlier. This asymmetry is more severe in BTC and ETH returns relative to the other returns. For example, the magnitude of the minimum return for BTC is more than twice as large as the magnitude of the maximum return, while for S&P 500 and Nasdaq they are only 40 to 50% larger.

3) Cryptocurrencies are much riskier than the other asset classes but their returns are also much higher.

8. Since cryptocurrencies trade continuously and the ones we study in this paper are the 50 largest with sufficient trading volume over the time sample analyzed, the asynchronous trading issue that exists for international equities or thinly traded stocks is insignificant in our case. So methods like Dimson's adjustment (see Dimson 1979) are not employed in our estimation of correlations and betas.

Table 2A. Daily Return Statistics Comparison

(The daily data used in this table is aligned with the US stock market hours. As such, for BTC and ETH, the daily return on Monday is actually a three-day return, from the close on Friday to the close on Monday since they are continuously traded. The same holds for NYSE holidays. All the returns related data (mean, median, maximum, minimum and std. dev.) are in decimals. For example, BTC has a daily mean log return of 0.189%, the annualized log return is then calculated as 250 x 0.189% = 47.63% and the simple annualized arithmetic return is $e^{0.4673} - 1 = 61.01\%$)

	BTC	ETH	S&P 500	Nasdaq	GLD	Dollar Index
Mean	0.00189	0.00130	0.00034	0.00048	0.00015	0.00012
Median	0.00204	0.00101	0.00060	0.00107	0.00045	0.00010
Maximum	0.225	0.344	0.090	0.089	0.048	0.020
Minimum	-0.465	-0.551	-0.128	-0.131	-0.055	-0.024
Std. Dev.	0.046	0.063	0.012	0.014	0.009	0.004
Skewness	-0.69	-0.66	-0.92	-0.78	-0.18	0.01
Kurtosis	11.74	10.68	19.89	12.27	6.29	4.51
Count	2003	1209	2003	2003	2003	2003

Table 2B shows the daily returns correlations between BTC and ETH and the other four asset sectors analyzed. We calculate the correlations for each year from 2014 to 2022 and also for the whole sample period. It can be seen that the correlation between BTC and ETH is always the highest, which is not surprising. Prior to 2020, there is no significant correlation between BTC returns and broader stock market returns. However, for the past three years from 2020 to 2022, the return correlation becomes very significantly positive, especially between BTC and Nasdaq. So our analysis confirms the general perception that cryptocurrencies and the US stock market have become more correlated. On the other hand, GLD and BTC returns had significant positive correlation in 2019 and 2020, but insignificant and usually negative correlations in other years. For the Dollar index, the correlation at the daily return level is muted and mostly insignificant.

Prior to 2020, BTC has no significant correlation with the broader equity markets. However, it has become significantly positive since then.

Table 2B. Daily Return Correlation with BTC

(The 95% significance value for the correlation is $\pm 2 / \sqrt{n}$, where n is the number of observations used in correlation calculation. So for each year from 2015 to 2021 the significance value is $\pm 2 / \sqrt{252} = \pm 0.126$; for 2022 (with 80 daily observations from 1/1/2022 to 4/27/2022), the significance value is $\pm 2 / \sqrt{80} = \pm 0.158$; for the whole sample for ETH (with 1209 daily observations), the significance value is $\pm 2 / \sqrt{1209} = \pm 0.058$; and for the whole sample for other asset classes (with 2003 daily observations), the significance value is $\pm 2 / \sqrt{2003} = \pm 0.045$)

	2015	2016	2017	2018	2019	2020	2021	2022	Entire Sample	Nobs
ETH			0.217	0.762	0.810	0.873	0.746	0.910	0.772	1209
S&P 500	0.058	-0.035	0.067	0.077	-0.113	0.446	0.264	0.567	0.204	2003
NASDAQ	0.052	-0.001	0.075	0.076	-0.100	0.462	0.273	0.608	0.220	2003
GLD	-0.021	0.087	-0.030	-0.047	0.223	0.301	-0.014	0.052	0.075	2003
Dollar Index	-0.006	0.019	0.010	0.017	0.043	0.081	0.039	-0.111	0.008	2003

We also calculated the return correlation of BTC with other assets using rolling monthly and annual data frequencies. Table 2C shows the results. The correlations between BTC and S&P 500 and Nasdaq stock returns are still very significant. The correlations between BTC and ETH, S&P 500 and NAQDAQ returns become larger when moving from a monthly horizon to an annual horizon. One notable difference in Table 2C is the correlation between BTC and U.S. Dollar Index for annual returns. While there is little correlation between BTC and U.S. Dollar Index for daily frequencies, the correlation gradually becomes significantly negative as one goes from daily to monthly data, and from monthly to annual. Our analysis shows that the annual return correlation between BTC and U.S. Dollar Index reaches a very significant -0.75 level. This lends credence to the popular narrative that over a longer horizon, if the US dollar weakens, one would expect BTC returns to be stronger with negative correlation to the dollar.

Inverse correlation observed between BTC and the U.S. Dollar index.

Table 2C. Monthly and Annual Return Correlation

(Columns Ret_1m and Ret_12m show the correlation numbers between BTC and other assets for 1 month and 12 months horizons. Columns Nobs_1m and Nobs_12m show the number of observations used in the correlation calculation. Columns Stderr_1m and Stderr_12m show the one side 95% confidence interval value for the correlation estimation. For example, the "Stderr_12m" for NASDAQ is 0.218, then with the estimated correlation at 0.625 we have 95% confidence that we can reject the hypothesis that there is no correlation between BTC and NASDAQ since the estimated correlation number is outside [-0.218, 0.218])

	Ret_1m	Nobs_1m	Ret_12m	Nobs_12m	Stderr_1m	Stderr_12m
ETH	0.742	57	0.899	46	0.265	0.295
S&P 500	0.365	95	0.638	84	0.205	0.218
NASDAQ	0.354	95	0.625	84	0.205	0.218
GLD	0.059	95	0.049	84	0.205	0.218
Dollar Index	-0.174	95	-0.751	84	0.205	0.218

04 The Autocorrelation Structure of Cryptocurrency Returns

One striking stylized fact for financial returns is that while the returns themselves are not predictable using their own past, their magnitude, hence their volatility, is strongly predictable (stylized facts D and E in introduction, see also Ding, Granger and Engle (1993), Cont (2001)). The GARCH model, which captures this feature of financial returns, is widely used for volatility prediction for financial returns. In this section, we present the term structure of volatility for various financial assets and compare them with cryptocurrency volatility. The research here can shed light on what kind of models we should use for cryptocurrency volatility modelling, a topic addressed in detail in Part II of this report.

The main statistical tool we use is the sample autocorrelation function (ACF) for the returns, absolute returns, and squared returns. Recall that the ACF at lag k is defined as follows:

$$\rho_k(x) = corr(x_t, x_{t-k}) \quad \text{for } k = 1, 2, \cdots$$

i.e., the ACF measures the serial correlation of a random variable with its own past history. When the ACF is significant, we can use the variable's past to predict its future. In the following panels, the x-axis is the lag k, the blue line is the ACF for returns themselves (retc), the orange line is for absolute returns (abs(retc)), the green line is for squared returns (retc^2) and the purple and red lines are the +-95% confidence intervals. The lines within the confidence intervals are not statistically different from 0.

4.1 Bitcoin and Ethereum

Figures 4A and 4B show the ACF functions for BTC and ETH. It can be seen that the ACF functions for both BTC and ETH returns are not significant. However, all the ACFs for absolute returns are significant and positive till lag 1000. The ACFs for squared returns are mostly significant but they are in general smaller than the ACFs for absolute returns. Comparing with the ACF structures for S&P 500 and Nasdaq in Figures 4C and 4D, all absolute returns ACFs are very similar to each other. All start around 0.3 to 0.35 and decay sharply for the first 100 lags or so and then decay slowly.

Figure 4A. ACF Function for Bitcoin (Hourly)

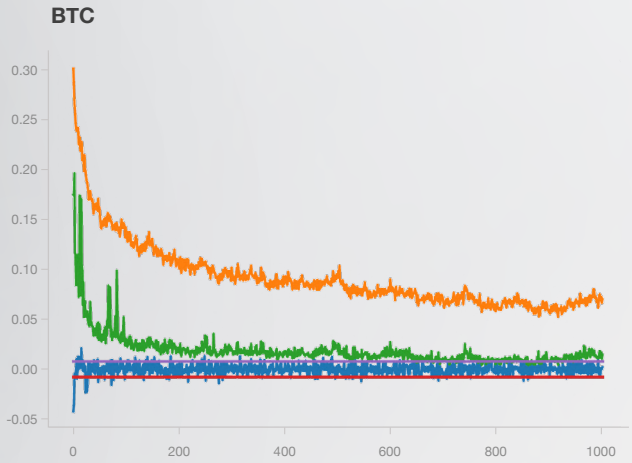
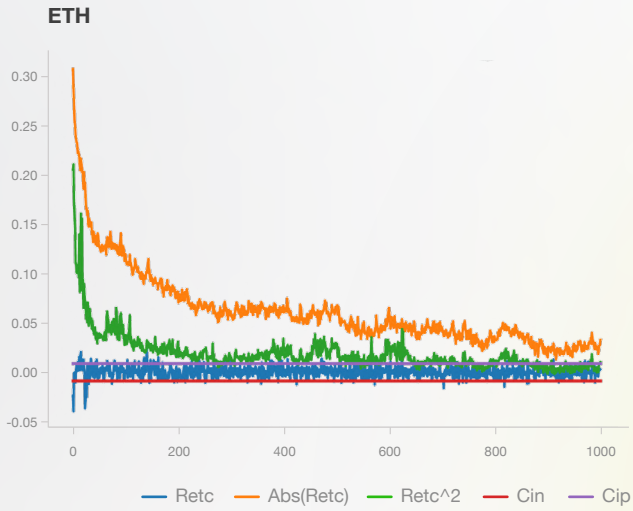


Figure 4B. ACF Function for Ethereum (Hourly)



A non-mean-reverting volatility process (a random walk model structure in volatility) would imply that the ACFs decay much slower in both the short-run and the long-run. The ACF structures in Figures 4A and 4B for absolute and squared returns suggest that volatility for both BTC and ETH is mean-reverting. A more careful study will be performed in Part II of this report, where we construct various volatility models using actual estimated parameters.

