Assessment of Cryptocurrency Risk for Institutional Investors

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Introduction

Since the circulation of the original Bitcoin white paper in 2008 the value of all cryptocurrencies has risen to exceed one percent of all traded wealth. In recent months there have been large variations in the values of major cryptocurrencies like Bitcoin and Ethereum, in addition to frequent massive shifts in the values of lesser known cryptos. The institutional landscape continues to evolve rapidly with firms like Goldman Sachs and Fidelity setting up trading facilities, while other organizations like HSBC have steadfastly advised clients to keep away from crypto. A useful overview of the current state of play appears in Horne (2021). Irrespective of intrinsic or extrinsic value, we expect that such items will be present in institutional investor portfolios from time to time.

As such it is necessary to have methods in place to assess the risk of holding cryptocurrencies and the incremental impact of crypto holdings on overall institutional portfolios. The main portion of our proposal focuses on key building blocks for understanding the risk of cryptocurrencies and *what magnitude of return expectations would justify those risks for a typical investor*. Our process involves both historical and forward-looking information, as well as several nuances in the statistical estimation of a covariance matrix (within crypto and between crypto and other assets).

An additional feature is a means to incorporate "tail risk" as might arise from geopolitical events (being outlawed or severely regulated) and operational risks (*e.g.,* theft, loss of private keys) based on use of mixture distributions and the method of Cornish and Fisher (1938). This relevance of tail risk is motivated by real world events such as the aggressive regulation of crypto activities by China and other countries, and the persistent occurrence of large hacks (*e.g.,* Poly Networks in August 2021) wherein losses of a half billion dollars or more are almost ordinary.

While the emergence of cryptocurrencies has led to numerous working papers within the academic community, we draw attention to Alexander and Imeraj (2019), which addressed the empirical volatility of major cryptos as being on the order of 80% annualized. Schwenkler and Zheng (2020) identify pairwise covariance structures in the behavior of cryptocurrencies, which they ascribe to news coverage. The classic work of Hotelling (1929) also offers a relevant foundation given that a major purported benefit of cryptocurrencies is their built-in limitation of a finite supply (at least for each individual cryptocurrency).

Analytical Method for Market Risk

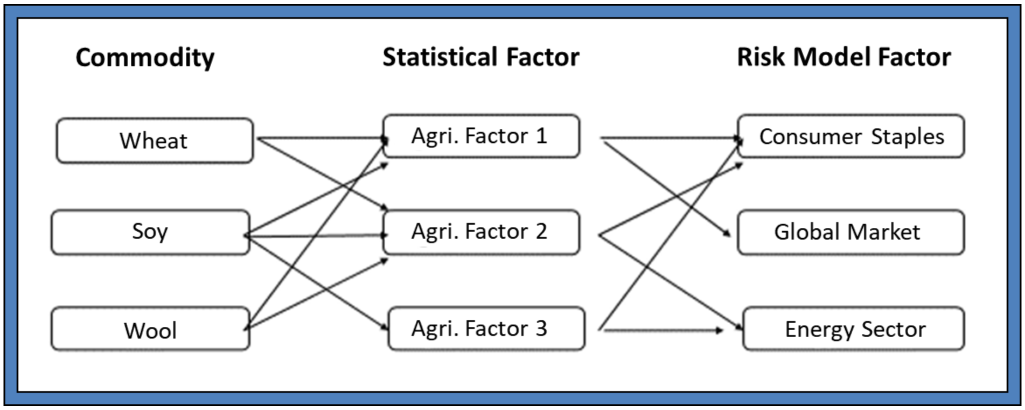
Our coverage of cryptocurrencies is closely related to the methods we routinely use for commodities and fiat currencies of frontier market countries. For fiat currencies, we create groups of currencies based on geographic proximity, trade relations, and cultural similarity. A similar grouping concept is used for cryptos. The grouping scheme allows us to build principal component factor exposures for crypto currencies, which are then mapped onto existing risk model factors for non-crypto assets.

The first step is to use a principal component analysis (PCA) of one or more groups of crypto assets to estimate statistical factors that are common drivers of observed returns. These factors may be difficult to identify and may change over time. PCA is a traditional way to deal with such situations which generates factors based on the covariance matrix of the asset returns themselves. In the usual manner of a statistical risk model, we keep the statistical factors which contribute the most to variance and dismiss smaller ones as representing noise. A useful model for drawing the line between PCA factors and noise is presented in Laloux *et al.* (2000).

