DOI: https://doi.org/10.37075/EA.2022.1.07 Economic Alternatives, 2022, Issue 1, pp. 111-131

Risk Management for Crypto Assets: Towards Volume-Adjusted Metrics

Received: 10.12.2021
Available online: 29.03.2022

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Abstract:

Cryptocurrencies (or coins) have attracted a significant interest from amateur and professional investors alike. Those currencies are traded on specialized exchanges and are characterized by extreme price dynamics and pockets of significant volatility with liquidity risk being a major concern. The article studies 20 cryptocurrencies over the period Q4.2013-Q2.2021 to glean key stylized facts about their dynamics. We demonstrate that traditional risk metrics may be insufficient to fully evaluate their risk profiles and so propose to leverage a set of novel volume-adjusted metrics. Adjustments to the Sharpe ratio, the Value at Risk (VaR) and the Expected Tail Loss (ETL) measures are outlined so they better reflect the specifics of cryptocurrencies. This enhances the classical two-dimensional mean-variance optimization with a third dimension – volume traded, thus engendering a new three-dimensional asset map that can be used for improved risk management. This new framework is illustrated over the 20 major cryptocurrencies and corresponding adjusted metrics are calculated and interpreted.

Keywords: cryptocurrency, coin, risk, returns, asset selection, liquidity risk

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I. Introduction

The rapid IT transformation of modern economy has given rise to a set of particularly digital phenomena, and the financial markets have been no exception. The confluence of technological breakthroughs such as the application of advanced cryptography on distributed network infrastructures and the rise of digital marketplaces needing novel payment mechanisms have, in part, led to a proliferation of new classes on assets that reside exclusively in the virtual space (Henderson & Taskin, 2019). While such novel assets provide a number of possibilities to generate return and enable extensive hedging strategies, their emergent nature predicates a higher level of risk that must be managed through new methods and approaches. The aim of this article is to mount an in-depth study of the most popular class of emerging digital assets – the cryptocurrencies – and outline key stylized facts and risk management considerations related to them.

We thus study the cryptocurrency market, and more specifically – the risk management implications of its extreme volatility. Our

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expectation is that the current research is able to unravel new insights from this market, hypothesizing that additional risk characteristics may have to be taken into account when optimizing cryptocurrency portfolios. To achieve this, the article takes up a few major tasks: to collate and process pricing data for crypto assets, to investigate their dynamics, to apply traditional risk management methodologies, and based on their deficiencies – to propose complementary risk metrics. By outlining the market behavior of the largest cryptocurrencies by market capitalization, we are able to distill a few novel characteristics that differentiate them from classical financial assets in important ways. Building on that, we propose moving from the standard two-dimensional mean-variance optimization framework towards an enhanced volume-adjusted one that is more suitable for emerging crypto tokens and securities.

To do this, we begin by a short literature overview in the next section that outline the types of digital financial assets and their key characteristics. Key risk sources for crypto assets are also outlined and briefly discussed. Section Three proceeds to present price dynamics of twenty key cryptocurrencies over the past years. The distribution of those time series serves to illustrate some of their key statistical properties. Most notably, we show that non-gaussian distributions are the undoubted norm. Section Four outlines the key difference between traditional and crypto assets that serves as a major risk driver. It then proposes a more advanced optimization framework for managing crypto risks. Section Five presents some key results of applying this framework. Section Six provides a few comments on the results and concludes.

II. Essence and Risks of Crypto Assets

The emergence of digital assets is taking place in mostly deregulated markets. On the one hand this has led to accelerated innovation but on the other, unified definitions and regulatory oversight practices are still lacking (Henderson & Taskin, 2019). At the most basic level, one can define digital assets as sets of binary information that represent financial value (see Toygar et al., 2013 and references therein). Those assets may resemble the function of money (as in cryptocurrencies), of securities (as in crypto tokens) or as representations of objects of value as is the case of non-fungible tokens, NFTs). Building upon previous work (Milos & Gerasenko, 2020; Schär, 2021) we can generally subdivide the new digital assets into three major groups: crypto assets, digital fiat currencies, and miscellaneous assets (see Figure 1).

Crypto assets are usually powered by the blockchain technology which in its essence is an anonymized distributed ledger whereby transactions take place and are recorded via means of user consensus (for more details see Pilkington, 2016). Sometimes this whole class of assets is jointly referred to as tokens (Conley, 2017). Among this group are the cryptocurrencies that can be used as means of payment. Prime examples of cryptocurrencies include Bitcoin and Ether. Digital crypto assets that give rights to their holders over a given entity or store of value are the crypto securities (Roth et al., 2019; Liu & Wang, 2019). Tokenized equity, whereby holders of the token have rights of ownership over a company, is a leading example of such securities. The first time that they are introduced into the market is called an initial coin offering (ICO), thus mirroring the term for the initial public offering (IPO) of traditional shares. Finally, the blockchain technology may underline tokens that represent an object of value. Non-fungible tokens (NFTs) represent unique assets in digital form such as images, sounds, algorithmically trained models, and others, and can be exchanged in designated marketplaces (Trautman, 2021).