4.2 Stocks (S&P 500 and NASDAQ)

Figure 4C is simply a replication of the ACF chart for S&P 500 in Ding et al. (1993). This is the empirical finding of the so-called long memory property in volatility of financial returns. We also present the ACF chart for NASDAQ in Figure 4D for comparison with that of BTC and ETH. It is evident that BTC and ETH display similar long memory properties.

Figure 4C. ACF Function for S&P 500 (Daily)

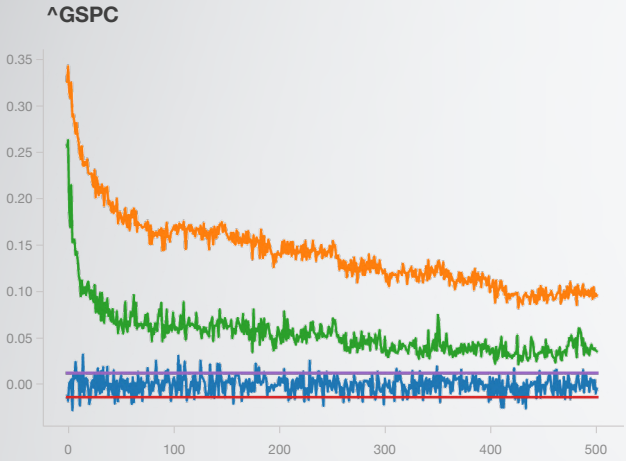
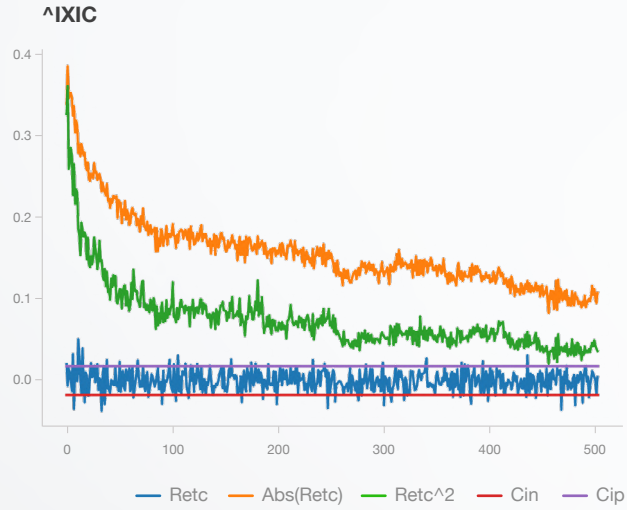


Figure 4D. ACF Function for Nasdaq (Daily)



As discussed in Ding et al. (1993), Ding and Granger (1996), Baillie et al. (1996) and numerous other academic research studies thereafter, the slow decay (long memory) structure of the absolute or squared returns in the figures above suggests that the popular EWMA model or the simple GARCH (1,1) model used by practitioners may not offer a good fit for the underlying data and thus may provide a sub-optimal forecast for volatility. A better model should be able to capture this empirical phenomenon. We will have a more detailed discussion on this phenomenon in Part II of this report.

4.3 Bonds (AGG) and Gold (GLD)

Figure 4E. ACF Function for Aggregated Bond AGG (Daily)

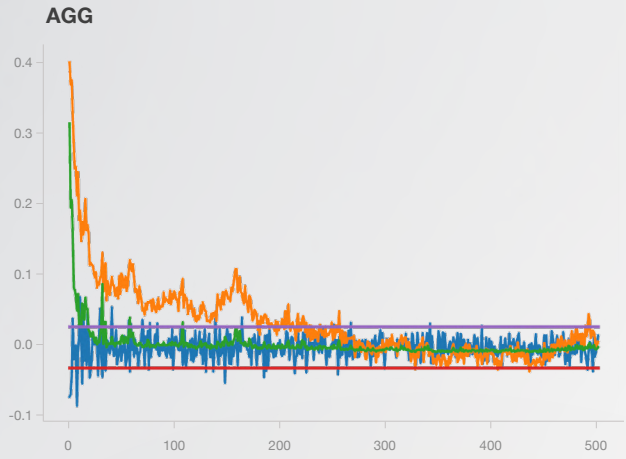
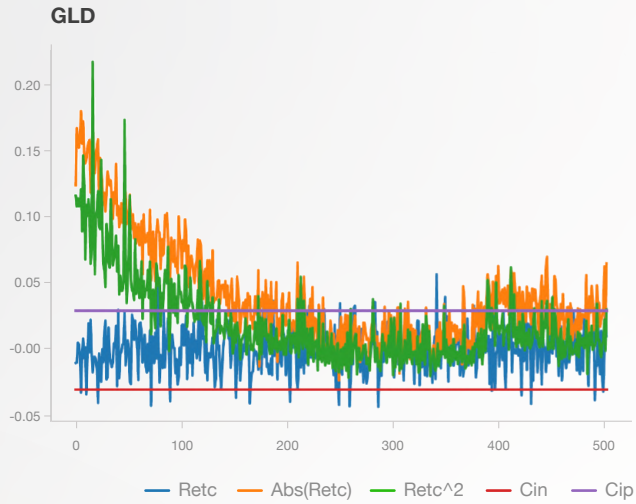


Figure 4F. ACF Function for GLD (Daily)



The ACFs for AGG (iShares Core US Aggregate Bond ETF) and GLD are comparably more different. The bond return volatility decays steeply and has a shorter memory. The gold return is more like an exponential decay and the ACFs for absolute and squared returns are quite similar, a property which is very unique to gold returns. It suggests that volatility for both bonds and gold mean-revert more quickly.

4.4 Foreign exchange rates

For foreign exchange rates, we used higher frequency data at 15 minutes interval. The general conclusion is the same. All the returns have no serial correlation themselves. But the absolute and squared returns all have significant ACFs. The ACFs for absolute returns are larger than that of the squared returns. FX also has a steep decay in the beginning and then relatively slow decay. One remarkable difference is the daily cycle in the volatility correlation structure. Since the data is at 15-minute intervals, there are 96 observations each day. The cycle peaks all occurred at lag 96, 192 , etc. which implies FX data has daily seasonality in volatility at a particular hour. It is unclear why the magnitude of returns should be clustered so regularly. One possible explanation would be if some event or process occurs at regular time intervals. Close examination of FX volumes and bid/ask spreads reveals that bid/ask spreads are narrowest and volumes are highest for most currency pairs when both the London and New York FX markets are open. This is at the London close and the New York open or between 2:30pm and 4:30pm in London. It is still unclear why lower bid/ask spreads and higher volume should result in a higher correlation of the magnitude of returns.

Figure 4G. ACF Function for Yen/$ Exchange Rate

(15 minutes data from 1/1/2005 to 12/31/2020)

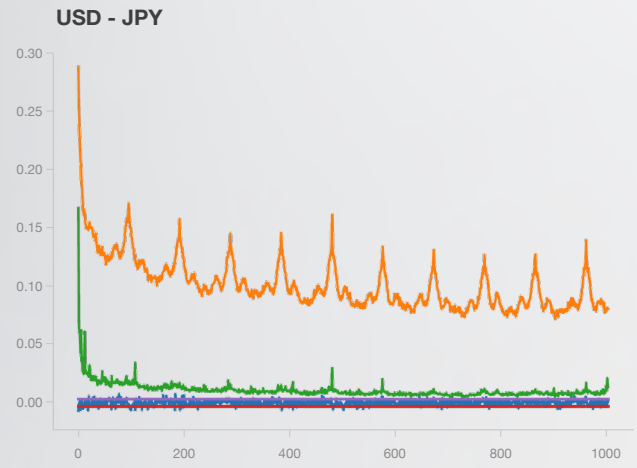


Figure 4H. ACF Function for EUR/$ Exchange Rate

(15 minutes data from 5/4/2003 to 12/31/2020)

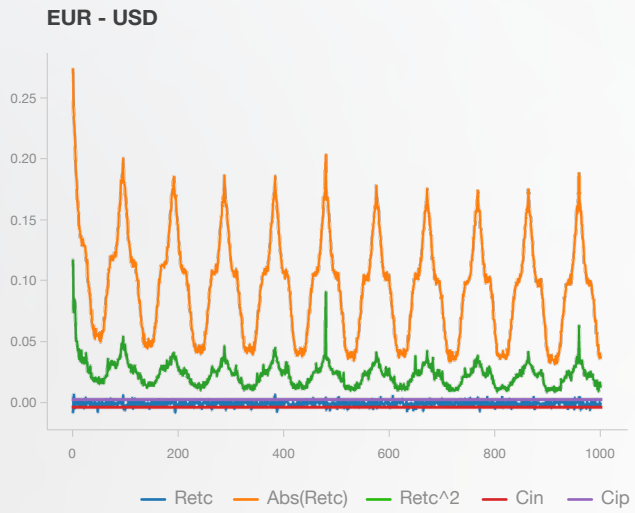
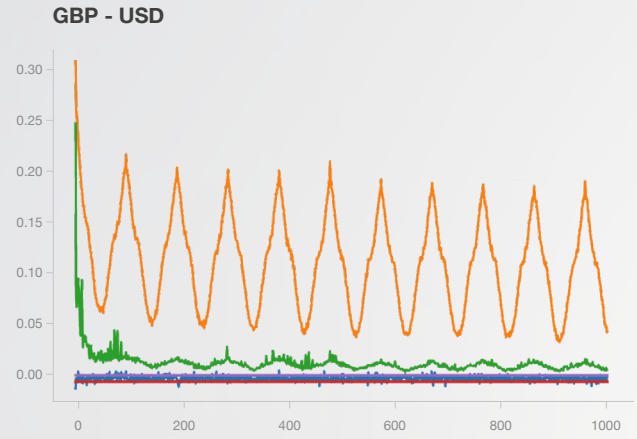


Figure 4I. ACF Function for GBP/$ Exchange Rate

(15 minutes data from 1/1/2005 to 12/31/2020)



Overall, the study in this section shows that cryptocurrency volatility is similar to volatility patterns exhibited by other financial asset returns. However, cryptocurrencies behave more like equities than FX or bonds or gold. Their volatility has a long memory structure as shown by Ding, Granger and Engle in their 1993 paper for S&P 500 returns. It should also be noted that even though the data frequency we used for different asset classes is different based on data availability, the general autocorrelation structures are still the same. This property of financial returns is referred to as “self-similarity” in literature (see Mandelbrot, 1985).