Once the statistical factors for a sample period have been identified, the second step maps the statistical factors onto existing factors in other models to determine the correlations between a crypto asset and traditional assets. A general discussion of factor modeling methods is in diBartolomeo (2014).

To keep the model parsimonious and to try to avoid overfitting, the number of identified factors onto which each statistical factor is mapped should be limited. One does not know the nature of statistical factors: hence one does not know which risk model factors are most likely to be relevant to it. To select among traditional risk model factors in a systematic fashion, a cross validated LASSO regression is used. This procedure automatically drops factors which do not add to the explanatory power of the model for cryptocurrencies, while simultaneously shrinking remaining risk factor loadings towards zero to combat overfitting. An illustration of the same process applied to commodities is presented in Figure 1 on the next page.

Figure 1
A Conceptual Diagram Illustrating the Stages of Our Modeling Process



Preliminary results show that PCA in this case picks up a crypto "market" factor which loads positively on all the major cryptocurrencies. Subsequent statistical factors tend to reflect the movement of cryptocurrencies around this market factor. These statistical factors can then be mapped onto our risk model with the LASSO regression. Some unique challenges are presented in this case by the very short history of most cryptocurrencies. One simple approach is to take Bitcoin as an indication of the crypto market and use traditional regressions to estimate "beta" to Bitcoin as a metric of risk for small cryptos that cannot be not included in the original PCA cohort.

Table 1

	Statistical Factor 1	Statistical Factor 2	Statistical Factor 3
Bitcoin	0.33	-0.01	0.40
Ethereum	0.44	0.10	0.39
XRP	0.46	0.32	-0.78
Cardano	0.53	0.35	0.24
Binance Coin	0.44	-0.87	-0.15

An example result for five cryptocurrency loadings on statistical factors for a single time period is presented in Table 1.

Besides defining the cohort set, the statistical process for cryptocurrency must account for several uncommon features. The first is the very large departure from our usual independent and identically distributed (IID) return assumptions. Cryptocurrencies have exhibited high degrees of skew, kurtosis, and serial correlation in their returns. These behaviors may arise from speculative interest from retail investors, the erratic nature of interest from major financial institutions, or fear of cryptocurrencies being severely hampered by regulation (as seen in China).

With respect to non-IID behavior we employ four analytical nuances to improve the transformation from purely historical observation to forward-looking risk forecasts. The first is the use of "root mean square" (RMS) rather than standard deviation as the measure of dispersion of factor returns. We are treating factor return time series as if markets are relatively efficient so mean returns to a factor should be close to zero, rather than whatever time series mean is observed. For example, a return time series that goes up 10% per month every month for two years (as was roughly observed with Internet stocks in the late 1990s) would have a standard deviation of zero but a significant value for root mean square.

The second technique is the idea of "range based" volatility measures, also replacing the usual definition of standard deviation of returns. One way to think about the volatility of an asset is to consider the percentage distance between the highest and lowest prices observed during a particular period (*e.g.,* day, month, year). If the high and low prices are close together, the asset has low volatility. If the high and low prices are far apart, the asset is volatile. Several papers starting with Parkinson (1980) have shown that if returns are IID, there is a direct algebraic transformation between traditional return volatility and range-based measures. A very simplified range based measure of volatility would just be (high - low)/(high + low). For example, if we observe that a cryptocurrency had a low price of $1000 and a high price of $3000 over the past month, we get a volatility of *50% per month*.

The third proposed input to ex-ante currency risk estimation is the availability of a "carry trade" wherein bank deposits denominated in a particular currency offer higher interest rates than in major currencies. As cryptocurrency deposit accounts do not carry any form of government deposit insurance, the risk of counterparty failure is substantial. As of the writing of this article, retail "Bitcoin savings accounts" are available with yields over 8% annually, as compared to close to zero for ordinary bank accounts in the U.S.

Our final key input is the concept of "convenience yield." The anonymity and ease of global transactions has material economic value to certain market participants (criminals, tax evaders, investors in countries with capital controls). While this effect is hard to quantify directly there is a long history of low or negative interest rates in countries with strong banking secrecy laws. In the 1980s Swiss banks routinely offered negative interest rates on deposit accounts while U.S. banks were offering a rate of around 5% (the maximum allowable under Federal Reserve Regulation Q until 1986).