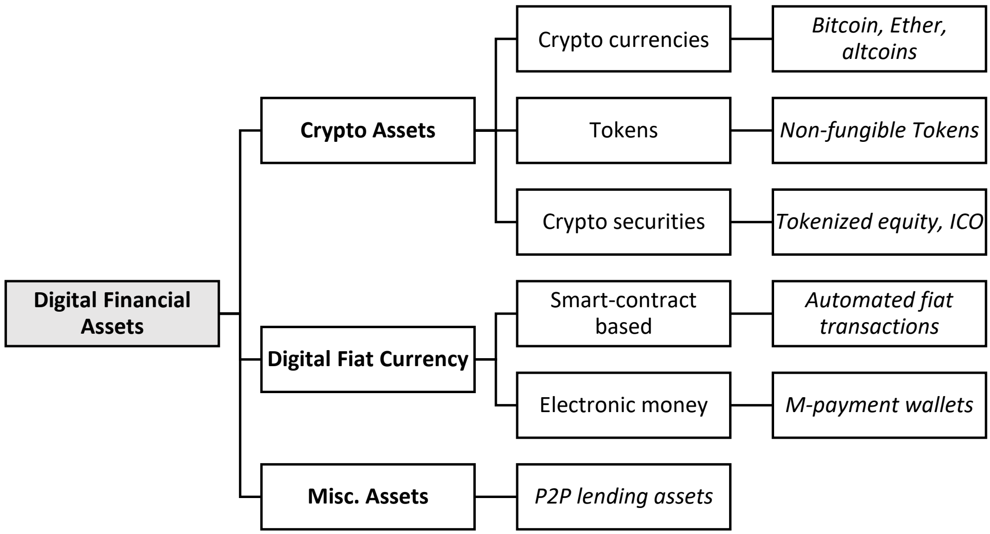

Figure 1: *Types of Digital Financial Assets, source: own illustration based on Milos & Gerasenko, 2020; Schär, 2021*

The second large group of crypto assets is the digital fiat currency. Following Bordo & Levin (2017) we define it as an asset stored in electronic form as physical currency. While this may seem close to the idea of cryptocurrencies, digital fiat does not need to be powered by the blockchain technology. Furthermore, it is often not a decentralized community-driven ledger but is rather issued by the central bank (Raskin & Yermack, 2018). It may be based on a smart contract (for details see Huckle et al., 2017) or be in the form of electronic money (Vlasov, 2017). Again, electronic money is usually not decentralized – it is considered to be digital money that has a virtual representation, centralized transaction handing and are issued by a monopoly issuer (Berenstein & Schär, 2018). Finally, the third group contains a plethora of other digital assets with varying characteristics such as cash flow from peer-to-peer lending. The key question here is whether these assets have the characteristics of currency or mostly that of a security (Conley, 2017). In the former case the price can be estimated using the familiar quantity equation. In the latter, one may find it more appropriate to leverage a discounted cash flow (DCF) model instead.

At any rate, emergent digital assets can be traded on exchanges that resemble traditional financial markets or be subject to direct transactions. This engenders two key economic characteristics they have. First, as these are traded, a price is formed that results from a concrete transaction. This price is supposed to be reflective of underlying value but this is not guaranteed. Second, this pricing takes place in a novel, unique or even one-off situation. Both of these, coupled with the fact that the assets are novel and not fully understood, predicates a key fact about them – the market price may not be reflective of fundamentals and thus bubbles of over-valued assets may form (Gronwald, 2021). To better understand the specifics of risk management for emerging digital assets, we further study cryptocurrencies and their dynamics. The choice is predicated not merely on their ubiquity but also on their representativeness and wider data availability.

The market behavior of cryptocurrencies can be understood as the result of the confluence of both economic forces and technological determinants. The blockchain technology is an apt example of the latter. In its essence it is a technology that enables the creation of a decentralized immutable digital ledger whereby transactions can be written, and thus corresponding balance can be calculated. Each transaction is a block of data that include the sender, recipient, amount, and other technical details. A specific mathematical function is then applied and the whole transaction is hashed, thus creating a unique fingerprint of this activity. Apart from the hash of the transaction itself, usually the block contains a hash of the whole preceding sequence of transactions (the chain). This snapshot of the chain ensures that everybody on the decentralized network agrees on the state of affairs. Transactions are thus possible after achieving consensus by all participants in the network (Pilkington, 2016). It is from this chain of blocks that the technology has its name. As usage proliferated, some applications choose to only use a blockchain with restricted access (private or permissioned one) but most cryptocurrencies still leverage public blockchains. This distributed ledger allows the creation of a currency, and records monetary flows without the control or involvement of a sanctioned centralized authority such as a Central Bank. It is thus practically possible to record transactions, calculate balances, and settle payments in a broadly unregulated decentralized financial system.

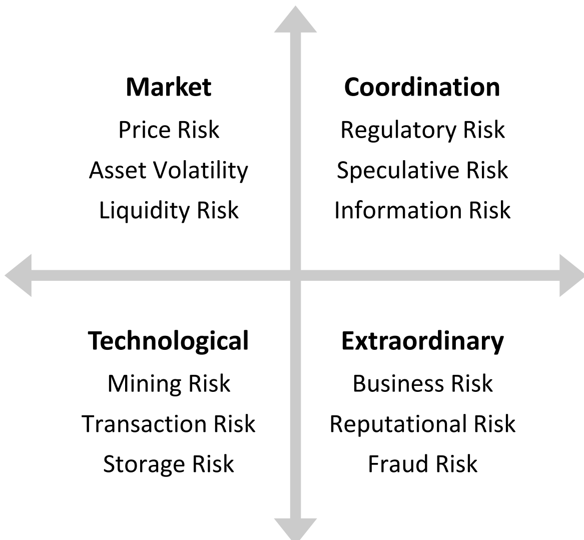

Figure 2: *Risk Groups for Crypto Assets, source: own illustration based on Shatohina & Kochetkov, 2020*