05 Asymmetric (Leverage) Effect in Cryptocurrency Volatility

Another important observation for equity returns volatility is the so called "leverage effect" (see Black 1976, Glosten, Jagannathan and Runkle 1993). For example, it is found that in general, a market going down will usually lead to higher volatility than if the market were to go up by the same amount. S&P 500 volatility is inversely correlated with the underlying price returns. It will be interesting to see if cryptocurrencies exhibit the same kind of asymmetric leverage effect. To study this, we run a linear regression as specified below:

$$|r_t| = c + a_1 |r_{t-1}| + b_1 r_{t-1} I_{r_{t-1}<0} + a_2 |r_{t-2}| + b_2 r_{t-2} I_{r_{t-2}<0} + a_3 |r_{t-3}| + b_3 r_{t-3} I_{r_{t-3}<0} + error$$

where

$$I_{r_{t-k}<0} = \begin{cases} 0 & \text{if } r_{t-k} \geq 0 \\ 1 & \text{if } r_{t-k} < 0 \end{cases} \quad \text{for } k = 1,2,3$$

We would expect the regression coefficients b_1, b_2, b_3 to be significant and negative in general if cryptocurrencies exhibit the leverage effect.

Table 3A shows the regression result for the 50 cryptocurrencies. The left side panel is the regression parameters, and the right panel is the corresponding *t*-stats. In general, over half of the cryptocurrencies in our universe exhibit the volatility leverage effect. The two most prominent cryptocurrencies, Bitcoin and Ethereum, exhibit the most significant asymmetric leverage effects, with all three lags having significantly negative *t*-stats. On the other extreme, ETC, CVX, WAVES, SAND, FLOW and MANA exhibit the "anti-leverage effect", i.e., when their prices go up, the subsequent volatility is usually higher than when the prices go down by the same amount. This is opposite to what is observed for S&P 500, BTC and ETH. It should be noted that these cryptocurrencies have a shorter history. As time goes by, this behavior might change.

Unlike equities, we did not observe a consistent "leverage effect" phenomenon across our cryptocurrency universe. This has significant implications for hedging risk.

One observation from Table 3A is that more cryptocurrencies with longer histories exhibit the leverage effect. A natural question to ask then is whether smaller sample sizes might perhaps be adversely impacting results and hence conclusions. To answer this question, we ran another regression using the above specification but only with the first year's data for every currency. If sample size were to be a factor, then we would expect the majority leverage effect to be opposite (the regression coefficient to be positive instead of negative). The left panel of Table 3B in Appendix B shows the *t*-stats of the asymmetric leverage term when we use only a one-year sample. It can be seen that about 1/3 are significantly negative, 1/3 insignificant, and 1/3 are significantly positive. This is not that much different from using the whole sample (listed in the right panel of Table 3B in Appendix for comparison purpose). Currencies like BTC, ETH, DOGE, DOT, VET, EGLD, CAKE, MATIC, ZEC, XMR etc. are always significantly negative, while XLM, CVX, HBAR, CRO, BCH, SHIB, FLOW, SAND etc. are always significantly positive. So it is fair to conclude that this is some inherent property for different cryptocurrencies instead of the result of using shorter samples.

Finally, as a combined representative of the general cryptocurrency market, we study the asymmetric effect for the CCI30 index[10] using daily data. The t-stat for the first lag (one day apart) asymmetric effect is again very significant at -4.4. The second and third days are no longer significant.

Overall, the lagged asymmetric effect exists in hourly as well as daily frequencies.

Table 3A. Asymmetric (Leverage) Effect in Cryptocurrency Volatility

	Parameters							*t*-stat						
Asset	c	a_1	b_1	a_2	b_2	a_3	b_3	c	a_1	b_1	a_2	b_2	a_3	b_3
AAVE	0.006	0.160	-0.022	0.119	-0.024	0.128	-0.019	38.2	15.5	-1.9	11.5	-2.0	12.4	-1.6
ADA	0.004	0.196	-0.026	0.151	-0.004	0.130	-0.035	55.8	31.0	-3.6	23.8	-0.5	20.7	-4.8
ALGO	0.006	0.172	-0.018	0.125	-0.016	0.122	-0.024	50.6	22.2	-2.0	16.1	-1.8	15.8	-2.7
ATOM	0.005	0.177	-0.020	0.134	-0.020	0.100	-0.038	52.3	23.5	-2.2	17.8	-2.3	13.5	-4.3
AVAX	0.007	0.186	-0.009	0.118	-0.001	0.103	-0.013	40.0	18.7	-0.8	11.8	-0.1	10.4	-1.1
AXS	0.008	0.212	0.007	0.138	0.030	0.121	-0.016	34.8	21.2	0.5	13.6	2.3	12.0	-1.2
BCH	0.004	0.246	0.032	0.166	-0.001	0.137	-0.048	50.9	40.7	4.3	27.2	-0.1	22.5	-6.6
BNB	0.003	0.185	-0.042	0.159	-0.023	0.151	-0.025	44.5	23.9	-4.8	20.6	-2.6	19.9	-2.9
BSV	0.004	0.244	0.005	0.111	-0.003	0.111	-0.021	47.7	33.7	0.5	15.2	-0.4	15.3	-2.4
BTC	0.002	0.165	-0.071	0.163	-0.022	0.137	-0.037	66.1	32.9	-12.1	32.6	-3.7	27.8	-6.3
CAKE	0.005	0.183	-0.056	0.122	-0.035	0.177	0.008	28.8	14.7	-4.0	9.8	-2.5	14.5	0.6
CRO	0.004	0.278	0.052	0.117	-0.031	0.120	-0.019	44.2	38.4	5.7	15.8	-3.3	16.3	-2.1
CVX	0.010	0.286	0.153	0.129	0.024	0.063	-0.020	28.5	21.3	8.8	9.3	1.4	4.5	-1.1
DOGE	0.007	0.222	-0.062	0.122	-0.010	0.132	0.010	73.4	45.6	-10.4	24.6	-1.6	27.7	1.7
DOT	0.006	0.146	-0.072	0.114	-0.006	0.099	-0.031	41.0	14.5	-6.1	11.3	-0.5	10.0	-2.6
EGLD	0.006	0.155	-0.056	0.131	0.008	0.118	0.000	39.9	15.1	-4.8	12.7	0.7	11.7	0.0
EOS	0.004	0.209	-0.002	0.153	-0.003	0.143	-0.017	55.0	34.0	-0.3	24.7	-0.4	23.3	-2.4
ETC	0.004	0.287	0.082	0.174	0.008	0.124	-0.013	55.2	52.0	11.9	30.8	1.1	21.9	-1.8
ETH	0.003	0.167	-0.075	0.155	-0.037	0.146	-0.034	60.2	30.2	-11.7	28.1	-5.8	26.9	-5.3
FIL	0.005	0.205	0.005	0.145	0.030	0.113	-0.006	35.4	18.8	0.4	13.2	2.3	10.4	-0.5
FLOW	0.005	0.222	0.049	0.143	0.018	0.115	0.009	31.6	18.8	3.3	12.0	1.3	9.6	0.6
FTM	0.007	0.204	0.017	0.154	0.016	0.110	-0.017	50.1	27.3	1.9	20.5	1.8	14.6	-1.9
FTT	0.003	0.196	-0.018	0.120	-0.066	0.118	-0.021	45.5	24.7	-1.9	15.1	-7.1	14.9	-2.3
GRT	0.007	0.203	0.029	0.145	0.014	0.142	-0.006	34.3	19.2	2.3	13.6	1.1	13.4	-0.4
HBAR	0.005	0.236	0.028	0.152	0.003	0.147	-0.017	40.2	29.8	2.9	18.9	0.3	18.4	-1.7
HNT	0.006	0.214	0.016	0.131	0.011	0.119	-0.019	37.6	22.0	1.4	13.3	0.9	12.2	-1.6
ICP	0.007	0.143	-0.033	0.091	-0.008	0.082	0.002	30.1	9.2	-1.9	5.9	-0.4	5.3	0.1
LEO	0.002	0.257	0.027	0.137	0.037	0.103	-0.054	36.2	32.9	2.6	17.2	3.6	13.0	-5.2
LINK	0.005	0.212	-0.013	0.142	-0.032	0.154	-0.036	53.8	35.9	-1.8	23.9	-4.5	26.0	-5.0
LTC	0.004	0.215	-0.034	0.150	-0.017	0.120	-0.017	72.8	46.4	-6.1	32.2	-3.1	26.2	-3.1

10. The CCi30 index tracks the 30 largest cryptocurrencies by market capitalization, excluding stablecoins. The index was launched on January 1, 2017. Its starting value is arbitrarily set at 100 on Jan 1, 2015. See https://cci30.com for details. The index tracks the 30 largest cryptocurrencies on a daily basis.