At the current time the combination of convenience yield and interest premium is probably around 12-13% which implies a volatility equivalent (*i.e.,* inclusive of higher moments) of 70-80% annually for major cryptos. For a derivation of this relationship see diBartolomeo (2020), which is an extension of Litzenberger and Rubinstein (1976) and Wilcox (2000 & 2003). There is also a thinly traded Bitcoin Volatility Index (BVOL) whose value has ranged from a low of around 19% to a high of 188% annualized. As of this writing, the BVOL value was 79.3%.

Modelling Event Risk

In addition to large scale thefts and the possibility of being outlawed in some countries, there have been many cases of lost computer files, passwords known only to a decedent, and other means creating situations where cryptocurrencies are inaccessible to the rightful owners. There have been successes by law enforcement or quasi self-regulation in recovering significant amount of stolen crypto as in the

Colonial Pipeline case and the recent seizure of purportedly stolen crypto valued at $3.6 Billion by the U.S. Department of Justice. Perversely this trend may decrease the acceptability of cryptocurrencies among participants seeking anonymity decreasing the "convenience yield" premium in crypto valuation into question. On the other hand, the East Caribbean Currency Union is the first central bank to issue a blockchain based, central bank digital currency (CBDC), and other countries are exploring or have launched pilots. In addition, El Salvador has recently recognized Bitcoin as legal tender.

To provide a framework for modeling such event risks, we propose a simple two state model. In one state, there is an event risk incident with probability P, and an expected return (loss) L with standard deviation S0. In the other state, there is no operational risk incident with probability (1-P), but there is market risk with expected return E and volatility S. We combine the two states into a single distribution using a "mixture of normal distributions" process. See Robertson and Fryer (1969). The resultant combined distribution will have four moments with negative skew and positive excess kurtosis. We use the aforementioned method of Cornish and Fisher to convert to the closest fit normal distribution.

As an example, we can assume our "regular state" has .999 probability per day with a daily volatility of 5% and an expected arithmetic return of .1% per trading day. The "incident" state has a probability of .001 per day. We assume that in the event of an incident, the expected loss is 80% with a standard error of 3%. Including both market risk and "event" risk we get a combined equivalent daily volatility of 9.08%. Annualizing under IID assumptions we get 144% per annum. It should be noted that if we cut the incident probability to .0001, we get a volatility of 5.07% per trading day, just a tiny bit higher than with a zero probability of an incident.

Stablecoins

A sidelight to the cryptocurrency discussion is the matter of "stablecoins" like Tether where a coin issuer functions like an 18th century bank issuing its own currency. Commercial banks in Hong Kong and Scotland still routinely issue their own "bank notes." To stabilize the value of cryptocurrencies at a relatively fixed value in U.S.$ (like a pegged currency), the "custodian" holds financial reserves that purportedly assure that the stablecoins have a claim on assets that can be converted to conventional currency.

However, experts including Gary Gorton of Yale have questioned the validity of the collateral in these structures (Coy, 2021). Lacking complete confidence in the collateral, we can treat this concern as we would counterparty risk in an over-the-counter (OTC) derivative acting in reliance on a clearing organization for sound collateral management, or a recognized credit rating for the counterparty.

Liquidity as the Risk Mitigation Method

On annualized basis, the return volatility of cryptocurrencies looks enormous (80% for the majors, far higher for many of the less known). Investors are depending on high liquidity to allow them to exit an asset quickly to limit losses. Under typical IID assumptions, 80% per annum is about 5% per trading day, so a three standard deviation event is a 15% loss per trading day. Even if we "fatten the tails" consistent with a t-5 distribution, we end up around a 20% loss.

However, it should be noted that liquidity is not infinite for any asset. On October 19, 1987, the U.S. stock market loss $1 trillion in capitalization (a roughly 22% decline) when the New York Stock Exchange (NYSE) Designated Order Turnaround (DOT) execution system got overwhelmed. This massive decline was the result of only *$15 Billion in trading volume*. While the core blockchain capacity for Ethereum was significantly upgraded in 2021, crypto transactions done on "Decentralized Finance" peer-to-peer networks are highly vulnerable to disruption which could lead to extreme cases of "jump diffusion" in prices.

Conclusions

Our proposed analytical process for crypto risk is closely related to our current practices for commodities and frontier currencies. This process makes for relatively simple integration with risk models for other asset classes.

The assessment of volatility and market risk is highly dependent on a nuanced understanding of the extent of non-IID returns with unstable means. If we include operational risk, the resultant volatility estimates are extremely sensitive to the probability of an "incident." Even seemingly low probabilities like 1 in 1000 create a profound increase in volatility equivalence and related risk metrics (*e.g.,* Value at Risk).

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