As with any currency, cryptocurrencies may not only be used for direct payment for goods and services but also traded for speculative and hedging purposes. This tends to take place into specialized exchanges whereby the exchange rate of one cryptocurrency vis-à-vis the others is obtained. There is also an exchange rate between major cryptocurrencies and traditional ones, allowing the investor to switch from assets (Hileman & Rauchs, 2017). Most cryptocurrencies feature floating prices and are thus determined by the market forces of supply and demand. Since they can be obtained and then gainfully liquidated, cryptocurrencies may serve as a viable part of investment portfolios, which necessitates their rigorous risk management. However, their emergent nature has also meant significant price volatility that has attracted not only long-term investors but also a large amount of speculative interest (Grobys & Junttila, 2021). This puts cryptocurrencies in the group of high-risk but also high-return assets.

Some of the risks from holding a crypto portfolio are clearly parallel to those of holding traditional financial assets, while others are specific to this asset class. Following Shatohina & Kochetkov (2020) we may outline four major groups of risks: market risks, technological risks, coordination risks, and extraordinary (or idiosyncratic) risks. **Market risks** are connected to the general economic and trading environment. These tend to be closely connected to macroeconomic dynamics such as the economic cycle or target monetary policy and are difficult to diversify or hedge away (see also Arsi et al., 2021). The most salient types of market risks are as follows:

- Price risk – the level and dynamics of the price, as well as its difference from asset valuation is a major consideration for investors. This risk is typical of all financial assets but is somewhat exacerbated in the case of crypto assets.
- Asset volatility – the novelty and complexity of crypto assets have spelled large variances in the price level and returns. High levels of volatility are particularly common for emergent assets as the market searches for equilibrium in an environment of rapidly shifting demand conditions.
- Liquidity risk – as crypto assets are relatively new there may not yet be enough investor interest to guarantee a deep enough market. This means they may not be easily liquidated on demand or that the investor will have to accept a significant price discount.

The loosely labelled group **Coordination risks** contains a number of familiar financial assets risks that also pertain to cryptocurrencies:

- Regulatory risk – the risk of non-compliance is particularly salient for cryptocurrencies as they are currently lightly regulated but competent national authorities are taking increasing interest in them. This is true for both crypto assets with purely currency (utility) functions, as well as for those that also have equity characteristics.
- Speculative risk – high volatility and large returns may attract speculative interest that lead to artificial price inflation or deflation. As the market moves through its fundamentals, the difference to the artificial price may turn into profit or loss to the individual investor.
- Information risk – the usual issue of asymmetric information here is more pronounced than with traditional financial

assets. In the case of cryptocurrencies, the investor may fail to uncover not only business and market data but also technological implementation details of the asset.

Technological risks are very specific to cryptocurrencies. While most traditional financial assets and transactions are digital, the specifics of the technology does not underlie their market behavior. In stark contrast, technological implementations of a specific cryptocurrency does affect its price through imposing constraints and limiting conditions such as capping supply, defining transaction time, or levying a transaction tax. Since those risks tend to be asset-specific they could be diversified away by an appropriate portfolio choice. The major types of technological risks are:

- Mining risk – some cryptocurrencies (e.g. Bitcoin) are created following the successful completion of tasks online (e.g. solving specific algorithmic challenges). Thus the supply of such currencies is dependent on the smooth functioning of this "mining" process and problems with it may engender large-scale downside risks.
- Transaction risk – since many cryptocurrencies rely on mostly or fully anonymized transaction protocols, any transaction-related problems are difficult to address and remediate. This rings especially true in the absence of a centralized settlement and remediation entity, thus increasing the investor's risk exposure.
- Storage risk – unlike traditional assets, the storage of cryptocurrencies is more complicated and relies heavily on cryptographic protocols rather than on a certain trusted authority. This essentially shifts a large part of responsibility to the investor, thus pushing the risk of malicious attacks or of losing access entirely to the individual.

The final large groups of risks is the **extraordinary (idiosyncratic) risks** that are typical of traditional financial assets but are somewhat more pronounced in the case of crypto assets. These include:

- Business risk – this is the risk inherent in carrying out standard business operations and pertains to market conditions, user behavior, and internal processes. The crypto asset may thus be beset by problems such as low adoption or lack of commercial viability that depress its price.
- Reputational risk – as the cryptocurrencies are still operating in markets with sparse regulation and are sometimes used for illicit activities due to their ability to enable anonymized transactions, they may engender risks to the reputation and credibility of the investor.
- Fraud risk – while this is a typical risk across all financial assets, the emergence of cryptocurrencies has spelled a particularly large number of fraudulent offerings and financial scams (Massad, 2019). The anonymized nature of transactions adds an additional layer of insecurity on top of that.

In a recent study Liu and Tsyvinski (2021) show that cryptocurrencies can be analyzed through traditional financial risk and return metrics but that these are also driven by crypto-specific factors such as network factors (adoption). Interestingly, cryptocurrency production factors do not exhibit a strong effect, thus hinting that the nature of many trades may be still speculative and thus detached from production specifics.