	Parameters							*t*-stat						
Asset	***c***	a_1	b_1	a_2	b_2	a_3	b_3	***c***	a_1	b_1	a_2	b_2	a_3	b_3
LUNA	0.006	0.253	0.045	0.150	0.058	0.084	-0.034	41.7	29.3	4.1	17.0	5.3	9.6	-3.1
MANA	0.005	0.228	0.033	0.166	0.012	0.144	-0.009	50.4	35.3	4.1	25.5	1.5	22.1	-1.1
MATIC	0.006	0.195	-0.035	0.151	-0.028	0.151	-0.019	44.4	27.1	-3.9	20.9	-3.1	21.0	-2.2
MIOTA	0.005	0.241	0.014	0.148	-0.022	0.167	0.013	52.9	40.0	2.0	24.4	-3.0	27.9	1.8
MKR	0.005	0.216	0.020	0.097	0.001	0.120	-0.008	57.0	32.7	2.4	14.4	0.1	18.1	-0.9
NEAR	0.008	0.155	0.002	0.122	0.008	0.096	-0.015	41.5	15.4	0.2	12.0	0.7	9.5	-1.3
RUNE	0.009	0.150	-0.021	0.099	-0.005	0.094	-0.037	45.2	15.5	-1.9	10.2	-0.5	9.8	-3.4
SAND	0.007	0.213	0.043	0.147	0.033	0.139	0.022	38.7	22.5	3.6	15.3	2.8	14.5	1.9
SHIB	0.005	0.274	0.058	0.143	-0.038	0.159	-0.040	22.0	21.4	3.6	10.9	-2.4	12.3	-2.5
SOL	0.006	0.201	-0.012	0.133	0.010	0.116	-0.025	42.0	22.9	-1.1	15.0	0.9	13.2	-2.4
THETA	0.006	0.230	0.002	0.132	-0.009	0.129	-0.003	57.7	37.2	0.3	21.0	-1.2	20.9	-0.4
TRX	0.004	0.206	-0.006	0.139	0.010	0.127	-0.021	55.4	31.3	-0.7	20.9	1.3	19.2	-2.6
UNI	0.006	0.184	-0.003	0.145	0.006	0.135	-0.003	37.5	18.2	-0.3	14.3	0.5	13.4	-0.3
VET	0.006	0.187	-0.024	0.109	-0.014	0.125	-0.024	58.2	28.2	-3.0	16.2	-1.8	18.8	-3.1
WAVES	0.005	0.248	0.031	0.167	0.042	0.102	-0.008	55.8	39.4	4.0	26.1	5.4	16.1	-1.0
XLM	0.005	0.276	0.024	0.161	0.003	0.131	-0.025	63.8	59.3	4.1	33.9	0.4	27.9	-4.3
XMR	0.005	0.225	-0.029	0.117	-0.017	0.137	-0.017	74.3	48.3	-5.1	24.7	-3.0	29.6	-3.0
XRP	0.003	0.273	0.014	0.146	-0.020	0.163	-0.029	57.8	58.1	2.4	30.3	-3.5	34.4	-5.0
XTZ	0.005	0.249	-0.017	0.133	0.014	0.155	-0.004	53.4	39.9	-2.4	20.9	1.9	25.1	-0.6
ZEC	0.004	0.185	-0.049	0.116	-0.039	0.119	-0.025	58.1	29.1	-6.5	18.3	-5.2	19.0	-3.4
Asymmetric (leverage) effect for daily CCi30 index														
CCi30	0.018	0.083	-0.124	0.116	-0.042	0.139	0.052	17.6	3.1	-4.4	4.4	-1.5	5.4	1.9

06 Calendar Effect in Cryptocurrency Volatility

In this section, we study calendar related volatility effects in the cryptocurrency market. In the US equity market, it is observed that volatility and volume are “U- shaped” during a trading day, i.e., they are higher near the open and close and lower in the middle of the day. Given that cryptocurrencies trade 24 hours a day, seven days a week, it will be interesting to see what kind of volatility pattern they display during a trading day and across a trading week.

6.1 Hour of the day effect in cryptocurrency volatility

Figure 5A shows the average absolute return (the blue "mean" line, left axis) and absolute return standard deviation (the orange "std" line, left axis) during different hours of a day (based on UTC time with 1 being the first hour of UTC time), for Bitcoin over its cleansed sample time period as defined in Table 1C(11/1/14 – 4/27/22). It can be seen that the mean absolute return values for hours 2 and 15 through 18 are significantly higher than those of other hours. We conducted a mean difference *t*-test between hour 2 and the other hours and the result is shown in the green *t*-test line (right axis). As discussed above, the volatility in hour 2 is similar to that of hours 15 through 18 and statistically significantly higher than the other hours. The *t*-stats for hours other than 15 to 18 are all greater than 3 which is above the 99% statistically significant level. So BTC volatility is indeed different at different hours of the day.

The above findings are not too surprising given the regular working hours around the world. The hour 2 in UTC time corresponds to 9am Beijing time with people in east Asia starting a new trading day. The hours 15 through 18 correspond to 9am to 12pm New York time with people in the U.S. starting a new trading day. We would typically expect more trading activity during these hours.

Figure 5B shows the same analysis for Ethereum. The conclusion is qualitatively the same. Figure 5C shows the same analysis using average absolute returns for all 50 cryptocurrencies during different hours of the day. The conclusion is again the same, i.e., the volatility during hours 2 and 15 through 18 is significantly higher than during the rest of the day.

Figure 5A. Volatility, Hour of the Day Effect – BTC (*t*-test Right Axis)

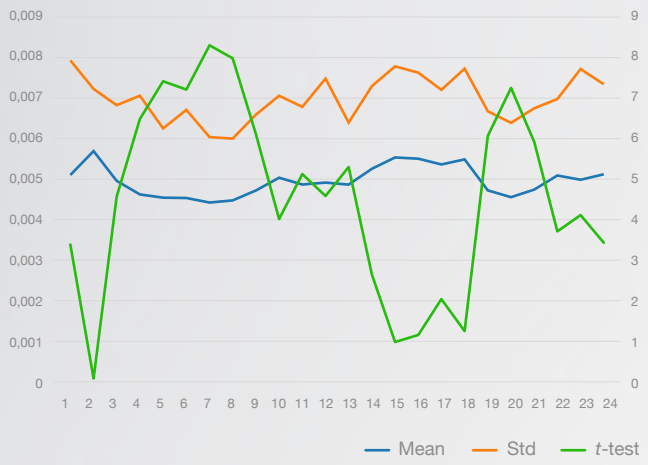


Figure 5B. Volatility, Hour of the Day Effect – ETH (*t*-test Right Axis)

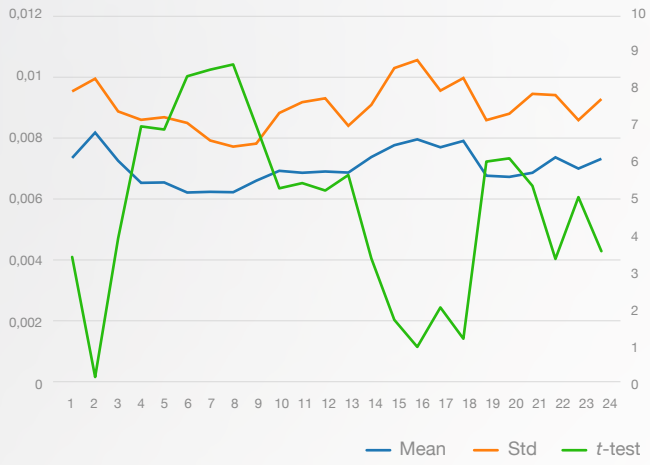


Figure 5C. Volatility, Hour of the Day Effect - All Currencies Average (*t*-test Right Axis)

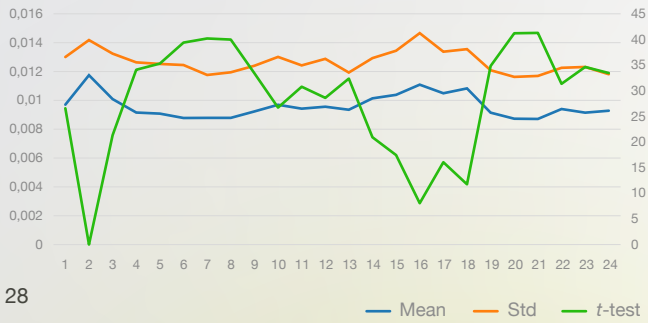
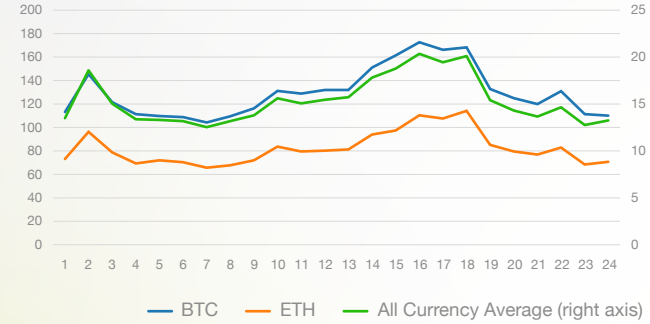


Figure 5D. Average Hourly Volume, Hour of the Day Effect[11] (in Million $)



11. Average dollar volume for each cryptocurrency is hourly average across the period specified in Table 1C ("Inception Time" through "End Time" as noted in the table). The volume statistic tracks average hourly volume for each hour across the time period.

Finally, Figure 5D shows the average trading volumes for BTC, ETH and all top 50 cryptocurrencies at different hours during the day (data sample used for each cryptocurrency is the entirety of the adjusted sample period as listed in Table 1C). It can be seen that the volumes are highest during hour 2 and hours 15 to 18 as well, consistent with the above analysis.

6.2 Weekday effect in cryptocurrency volatility

Having conducted the intra-day analysis in the prior section, it was logical to proceed to the next step, inter-day analysis, in order to examine if and how volatility varied during the week. Cryptocurrencies are unique in that they trade continuously 24 hours a day, seven days a week. However while crypto never sleeps, us market participants fortunately get our day(s) of rest. As such, one would expect lower volume over the weekends than during the weekdays.

Figure 6A shows the average absolute hourly return (the blue "mean" line, left axis) and the absolute return standard deviation (the orange "std" line, left axis) for BTC on different days during the week. It can be seen that the mean absolute return values and standard deviations for Saturday and Sunday are significantly lower than those of other days. We conducted a mean difference *t*-test between Tuesday[12] and other days and the result is shown in the green *t*-test line (right axis). It can be seen that the volatility for Saturday and Sunday is statistically significantly lower than the other days. Our analysis also shows that both returns and volatility have a pronounced pattern of peaking on Fridays. The biggest difference for returns and volatility occurs between Friday and the weekend days.