This is also underlined by the presence of strong momentum effects in overall market dynamics. Overall, all of this points at the importance of leveraging a formal and rigorous approach to risk management for crypto assets that goes above and beyond traditional approaches and metrics. In the next sections we aim to illustrate a possible enhancement of the current state-of-the-art.

III. Price Dynamics and Stylized Facts for Cryptocurrency Behavior

The birth of cryptocurrencies may be tracked to the early 2009 when the first version of the Bitcoin was introduced. While it combined already understood cryptographic primitives and network concepts, it combined them into a new asset construct. Initially touted as a decentralized currency with wide applications, it witnessed relatively slow initial adoption.

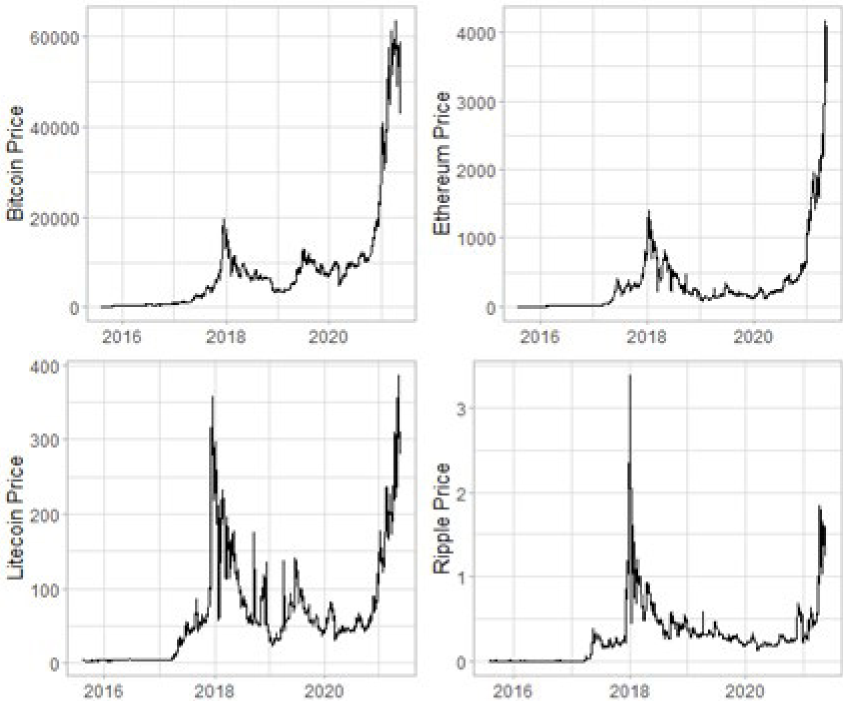

Figure 3: *Price Dynamics of Four Selected Cryptocurrencies, Q4.2015-Q2.2021*

As the concept of cryptocurrencies gained prominence, alternative blockchain-based tokens were introduced and later traded on dedicate exchanges. While technological implementations put important limitations on payment and settlement, initial attempts to understand cryptocurrencies from an economic perspective have been deeply rooted in traditional financial theory. From an empirical standpoint, those new asset classes have displayed significant volatility, and thus traditional mean-variance optimization (see e.g. Brauneis & Mestel, 2019) has only been able to tell part of the story on how to manage the risk of crypto portfolios. It is therefore important to study their overall dynamics over a longer time period and outline key stylized facts that will enable a more rigorous approach to studying crypto currencies and other crypto assets.

To do this, we look into the top twenty cryptocurrencies by market capitalization as of 2021 and track their time series back to 2013, or to the year when they were initially introduced (if after 2013). The time series thus spans the period Q4.2013 to Q2.2021, and the selected currencies are Bitcoin Cash, Binance Coin, Bitcoin, Cardano, Dogecoin, EOS, Ethereum Classic, Ethereum, Filecoin, Litecoin, Monero, Neo, Polkadot, Solana, Stellar, Terra, Theta, Tron, Vechain, and Ripple. Data was obtained from the publicly available modules of the CoinMarketCap exchange. While the cryptocurrency may have a slightly different technological underpinning and attempted application as detailed in their respective white papers, their overall dynamics are surprisingly similar. As a case in point we study further the four largest currencies in terms of market capitalization. Their comparable dynamics are visually presented in Figure 3.

Virtually all the cryptocurrencies exhibit similar dynamics post introduction and this is also broadly captured in the market behavior of Bitcoin, Ethereum, Litecoin and Ripple. Initially, the cryptocurrency is beset by the problem of low adoption and low investor interest in purchasing and trading with this asset. Over this first period, prices remain relatively low and are driven by purchases that are relatively few and far in between. In late 2017 and early 2018 the market saw exponential dynamics whereby large demand led to increases by orders of magnitude. The high growth could hardly be related to fundamentals and this has led many observers to propose that this is a speculative bubble. In a way the bubble burst in early 2018 which marked the loss of half or more of the value of many cryptocurrencies. The next couple of years the market reached a relatively more stable plateau as the cryptocurrencies' price and corresponding returns began drifting toward their equilibrium.