12. The goal of the *t*-test exercise is to compare a weekday vs. the weekend. We chose Tuesday because Monday has been shown to exhibit some lingering weekend effect as explained later in this section.

Figure 6A. Volatility, Weekday Effect – BTC (*t*-test Right Axis)

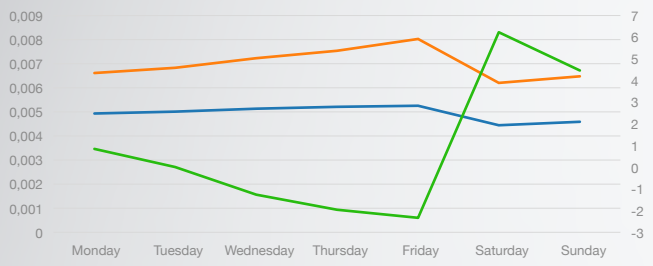
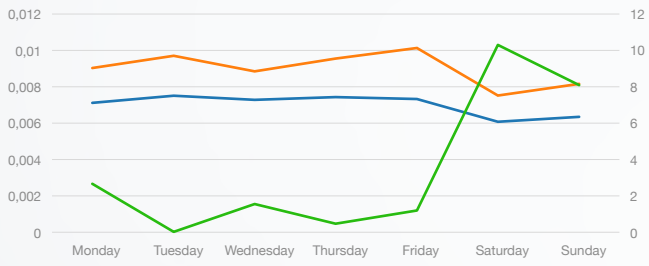


Figure 6B. Volatility, Weekday Effect – ETH (*t*-test Right Axis)

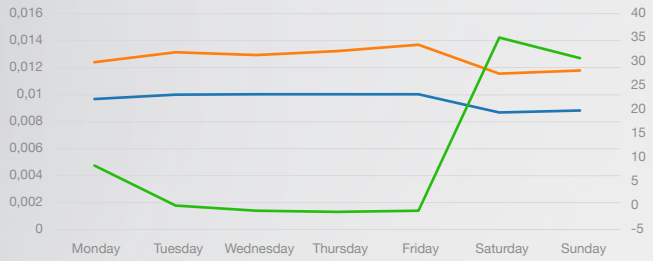


Mean Std *t*-test

Figure 6B shows the same analysis for Ethereum. The conclusion is qualitatively the same. One can observe that ETH's volatility on Monday is also statistically lower than on Tuesday. Since the time zone used is UTC, it is the case that part of the world (mostly North and South America) is still in weekend mode while the rest of the world is starting their week. By the time markets open in North and South America, it is end of day UTC across several geographies. That is likely why volatility on Monday is also lower than the remainder of the week. Figure 6C shows the same analysis for all top 50 cryptocurrencies, comparing their average absolute hourly returns and standard deviations over different days of the week. The conclusion is again the same.

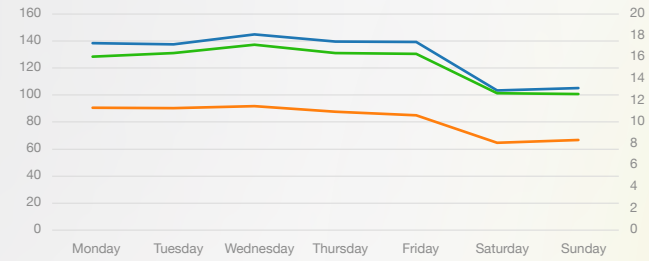
Both BTC and ETH demonstrate significant and persistent calendar effects, a fact directly impacting trading decisions.

Figure 6C. Volatility, Weekday Effect - All Currency Average (*t*-test Right Axis)



Mean Std *t*-test

Figure 6D. Figure 6D. Average Hourly Volume, Weekday Effect (in Million $)[13]



BTC ETH All Currency Average (right axis)

Figure 6D shows the average trading volumes for BTC, ETH and all the 50 currencies combined for the different days of the week. It can be seen that the volumes are markedly lower on Saturday and Sunday. Here it is interesting to note that the average trading volume on Monday is similar to Tuesday even though the volatility on Monday is lower.

Our analysis reveals distinct and persistent calendar patterns in volatility. This has potentially significant implications for designing investment strategies and trading algorithms that capitalize on the patterns revealed. For instance, a trading algorithm that sells volatility on Fridays and buys it on weekends would seem to make economic sense. A similar logic would apply to intraday strategies involving selling volatility either at 2 am UTC or between 3 pm – 6 pm UTC and buying volatility between 7 – 8 am UTC. The volume trends have implications for optimal trade entry and exit points.

13. Average dollar volume for each cryptocurrency is hourly average across the period specified in Table 1C ("Inception Time" through "End Time" as noted in the table). The volume statistic tracks average hourly volume on each weekday across the time period.

6.3 US and China holidays impact on cryptocurrency volatility

The above study shows that even though the cryptocurrency market is continuously open, the trading volume and volatility over the weekends are much lower than during the weekdays. Given that the US and China account for two of the largest investor bases within crypto, it will be interesting to see if US and Chinese calendar holidays have any impact on crypto trading volumes and volatility.

Table 4 shows the average absolute returns across different weekdays, weekends and US and Chinese holidays for BTC, ETH and all 50 cryptocurrencies combined. It can be seen that for BTC and ETH, volatility and returns are the lowest during the Chinese holidays. The volatility for BTC and ETH is also lower during US holidays, however the effect is similar to regular weekend patterns as established above. Looking at all 50 cryptocurrencies combined, the volatility during US and Chinese holidays is similar to weekends and is much lower than during the week.

Table 4. US and China Holidays Impact on Crypto Volatility

	All Curencies				BTC				ETH			
|r|	Count	Mean	Std. Dev	*t*-test	Count	Mean	Std. Dev	*t*-test	Count	Mean	Std. Dev	*t*-test
Monday	176174	0.0097	0.0125	8.54	7752	0.0050	0.0068	0.34	6000	0.0072	0.0092	2.11
Tuesday	198925	0.0100	0.0132	0.00	8760	0.0051	0.0069	0.00	6744	0.0076	0.0097	0.00
Wednesday	201902	0.0101	0.0131	-2.51	8879	0.0052	0.0073	-1.48	6863	0.0074	0.0090	0.83
Thursday	196596	0.0101	0.0133	-1.11	8568	0.0053	0.0077	-2.23	6696	0.0076	0.0098	-0.31
Friday	190017	0.0103	0.0140	-5.21	8328	0.0055	0.0083	-3.36	6552	0.0076	0.0104	-0.06
Saturday	213996	0.0087	0.0116	35.10	9384	0.0044	0.0062	6.60	7296	0.0060	0.0075	10.25
Sunday	214104	0.0088	0.0118	30.89	9384	0.0046	0.0065	4.87	7296	0.0063	0.0082	8.10
US Holidays	31896	0.0095	0.0119	6.73	1392	0.0047	0.0059	2.16	1080	0.0068	0.0085	2.64
China Holidays	75240	0.0090	0.0118	18.76	3192	0.0039	0.0048	10.01	2520	0.0058	0.0069	9.68

07 Impact of Broader Stock Market Volatility on Crypto Volatility

The TradFi and cryptocurrency markets are two very distinct market structures and ecosystems. The popular narrative, at least initially, was that crypto could play a valuable role as a diversifier as it tended to march to its own beat. Events of the recent past have in fact demonstrated that macro events in TradFi tend to have a knock-on effect on crypto returns. This section endeavors to separate fact from fiction and examine the interrelationships between TradFi and crypto volatility. More specifically, we investigate whether the VIX has any spillover effects on cryptocurrency volatility. To do this we run a Granger causality test[14] as follows:

$$|r_t| = c + a_1 |r_{t-1}| + b_1 r_{t-1} I_{r_{t-1}<0} + a_2 |r_{t-2}| + b_2 r_{t-2} I_{r_{t-2}<0} + a_3 |r_{t-3}| + b_3 r_{t-3} I_{r_{t-3}<0} + d \cdot vix_{t-1}$$

i.e., we try to test whether one hour lagged VIX levels have any explanatory power with regard to cryptocurrency returns, beyond those already explained by lagged absolute returns (up to 3 lags here).

Table 5A in Appendix C shows the regression outcome using the longest possible sample for each cryptocurrency (sample periods as listed in Table 1C). The result is somewhat mixed. About half of the estimated d parameters are positive and the other half negative. Out of both the positive and negative groups, exactly 12 of them are significant in each group.

To test if the sample size impacted our analysis, we ran a subsample analysis using 7 currencies with the longest histories. Table 5B shows the regression outcome. The top panel is the result using samples before 12/31/2018, the middle panel uses samples after 12/31/2018[15], and the bottom panel uses the whole sample. Two observations can be made here:

1. For the two most important cryptocurrencies, BTC and ETH, broader equity market volatility (VIX) has a significant positive impact on the volatility of these two currencies in both sub-samples.

2. For the latest sample starting from 01/01/2019, broader equity market volatility (VIX) has a significant positive impact on the volatility of all seven currencies even though the impact to 5 out 7 currencies in the period before 12/31/2018 was negative.

So it seems that as a cryptocurrency becomes more mature, it gets more closely tied to the broader equity market. The impact of broader equity market volatility (VIX) on cryptocurrency volatility tends to become more significantly positive. Intuitively this makes sense. As a cryptocurrency becomes a meaningful driver of the overall size and sentiment

14. A time series X is said to Granger-cause Y if it can be shown, usually through a series of *t*-tests and F-tests on lagged values of X (and with lagged values of Y also included), that those X values provide statistically significant information about future values of Y.

15. The data sample periods are divided this way so that the 5 currencies with shorter history will have roughly the same number of observations in the two sub-samples.

of the sector, it attracts more institutional and mainstream investors and given the resultant overlap in investor bases, events in TradFi inevitably bleed into and impact investor sentiment in crypto markets.

Significant volatility spillover observed although it currently appears to be one-way.

Volatility spillover can flow both ways, so another important question to consider is whether significant market movements in the crypto ecosystem might have an impact on volatility in traditional markets. Our hypothesis was that events in crypto are largely self-contained and do not impact broader equity markets. In other words, volatility spillover is one-way. However, the Granger causality tests were indeterminate in that respect. Further work needs to be done to confirm or disprove that hypothesis.

Table 5B. Broader Stock Market Volatility (VIX) Impact on Crypto Volatility – Sub Sample Analysis

	Parameters								t-stat							
Asset	*c*	*a1*	b_1	a_2	b_2	a_3	b_3	*d* x1E5	*c*	a_1	b_1	a_2	b_2	a_3	b_3	*d*
Sample before 12/31/2018																
BTC	0.002	0.192	-0.143	0.122	-0.050	0.079	-0.040	5.9	9.28	20.89	-12.75	13.26	-4.45	8.93	-3.55	3.96
DOGE	0.014	0.169	-0.076	0.070	-0.041	0.076	-0.016	-26.2	21.62	16.04	-5.83	6.56	-2.99	7.37	-1.23	-6.66
ETH	0.003	0.149	-0.124	0.068	-0.088	0.085	-0.119	12.8	6.43	12.14	-7.99	5.51	-5.63	7.14	-7.66	4.19
LTC	0.006	0.312	0.070	0.079	-0.005	0.092	-0.031	-5.3	10.80	30.85	5.17	7.51	-0.33	8.90	-2.27	-1.53
XLM	0.008	0.213	-0.066	0.202	0.037	0.090	-0.015	-16.0	15.48	20.05	-5.01	18.91	2.76	8.54	-1.16	-4.79
XMR	0.006	0.253	0.016	0.119	-0.038	0.109	-0.064	-1.1	12.95	23.65	1.25	10.92	-2.96	10.18	-5.03	-0.39
XRP	0.006	0.258	-0.004	0.133	-0.021	0.140	0.006	-7.3	12.17	25.08	-0.26	12.58	-1.48	13.46	0.46	-2.43
Sample after 12/31/2018																
BTC	0.002	0.143	-0.026	0.164	0.013	0.083	-0.028	6.0	10.21	12.45	-1.85	14.25	0.93	7.21	-2.00	8.84
DOGE	0.005	0.276	0.088	0.181	0.037	0.160	0.043	6.2	11.97	25.59	6.26	16.30	2.56	14.52	3.07	3.73
ETH	0.002	0.176	0.007	0.177	0.030	0.104	0.002	5.9	12.18	14.87	0.50	14.96	2.20	8.79	0.17	7.53
LTC	0.004	0.219	0.017	0.118	0.009	0.085	-0.004	3.4	15.87	18.73	1.19	10.02	0.64	7.25	-0.26	3.77
XLM	0.003	0.208	0.002	0.141	0.017	0.173	0.011	3.7	12.73	18.64	0.13	12.55	1.25	15.53	0.81	3.74
XMR	0.003	0.178	-0.017	0.187	0.069	0.107	-0.017	4.0	15.05	15.17	-1.28	15.94	5.20	9.09	-1.25	4.97
XRP	0.003	0.264	0.038	0.121	-0.014	0.171	-0.010	2.4	11.37	22.79	2.71	10.29	-0.97	14.70	-0.74	2.46
Whole Sample																
BTC	0.002	0.154	-0.063	0.159	-0.041	0.150	-0.071	2.1	17.66	18.83	-6.44	19.07	-4.22	17.92	-7.20	3.78
DOGE	0.008	0.227	-0.042	0.127	-0.018	0.131	0.005	-2.9	25.23	28.74	-4.25	15.62	-1.70	16.58	0.46	-2.06
ETH	0.003	0.168	-0.050	0.160	-0.044	0.167	-0.034	0.4	20.20	18.72	-4.86	17.87	-4.24	18.74	-3.29	0.54
LTC	0.003	0.220	-0.030	0.161	-0.031	0.127	-0.021	0.0	21.53	27.72	-3.25	19.88	-3.28	15.41	-2.20	0.02
XLM	0.006	0.215	-0.049	0.178	-0.001	0.120	-0.029	-6.8	24.77	27.87	-5.16	22.87	-0.11	15.34	-3.02	-6.16
XMR	0.005	0.228	0.000	0.124	-0.018	0.139	-0.033	-2.9	26.55	28.66	-0.02	15.31	-1.94	17.43	-3.54	-3.33
XRP	0.004	0.284	-0.001	0.134	-0.037	0.163	-0.030	-3.3	19.22	37.53	-0.11	17.03	-3.73	20.36	-2.97	-3.37

08 Concluding Comments

In this paper we studied the statistical properties of returns for the 50 largest cryptocurrencies. As far as we know, this is the most exhaustive study done to date on cryptocurrency returns and volatility. Our objective in publishing this research is to help investors, advisors and service providers in the crypto ecosystem be more informed about this nascent sector and to serve as a solid foundation for future research initiatives.

Our study shows that most stylized facts associated with other financial returns are also exhibited in cryptocurrency returns. However, crypto's behavior is distinctly different in certain cases as illustrated in our summary findings below:

A. **Inconsistent Leverage Effect:** Equity markets exhibit a widely observed "leverage" effect, the phenomenon that an asset's volatility is negatively correlated to its returns. Typically, rising asset prices are accompanied by declining volatility, and vice versa. We did not observe such a consistent effect in our analysis of cryptocurrencies. We generally found that 1/3rd of our universe exhibited a leverage effect, 1/3rd exhibited an anti-leverage effect and 1/3rd was inconclusive. This has potentially significant implications. It means that one can't necessarily hedge long underlying crypto exposure by being long volatility. If the underlying crypto happens to be one that exhibits an anti-leverage effect, such a strategy would essentially double one's downside exposure instead of hedging it.

B. **Strong Persistent Calendar Effect:** We also found that cryptocurrencies exhibit significant calendar effects. Specifically, there are distinct and persistent "hour of the day" and "day of the week" patterns in cryptocurrency volatility. We found that intra-day volatility was persistently and significantly higher during hours 2 and hours 15 – 18 (UTC) each day. A similar analysis looking at daily returns across the week revealed that Saturdays and Sundays exhibited significantly lower volatility and volume relative to weekdays. The lower volumes on weekends makes intuitive sense. However, one would ordinarily expect the lower volumes on weekends to lead to higher volatility -- our analysis indicates otherwise. We also found that US and Chinese holidays exhibited volatility patterns similar to weekends. These findings naturally have implications for crafting effective trading/investment strategies centered around optimal inter and intra-day periods for buying/selling volatility and entering or exiting trading positions.

C. **The Curious Case of LEO:** In looking at correlations among the top 50 cryptocurrencies, LEO (Unus Sed Leo) stands out as a confoundingly unique case. The average correlation among all the 50 currencies is 0.524 while Bitcoin and Ethereum have the highest correlation at 0.872. LEO has the lowest correlation with other cryptocurrencies across our universe. The average correlation between LEO and the 49 other cryptocurrencies is only 0.013, the maximum correlation is 0.03 and the minimum correlation is -0.014. So LEO is basically not correlated to any of the other cryptocurrencies in our universe. LEO, by way of quick background, is a utility token of centralized exchange Bitfinex and was issued through an IEO in 2019. Bitfinex is owned by iFinex, which is also the parent company of Tether. There have been reports in the past around inappropriate transfers between affiliated companies Bitfinex and Tether to cover losses at Bitfinex[16]. Tether of course has been the subject of consistent speculation regarding the adequacy and liquidity of its stablecoin reserves. Is it mere coincidence that LEO has the unique trading

16. See Section 3.2 for further details.

pattern it does? This issue bears further examination given the controversial past of both Bitfinex and Tether.

D. **Volatility is Predictable:** Our analysis reveals that while cryptocurrency returns themselves are not predictable using their own past, their magnitude, hence their volatility, is strongly predictable. Overall, the study shows that cryptocurrency volatility is similar to volatility patterns exhibited by other financial asset returns. However, they behave more like equities than currencies. The volatility has a long memory structure as shown by Ding, Granger and Engle in their 1993 paper for S&P 500 returns.

E. **Returns have Leptokurtic Distribution:** Unsurprisingly, cryptocurrency returns have a non-normal distribution and are fat-tailed with greater likelihood of extreme events occurring. As with most other financial asset returns, they exhibit the so-called leptokurtic property with fat tails. Out of the 50 cryptocurrencies analyzed, 40% have a negative skewness number. The standard deviations over the sample period are also very different for different cryptocurrencies. LEO has the lowest annualized standard deviation at 76% while MANA (Decentraland) has the highest at 338%. As a reference point, the annualized standard deviation over the past two decades is 20% for the S&P 500 and 25% for Nasdaq.

F. **Magnified Gain/Loss Asymmetry:** Cryptocurrencies exhibit gain/loss asymmetry, which refers to the observation that it usually takes less time for a financial instrument to drop a certain amount than it takes to move up by the same amount. This attribute of crypto is similar to broader equity markets and in contrast to FX exchange rates which exhibit greater symmetry in up/down moves.

G. **Increasingly Correlated with Broader Equity Markets:** In comparing returns against other asset classes, it is observed that prior to 2020, there was no significant correlation between BTC returns and broader stock market returns. However, for the past three years from 2020 to 2022, the return correlation has become very significantly positive, especially between BTC and Nasdaq.

H. **Evidence of Negative Correlation to USD:** While there is little correlation between BTC and the Dollar Index for daily frequencies, the correlation gradually becomes significantly negative as one goes from daily to monthly data, and from monthly to annual. The annual return correlation between BTC and the Dollar Index reached a very significant -0.75 level. This lends credence to the popular narrative that over a longer horizon, if the US dollar weakens, one would expect BTC returns to be stronger with negative correlation to the dollar.

I. **One-way Volatility Spillover:** Finally, we found significant volatility spillover from the broader US stock market to crypto, especially in recent years. This is more pronounced for some of the more mature cryptocurrencies. Our hypothesis is that the spillover currently is unidirectional i.e. while volatility in traditional financial markets has an impact on crypto markets, volatility in crypto is self-contained and does not flow into traditional finance ("TradFi"). However, we could not statistically establish that there was no spillover from crypto to broader markets.