However, another unexpected exogenous shock gave rise to a new cycle of rapid price increases, coupled with pockets of significant volatility. The global coronavirus pandemic that began in 2020 spelled the move of many amateur investors into the financial markets, with some of them looking to realize large profits through the timed purchase and sale of cryptocurrencies. This large uptick in demand, coupled with renewed market optimism, led to another cycle of rapidly rising prices. This went on in 2020 up to 2021, where they reached a peak, followed by another collapse. The global pandemic is a naturally interesting case in point. While economic calamities may be expected to depress asset prices, this is not what was observed during the 2020-2021 one. Under expansionary fiscal and monetary policy, many market assets increased in value against the backdrop of simmering issues in the real economy. This was even more pronounced in the case of crypto assets. While increases in money supply and low interest rates are certainly part of the story, the increase was orders of magnitude larger than fundamentals would imply. This clearly points out to non-economic factors behind the volatility. Among those are probably the favorable cultural perception of cryptocurrencies as well as the influx of digital natives (Millennial and Generation Z traders) into the investment process (Fink, 2021; Ghaissani & Kannan, 2021). At any rate, the initial waves of the coronavirus seem to have increased not only the volume but also the efficiency of the market for established cryptos (see e.g. Mnif et al., 2020).

These dynamics clearly illustrate that cryptocurrencies in the immediate years after introduction are characterized by very pronounced volatility which translates into correspondingly large risk on both the upside and the downside. The investor may thus realize both sizable gain and calamitous losses should they decide to tolerate such levels of risk. At any rate, we should note that trading volumes are closely related with those dynamics – initially trade is small but as growth becomes exponential, volumes closely follow suit. As markets cool off, the amount of trades decreases, too.

The key insights from the visual inspection of price dynamics is also confirmed by key metrics for the daily returns of all twenty cryptocurrencies under consideration. Overall mean daily return is not guaranteed to be positive. In fact, more than half of cryptocurrencies in our sample – as Bitcoin Cash, Bitcoin, Dogecoin, EOS, Ethereum Classic, Filecoin, Litecoin, Monero, Neo, Polkadot, and Tron – have produced negative daily returns. It seems that the worst investment over the period is in Fielcoin with an average daily return of -1.95%, followed by Bitcoin Cash (-1.44%) and Polkadot (-0.83%). We should note that negative returns are also an artefact of the period chosen and are driven by the earlier parts of the time series.

Conversely, the cryptocurrencies that have yielded the highest average daily return over the period are Solana (1.10%), Theta (0.44%), and Stellar (0.36%). The skewness and kurtosis results further underline that those returns do not follow the normal distribution. This is also formally tested – all time series of the cryptocurrencies under study are tested with five normality tests (Anderson-Darling, Cramer-von Mises, Pearson, Shapiro-Francie and Jarque-Bera). In every single case in those 100 test statistics we obtain a significance level well below 1% (results available on demand). Thus, the hypothesis of normality is squarely rejected.

Table 1: Key Parameters and Risk Metrics for 20 Selected Cryptocurrencies, Q4.2013-Q2.2021

Coin	Mean	Standard Deviation	Skewness	Kurtosis	Sharpe	VaR (95%)	ETL (5%)
Bitcoin Cash	-1.44%	18.55%	-1.330	14.443	-0.078	-31.9%	-39.7%
Binance Coin	-0.59%	17.21%	-1.795	17.241	-0.034	-28.9%	-36.1%
Bitcoin	-0.39%	15.27%	-2.199	25.389	-0.026	-25.5%	-31.9%
Cardano	0.10%	11.94%	-0.210	19.060	0.009	-19.5%	-24.5%
Dogecoin	-0.02%	10.69%	-0.205	32.136	-0.002	-17.6%	-22.1%
EOS	-0.57%	12.29%	-1.727	22.949	-0.046	-20.8%	-25.9%
Ethereum Classic	-0.35%	13.17%	-1.403	22.708	-0.026	-22.0%	-27.5%
Ethereum	0.25%	16.75%	-0.276	16.138	0.015	-27.3%	-34.3%
Filecoin	-1.95%	23.87%	-0.488	7.720	-0.082	-41.2%	-51.2%
Litecoin	-0.40%	14.14%	-1.594	23.719	-0.029	-23.7%	-29.6%
Monero	-0.50%	13.62%	-2.425	21.733	-0.037	-22.9%	-28.6%
Neo	-0.78%	18.28%	-1.074	14.705	-0.042	-30.8%	-38.5%
Polkadot	-0.83%	23.25%	-0.599	7.712	-0.036	-39.0%	-48.7%

Coin	Mean	Standard Deviation	Skewness	Kurtosis	Sharpe	VaR (95%)	ETL (5%)
Solana	1.10%	20.55%	0.431	7.015	0.054	-32.7%	-41.2%
Stellar	0.36%	10.26%	1.775	16.737	0.035	-16.5%	-20.8%
Terra	0.31%	11.34%	0.569	9.039	0.027	-18.3%	-23.1%
Theta	0.44%	15.52%	0.689	10.246	0.028	-25.1%	-31.6%
Tron	-0.10%	7.76%	-0.014	44.939	-0.013	-12.9%	-16.1%
Vechain	0.31%	9.92%	-0.071	19.070	0.031	-16.0%	-20.1%
Ripple	0.12%	7.31%	1.004	35.248	0.017	-11.9%	-15.0%

Source: Author's calculations

While the average daily return values are not large and are roughly in line with those of more traditional assets such as equity, the risk and volatility metrics are very different. One of the most common risk metrics – the standard deviation – register extremely high values of up to 24% daily. The most volatile assets are Filecoin (23.87%), Polkadot (23.25%), and Solana (21.55%). Even the cryptocurrencies with the lowest volatility display high standard deviations. The lowest three are still pretty high – Ripple (7.31%), Tron (7.76%), and Vechain (9.92%). From a methodological perspective we can apply standard research methods from finance to analyze cryptocurrencies. Those vary from the more traditional volatility metrics through advanced ones such as the Value at Risk and the Expected Shortfall calculations. The reader is referred to Roncalli (2020) for further details.

We can naturally use the Sharpe ratio to get a feeling for the risk-return tradeoff. We define it in a standard way so that the Sharpe ratio is equal to mean returns over standard deviation, or:

$$S_i = \frac{r_i}{\sigma_i} \tag{1}$$

Formally, the Sharpe ratio will also need to include risk-free returns (r_f), and the analyst must subtract those from the realized ones (r^{μ}_i), thus:

$$r_i = r_i^{\mu} - r_f \tag{2}$$

Since a large part of the period was dominated by very small or near-zero bond yields and for simplicity and tractability, we set r_f to zero. Calculated Sharpe ration across the sample of cryptocurrencies vary substantially. While some cryptocurrencies do provide some level of return over a unit of risk, the denominator of most is so large that it dwarfs the numerator. It is then natural that this metric provides a somewhat skewed idea of the actual risk associated with the asset. This is particularly exacerbated as both the numerator (mean returns) and the denominator (standard deviation) for most cryptocurrencies vary widely depending on the period selected for their calculation. Thus, the Sharpe ratio – a usual staple of risk metrics – may not be fully appropriate for crypto assets as it is largely driven by the analyst's choice of period, and not by underlying risk. However, we may still usefully study the tradeoff between risk and return.

To do this, we select all cryptocurrencies and truncate the time series so currencies are studied for the period in which all have valid observations. After removing outliers, we end up with 16 cryptocurrencies over the period 2016-2021. Their mean returns and risk levels (as proxied by the standard deviations) are plotted on Figure 4. It shows a clear and almost perfect association between the two, displaying the familiar risk-return tradeoff. Despite their novelty and almost intractable dynamics, cryptocurrencies operate like familiar financial assets whereby investors need to be rewarded for taking up extra risk. In a way, this is a fundamental feature of financial markets that seamlessly emerged also in the market for digital assets.

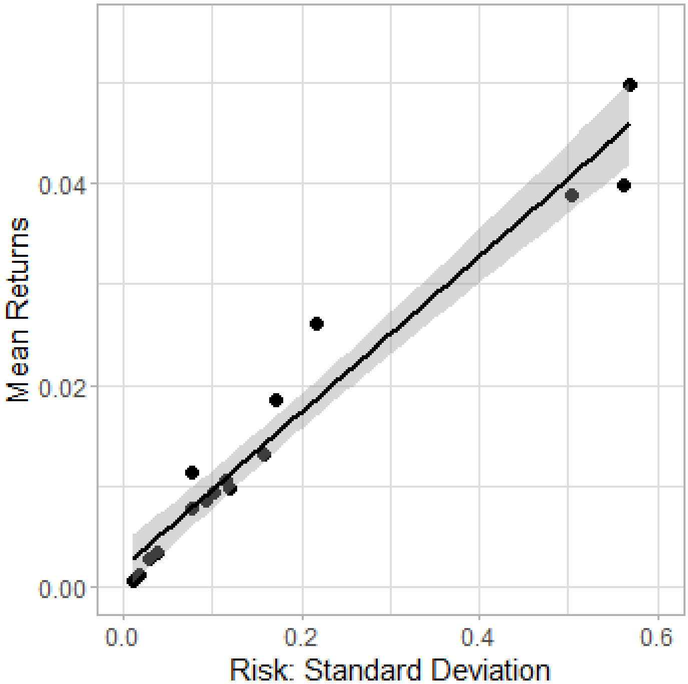

Figure 4: *Risk-return tradeoff for selected cryptocurrencies over the period 2016-2021*

To further investigate risk properties of cryptocurrencies, one can construe the value of two well-known risk metrics – the Value at Risk (VaR) and the Expected Tail Loss. Again, we define both metrics in a conventional way. The VaR_α is the largest expected loss in α% of the time. Denoting expected loss as L, and realized loss as l, then VaR_α is defined as follows:

$$VaR_\alpha(L) = \inf\{l \in \mathbb{R}: P(L > l) \leq 1 - \alpha\} \quad (3)$$

Should the expected loss L follow a defined statistical distribution function, then equation (3) simplifies to:

$$VaR_\alpha(L) = \inf\{l \in \mathbb{R}: F_L(l) \geq \alpha\} \quad (4)$$

While the Value at Risk at the 95% level shows what the maximum loss in the calm 19 out of 20 days is, the Expected Tail Loss at 5% metrics tries to calculate what the average expected loss on the twentieth outlying day is. It is thus calculated as:

$$ES_{1-\alpha} = \frac{1}{1-\alpha}\int_{0}^{1-\alpha} VaR_{\alpha}(X)d\alpha \qquad (5)$$