These findings have profound implications for risk managers, portfolio allocators, investors and traders as far as investing in cryptocurrencies is concerned.

For instance, the study suggests that constructing "diversified portfolios" of various crypto assets is harder to accomplish given the higher average correlations between crypto assets and their universally high correlation with Bitcoin. There is always the possibility that there are other tokens like LEO or CVX with little or no correlation with the broader universe of

cryptocurrencies, but a broader analysis needs to be conducted to prove/disprove that hypothesis. Risk managers shall be similarly challenged to construct hedges by being long volatility. In TradFi, higher volatility is synonymous with market declines. However, this phenomenon, called leverage effect, is inconsistent within the crypto universe. It is applicable for some cryptocurrencies, the opposite is true for others and for the remainder, there is no statistically significant relationship. We also found that the volatility of crypto volatility is significantly higher than the “vol of vol” of other asset classes. That makes it more difficult to forecast, compounding the woes of risk managers.

From a trader’s perspective, taking into account the calendar effects of crypto volatility would be a key data point in timing of trades. Our study reveals that there are specific times during the day and certain days in the week when volatility is markedly lower. A trader trying to build a large position would want to do it in a period of low volatility. Similarly a trader selling options would want to do so when volatility is observed to be higher and buy options in periods of low volatility.

Finally, from an allocator’s perspective, the increasing correlation between cryptocurrencies and the broader equity markets presents a sticky problem. How much should they allocate to a category that adds volatility to the portfolio without getting much in the way of diversification benefits?

As mentioned earlier, a primary motivation for undertaking this research initiative was to be able to reliably and accurately forecast volatility. That is one of the critical inputs impacting pricing of certain very unique risk-managed investment products created by The Risk Protocol. Derivative instruments requiring volatility inputs typically use estimates from either realized volatility, implied volatility or forecast volatility. Using data and insights gleaned from this exercise, we have developed highly sophisticated statistical volatility models that have been empirically proven to provide more accurate forecasts of crypto volatility than either implied or realized volatility. Part II of this report, to be published in the near future, will focus on the design and development of these models and the initial results.

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Appendices

Appendix A

Table 1B. Price (Vol) Spikes Up vs. Down (Outlier Returns)

Asset	5/19/2021 13:00	5/19/2021 14:00	Num(|ret|>0.3)
AAVE	-0.276	0.101	0
ADA	-0.257	0.164	0
ALGO	-0.208	0.167	0
ATOM	-0.361	0.254	0
AVAX	-0.285	0.145	0
AXS	-0.374	0.261	2
BCH	-0.307	0.125	0
BNB	-0.177	0.074	0
BSV	-0.473	0.145	2
BTC	-0.111	0.042	0
CAKE	-0.135	0.041	0
CRO	-0.095	0.001	3
CVX			4
DOGE	-0.296	0.227	5
DOT	-0.385	0.051	0
EGLD	-0.279	0.146	0
EOS	-0.317	0.134	0
ETC	-0.320	0.266	0
ETH	-0.154	0.077	0
FIL	-0.273	0.061	0
FLOW	-0.195	0.005	0
FTM	-0.345	0.064	1
FTT	-0.154	0.047	0
GRT	-0.316	0.259	0
HBAR	-0.181	0.074	2
HNT	-0.254	0.111	0
ICP	-0.241	0.060	0
LEO	0.003	-0.031	1
LINK	-0.271	0.150	1
LTC	-0.309	0.144	0
LUNA	-0.231	0.079	1

Asset	5/19/2021 13:00	5/19/2021 14:00	Num(|ret|>0.3)
MANA	-0.378	0.260	2
MATIC	-0.209	0.057	2
MIOTA	-0.336	0.197	0
MKR	-0.203	0.103	3
NEAR	-0.299	0.054	0
RUNE	-0.219	0.193	0
SAND	-0.367	0.211	1
SHIB	-0.356	0.163	0
SOL	-0.222	0.165	0
THETA	-0.327	0.146	1
TRX	-0.189	0.031	0
UNI	-0.274	0.174	0
VET	-0.265	0.153	1
WAVES	-0.304	0.114	0
XLM	-0.367	0.229	2
XMR	-0.367	0.231	0
XRP	-0.194	0.103	5
XTZ	-0.430	0.304	1
ZEC	-0.392	0.200	0

Appendix B

Table 3B. Sub-Sample Leverage Effect Analysis (*t*-stats Only)

t-stats	First Year Data for Each Currency				All Sample				
Asset	b_1	b_2	b_3	**Average *t*-stat**	b_1	b_2	b_3	**Average *t*-stat**	**Inception Date**
AAVE	-2.07	-2.15	-1.50	-1.91	-1.9	-2.0	-1.6	-1.84	2020-10-20
ADA	0.35	0.13	-2.39	-0.64	-3.6	-0.5	-4.8	-2.97	2018-01-11
ALGO	1.46	-3.13	-3.88	-1.85	-2.0	-1.8	-2.7	-2.15	2019-06-22
ATOM	0.67	-2.09	-3.01	-1.48	-2.2	-2.3	-4.3	-2.97	2019-05-01
AVAX	-0.44	-0.06	-1.24	-0.58	-0.8	-0.1	-1.1	-0.66	2020-09-23
AXS	0.37	2.24	-0.98	0.54	0.5	2.3	-1.2	0.53	2020-11-05
BCH	4.94	0.44	-3.77	0.54	4.3	-0.1	-6.6	-0.78	2017-09-01
BNB	-1.19	-2.73	-5.35	-3.09	-4.8	-2.6	-2.9	-3.43	2019-04-01
BSV	2.41	-0.56	0.08	0.64	0.5	-0.4	-2.4	-0.74	2019-01-01
BTC	-2.38	-1.58	-0.38	-1.45	-12.1	-3.7	-6.3	-7.38	2014-11-01
CAKE	-3.97	-2.88	0.60	-2.08	-4.0	-2.5	0.6	-1.99	2021-02-19
CRO	5.61	-3.20	-2.43	-0.01	5.7	-3.3	-2.1	0.09	2019-03-20
CVX	8.77	1.35	-1.14	3.00	8.8	1.4	-1.1	3.00	2021-06-03
DOGE	-9.40	-2.99	-1.31	-4.57	-10.4	-1.6	1.7	-3.43	2015-01-01
DOT	-5.17	-0.43	-2.01	-2.54	-6.1	-0.5	-2.6	-3.08	2020-08-20
EGLD	-4.04	1.02	0.90	-0.71	-4.8	0.7	0.0	-1.37	2020-09-04
EOS	1.10	-0.84	-2.26	-0.67	-0.3	-0.4	-2.4	-0.99	2017-08-01
ETC	1.88	1.23	-1.11	0.67	11.9	1.1	-1.8	3.71	2016-09-01
ETH	-7.53	-2.72	-0.66	-3.64	-11.7	-5.8	-5.3	-7.61	2016-07-01
FIL	0.43	2.09	-0.56	0.65	0.4	2.3	-0.5	0.74	2020-10-16
FLOW	3.49	1.12	0.65	1.76	3.3	1.3	0.6	1.74	2021-03-01
FTM	1.02	-1.87	-2.13	-0.99	1.9	1.8	-1.9	0.62	2019-06-18
FTT	6.08	-7.31	-1.06	-0.76	-1.9	-7.1	-2.3	-3.75	2019-07-30
GRT	2.02	1.27	-0.37	0.97	2.3	1.1	-0.4	0.98	2020-12-18
HBAR	6.40	-0.30	-1.58	1.51	2.9	0.3	-1.7	0.47	2019-11-01
HNT	0.99	-0.28	-0.57	0.05	1.4	0.9	-1.6	0.23	2020-08-19
ICP	-1.86	-0.44	0.10	-0.73	-1.9	-0.4	0.1	-0.73	2021-08-01
LEO	-5.71	-0.26	-1.19	-2.39	2.6	3.6	-5.2	0.33	2019-05-21
LINK	0.74	-2.81	-3.82	-1.96	-1.8	-4.5	-5.0	-3.78	2017-09-29
LTC	0.19	-0.72	0.96	0.14	-6.1	-3.1	-3.1	-4.10	2014-04-01
LUNA	5.35	6.39	-2.41	3.11	4.1	5.3	-3.1	2.12	2020-02-25

t-stats	First Year Data for Each Currency				All Sample				
Asset	b_1	b_2	b_3	**Average *t*-stat**	b_1	b_2	b_3	**Average *t*-stat**	**Inception Date**
MANA	1.18	3.90	-2.27	0.93	4.1	1.5	-1.1	1.51	2018-08-01
MATIC	-3.36	-2.97	-0.77	-2.37	-3.9	-3.1	-2.2	-3.07	2019-04-27
MIOTA	-6.03	-4.02	0.11	-3.31	2.0	-3.0	1.8	0.25	2017-06-13
MKR	1.57	-0.44	0.51	0.55	2.4	0.1	-0.9	0.51	2018-04-01
NEAR	0.43	1.47	-0.09	0.60	0.2	0.7	-1.3	-0.13	2020-10-15
RUNE	-2.04	0.70	-4.06	-1.80	-1.9	-0.5	-3.4	-1.91	2020-07-20
SAND	2.54	2.70	0.71	1.99	3.6	2.8	1.9	2.77	2020-08-15
SHIB	3.64	-2.39	-2.51	-0.42	3.6	-2.4	-2.5	-0.42	2021-05-11
SOL	0.22	2.57	-0.12	0.89	-1.1	0.9	-2.4	-0.87	2020-04-11
THETA	0.40	-0.14	1.11	0.46	0.3	-1.2	-0.4	-0.43	2018-01-17
TRX	-1.05	0.65	0.00	-0.13	-0.7	1.3	-2.6	-0.69	2018-04-01
UNI	0.57	0.70	-0.74	0.18	-0.3	0.5	-0.3	-0.02	2020-09-18
VET	-4.46	2.05	-0.23	-0.88	-3.0	-1.8	-3.1	-2.64	2018-07-14
WAVES	1.74	4.66	1.42	2.61	4.0	5.4	-1.0	2.80	2018-04-01
XLM	10.72	0.63	0.29	3.88	4.1	0.4	-4.3	0.10	2014-08-12
XMR	-2.10	0.38	0.54	-0.39	-5.1	-3.0	-3.0	-3.70	2014-08-01
XRP	-2.02	-0.80	0.64	-0.73	2.4	-3.5	-5.0	-2.04	2015-01-01
XTZ	-0.45	0.42	1.59	0.52	-2.4	1.9	-0.6	-0.36	2017-08-01
ZEC	-2.46	-4.73	-0.59	-2.60	-6.5	-5.2	-3.4	-5.02	2018-01-01