The $VaR_{95\%}$ and the $ETL_{5\%}$ are calculated on the time series of the cryptocurrencies and results are shown in Table 1. Again, both the VaR and the ETL metrics indicate a very high level of risk. It is conceivable that within a day, the investor may lose from a fifth to one half the value of their portfolio. Highest VaR metrics are found with Filecoin (41.2%), Polkadot (39.0%), and Solana (32.7%), while the lowest ones over the period are for Ripple (11.9%), Tron (12.9%), and Vechain (16%). The same results are also reflected in the ETL calculations. In a way, the VaR and ETL measures largely mirror the insights obtained from studying asset volatility. All traditional risk indicators clearly show high levels of risk that seem to be hardly offset by historical returns. This result may seem paradoxical – if cryptocurrencies are characterized by such unfavorable risk-return tradeoffs they should be dominated assets. Thus, instead of being vigorously traded, they should be fading into non-existence. Since this is hardly the case, a more useful approach to understanding crypto risk would be to complement the standard mean-variance optimization framework with a better understanding of actual trade patterns and trade drivers. It seems that trade is not moved by economic considerations alone, and thus volume metrics may hold the key to improving risk management for crypto assets. The next section looks further into this.

IV. Towards Richer Risk Management for Crypto

Liu & Tsyvinski (2021) have shown that cryptocurrencies have surprisingly little exposure to overall macroeconomic factors and are hardly affected by returns of other more traditional assets. Instead, crypto markets have large exposures to their internal dynamics and to investor attention. The relationship between volume traded and currency price (effectively its exchange rate) is surprisingly straightforward for many cryptocurrencies – the two metrics mostly move in a synchronous manner. Figure 5 shows the price and volume for Bitcoin over a period of seven years. From 2013 up until 2017 there was hardly any Bitcoin traded and the price has remained relatively stable with transaction few and far between affecting it. The overall upward is largely driven by few enthusiasts trading among themselves as the first years of the currency noted limited interest from institutional investors. However, as market enthusiasm, as proxied by volume traded, spiked in 2017, so did the price of Bitcoin. At the turn of the year it reached its local maximum of about USD 20,000.

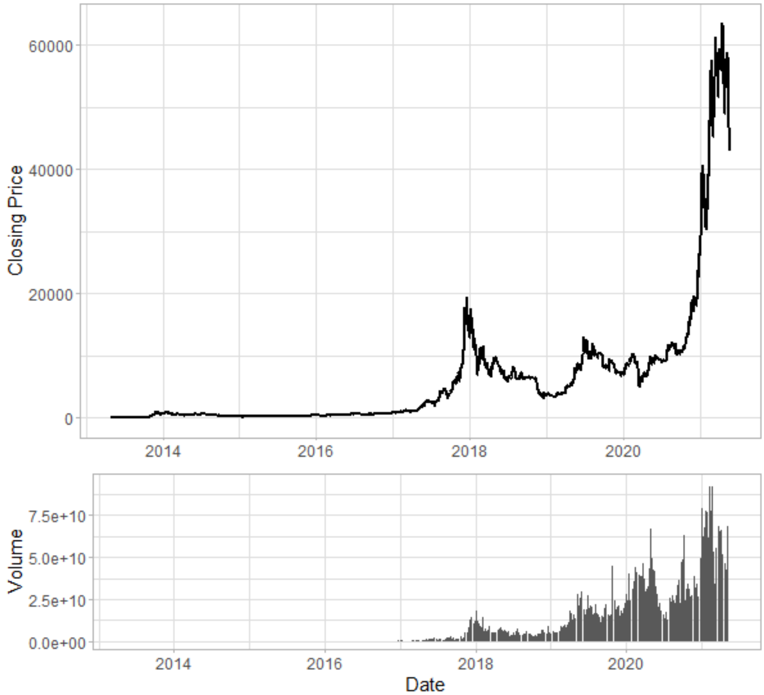

Figure 5: *Price Dynamics and Trade Volume of Bitcoin over the Period Q4.2013-Q2.2021*

This was then followed by a cooling off period, with dropping trade volumes and the price followed suit. Overall, within the next year and a half Bitcoin lost about three quarters of its value. A resurgence of trade in the second quarter of 2019 was able to start driving the price of the cryptocurrency up. In 2020 the market was joined by large groups of amateur investors that were partly spurred by a global health pandemic. The trade volume increased exponentially, and so did the price. We observe the same pattern in reverse direction in early 2021 – as enthusiasm cooled off, the amount of Bitcoin traded decreased notably and so did its price. Essentially, the Bitcoin market is not a deep and liquid market as with low-risk traditional assets but is rather subject to rapid bursts of activity driving its returns and volatility. This activity may either be spurred by bullish moods and generate significant returns; or it may be bearish and signal overall withdrawal from the market with a corresponding collapse in price. This clearly points that analyzing volume traded is a very important part of crypto risk management.

The patterns observed in Figure 5 are hardly unique for Bitcoin. We plot the trade volume as a proportion of total market capitalization of four selected cryptocurrencies in Figure 6. The overall pattern for Bitcoin (panel 1) is similar over for Ethereum, Litecoin, Ripple and most others (not pictured here). The parallels between price dynamics in Figure 3 and trade volumes in Figure 5 are striking. Across cryptocurrencies, major shifts in prices, and hence returns, are accompanied by large corresponding shifts in trading behavior. What is more, even realized high prices may not automatically translate into higher portfolio returns for the investor – if the market is so shallow that the asset cannot be liquidated, no returns can be achieved whatsoever. In short, the investigation of trade volume showed it is deeply connected with price dynamics and, by definition, with liquidation ability. We can thus say that for cryptocurrencies the one of the most (if not the most) salient risk is liquidity risk. Thus, volume traded needs to be formally included in crypto risk management.