Appendix C

Table 5A. Broader Stock Market Volatility (VIX) Impact on Crypto Volatility

	Parameters								t-stat							
Asset	*c*	a_1	b_1	a_2	b_2	a_3	b_3	*d* x1E5	*c*	a_1	b_1	a_2	b_2	a_3	b_3	*d*
AAVE	0.005	0.131	-0.027	0.126	-0.010	0.126	-0.021	6.57	7.52	8.15	-1.47	7.98	-0.52	7.90	-1.16	2.06
ADA	0.004	0.200	-0.023	0.136	-0.012	0.132	-0.038	2.54	17.25	19.92	-2.00	13.31	-0.98	12.70	-3.23	2.69
ALGO	0.006	0.141	-0.012	0.146	0.002	0.111	-0.023	1.80	18.22	11.73	-0.88	12.25	0.12	9.28	-1.62	1.50
ATOM	0.006	0.151	-0.022	0.147	-0.002	0.108	-0.048	0.79	18.29	11.97	-1.55	11.76	-0.16	8.73	-3.44	0.71
AVAX	0.008	0.174	0.001	0.110	-0.001	0.087	-0.029	-2.72	9.95	11.36	0.07	7.14	-0.08	5.66	-1.59	-0.78
AXS	0.007	0.226	-0.027	0.130	0.037	0.115	-0.005	0.70	6.13	14.33	-1.26	8.31	1.75	7.27	-0.21	0.13
BCH	0.004	0.240	0.010	0.141	-0.030	0.122	-0.079	-1.63	18.34	24.53	0.89	14.35	-2.59	12.22	-6.67	-1.69
BNB	0.003	0.178	-0.035	0.192	0.008	0.143	-0.040	2.13	12.96	15.02	-2.55	16.06	0.59	11.76	-2.92	2.37
BSV	0.004	0.241	-0.003	0.101	0.031	0.174	0.011	0.26	14.44	19.13	-0.18	8.02	2.04	14.11	0.71	0.23
BTC	0.002	0.154	-0.063	0.159	-0.041	0.150	-0.071	2.06	17.66	18.83	-6.44	19.07	-4.22	17.92	-7.20	3.78
CAKE	0.006	0.154	-0.070	0.147	-0.022	0.153	-0.017	-1.94	6.45	8.23	-3.21	7.90	-1.01	8.30	-0.82	-0.47
CRO	0.005	0.294	0.062	0.087	-0.048	0.126	-0.024	-3.01	15.73	28.11	4.30	8.21	-3.35	11.83	-1.70	-2.59
CVX	0.016	0.277	0.178	0.144	0.024	0.069	-0.044	-30.7	9.35	12.71	6.62	6.85	0.90	3.48	-1.68	-4.05
DOGE	0.008	0.227	-0.042	0.127	-0.018	0.131	0.005	-2.87	25.23	28.74	-4.25	15.62	-1.70	16.58	0.46	-2.06
DOT	0.007	0.155	-0.058	0.099	0.004	0.099	-0.040	-3.91	10.36	9.54	-3.11	5.96	0.19	6.04	-2.16	-1.35
EGLD	0.007	0.144	-0.082	0.104	0.000	0.102	-0.024	-0.80	9.72	8.99	-4.42	6.45	0.01	6.26	-1.25	-0.26
EOS	0.005	0.214	0.026	0.146	-0.028	0.154	-0.028	-5.38	22.07	21.49	2.22	14.73	-2.36	15.57	-2.41	-5.47
ETC	0.004	0.258	0.070	0.229	0.026	0.110	-0.021	0.87	17.45	29.27	6.44	25.40	2.38	12.08	-1.87	0.83
ETH	0.003	0.168	-0.050	0.160	-0.044	0.167	-0.034	0.38	20.20	18.72	-4.86	17.87	-4.24	18.74	-3.29	0.54
FIL	0.006	0.139	-0.021	0.151	0.074	0.114	0.008	-2.60	8.66	7.75	-1.00	8.45	3.53	6.40	0.39	-0.89
FLOW	0.006	0.224	0.067	0.140	0.011	0.153	0.041	-2.00	6.52	12.79	2.91	8.00	0.47	8.39	1.80	-0.48
FTM	0.005	0.179	-0.011	0.160	0.039	0.132	-0.008	10.91	12.78	15.39	-0.75	13.42	2.76	10.86	-0.53	6.64
FTT	0.004	0.169	-0.024	0.149	-0.030	0.141	-0.038	-0.63	16.01	13.65	-1.65	11.74	-2.00	11.19	-2.53	-0.77
GRT	0.005	0.117	-0.037	0.158	0.012	0.136	-0.007	8.50	5.83	7.05	-1.84	9.54	0.61	8.02	-0.36	1.99
HBAR	0.005	0.201	0.029	0.166	0.021	0.171	0.013	2.01	12.09	16.74	1.87	13.51	1.36	13.89	0.84	1.41
HNT	0.008	0.201	0.034	0.127	0.017	0.136	-0.013	-3.41	8.72	12.99	1.74	8.00	0.84	8.67	-0.66	-0.93
ICP	0.010	0.164	-0.007	0.012	-0.039	0.107	0.035	-13.7	9.86	6.41	-0.24	0.48	-1.33	4.11	1.15	-3.27
LEO	0.003	0.314	0.089	0.121	0.040	0.100	-0.045	-3.33	14.06	24.67	5.45	9.10	2.42	7.55	-2.64	-4.56
LINK	0.006	0.199	-0.004	0.174	-0.033	0.141	-0.047	-3.09	20.54	20.71	-0.32	18.03	-2.96	14.68	-4.12	-2.75
LTC	0.003	0.220	-0.030	0.161	-0.031	0.127	-0.021	0.02	21.53	27.72	-3.25	19.88	-3.28	15.41	-2.20	0.02
LUNA	0.006	0.286	0.084	0.120	0.073	0.126	-0.007	3.86	11.25	21.37	4.78	8.41	4.15	8.61	-0.40	2.12
MANA	0.005	0.201	0.010	0.156	-0.001	0.133	-0.008	1.39	17.00	19.88	0.76	15.75	-0.06	13.31	-0.66	1.18
MATIC	0.006	0.184	-0.046	0.161	-0.001	0.156	-0.021	0.08	15.18	16.44	-3.25	14.06	-0.05	13.42	-1.52	0.05
MIOTA	0.006	0.187	-0.028	0.169	-0.040	0.182	0.023	-5.67	21.64	19.40	-2.50	17.62	-3.63	18.56	2.08	-5.02
MKR	0.004	0.191	-0.007	0.132	0.024	0.137	0.029	6.68	13.58	17.94	-0.53	11.94	1.74	12.34	2.11	5.27
NEAR	0.008	0.173	0.032	0.087	0.007	0.115	-0.001	0.03	9.78	10.96	1.70	5.56	0.36	7.22	-0.04	0.01
RUNE	0.010	0.137	-0.021	0.069	-0.004	0.096	-0.054	0.61	10.76	9.10	-1.20	4.57	-0.23	6.30	-3.05	0.16

	Parameters								t-stat							
Asset	c	a_1	b_1	a_2	b_2	a_3	b_3	d x1E5	c	a_1	b_1	a_2	b_2	a_3	b_3	d
SAND	0.008	0.198	0.061	0.147	0.024	0.129	0.011	-1.30	8.82	13.56	3.33	10.41	1.37	9.15	0.59	-0.33
SHIB	0.006	0.275	0.066	0.116	-0.068	0.232	0.025	-7.81	5.34	12.88	2.56	5.25	-2.56	10.37	0.93	-1.47
SOL	0.006	0.192	-0.003	0.136	0.030	0.122	-0.023	3.35	9.21	14.19	-0.17	9.59	1.75	8.41	-1.33	1.24
THETA	0.006	0.251	0.031	0.136	-0.015	0.128	0.010	1.38	18.55	26.25	2.67	14.12	-1.28	13.18	0.91	1.11
TRX	0.004	0.211	0.012	0.148	0.021	0.141	-0.015	0.86	17.04	20.49	0.99	14.21	1.73	12.94	-1.20	0.94
UNI	0.004	0.204	0.020	0.142	0.032	0.129	0.006	7.48	6.27	12.21	1.05	8.57	1.71	7.74	0.32	2.43
VET	0.005	0.189	-0.020	0.097	-0.013	0.127	-0.037	4.65	17.90	18.10	-1.61	9.14	-1.01	12.01	-2.93	3.89
WAVES	0.004	0.248	0.055	0.176	0.058	0.094	-0.025	5.23	15.51	26.04	4.40	18.03	4.66	9.64	-2.05	4.78
XLM	0.006	0.215	-0.049	0.178	-0.001	0.120	-0.029	-6.85	24.77	27.87	-5.16	22.87	-0.11	15.34	-3.02	-6.16
XMR	0.005	0.228	0.000	0.124	-0.018	0.139	-0.033	-2.88	26.55	28.66	-0.02	15.31	-1.94	17.43	-3.54	-3.33
XRP	0.004	0.284	-0.001	0.134	-0.037	0.163	-0.030	-3.25	19.22	37.53	-0.11	17.03	-3.73	20.36	-2.97	-3.37
XTZ	0.007	0.262	0.000	0.139	0.032	0.166	-0.018	-7.23	21.22	26.24	0.03	13.65	2.71	16.47	-1.56	-5.38
ZEC	0.004	0.177	-0.045	0.133	-0.050	0.133	-0.005	2.85	17.27	17.28	-3.80	13.30	-4.27	12.98	-0.44	3.10

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