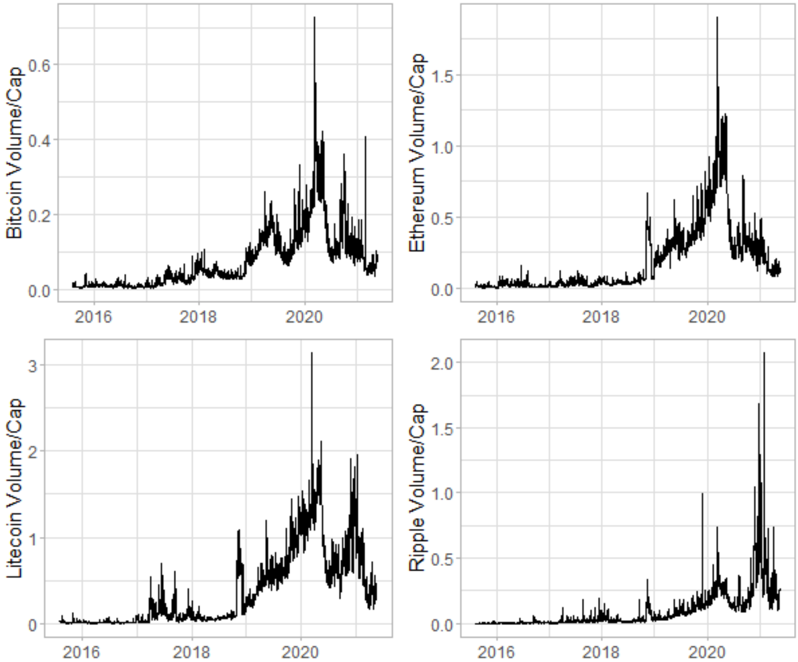

Figure 6: *Trade Volume as Proportion of Market Capitalization for Four Selected Cryptocurrencies*

The proposal to include volume is a shift away from the traditional two-dimensional mean-variance optimization framework which shows the risk-return tradeoff of a given asset. This proposition also reflects the conclusion of other studies that have found the traditional approach wanting (Boiko et al, 2021). When one analyzes crypto risks it will be useful to add a third dimension – the amount of asset traded. This correction for liquidity risk seems crucial in the cases of novel digital assets. Essentially, the analyst can conceptualize all crypto assets in a three-dimensional space, whereby they are located depending on their mean return, a risk metric (such as the standard deviation) and a trade metric (such as volume over market capitalization). This is visually presented in Figure 7. The move from a 2D to a 3D perspective on risk is a straightforward extension.

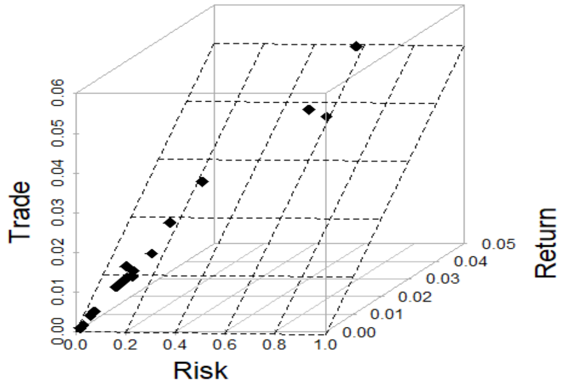

Figure 7: *Three-dimensional Risk Space for Cryptocurrencies*

Given the asset positioning, investors may choose an optimal asset or a combination (portfolio) of assets that is consistent with their pre-defined risk preferences. Just like in the 2D mean-variance framework, here one can also outline dominated assets – those that are worse in terms of trade and risk for a given level of return than an alternative asset. This then enables the analyst to construct an efficient assets frontier and choose assets or even portfolios on this frontier. However, since one operates in a 3D space, the efficient frontier will not be a line but rather a plane in 3D space. The construction of this efficient asset plane then enables one to dismiss assets below it and perform optimization of asset allocations.

Traditional risk metric can also be adjusted for volume, thus reaching new metrics that complement common risk management approaches. While there are many ways to perform volume-adjusted calculations, here we present a straightforward, albeit rough, approach to adjust the Sharpe ratio, the VaR, and the ETL metrics. We propose an adjusted Sharpe ratio for a given asset i, S_A, in the following form:

$$S_A = \frac{r_i}{\sigma_i} \cdot \frac{V_i}{C_i} \qquad (6)$$

In equation (6) we multiply the well-known metric from equation (1) by the proportion of volume traded V_i over total market capitalization C_i. In this way the adjusted Sharpe ratio decreases rapidly with the decrease of market depth. If a very small fraction of the available cryptocurrency is traded, then the adjusted Sharpe ratio is correspondingly lower. This, and the following, adjusted metric may be calculated over any desired period – e.g., daily, monthly, annually. As the ration of volume over capitalization approaches one (i.e. every bit of the asset may theoretically get traded over the reference period), then the adjusted Sharpe ratio approaches the traditional one (eq. (1)). A possible reservation for this form of adjustment would be that as market depth decreases, S_A falls too sharply. On the other hand, the magnitude of this adjustment depends crucially on investor risk preferences, with the SA version in eq. (6) supposing a relatively large degree of risk aversion. Essentially, one can incorporate risk aversion (*k*) to the degree of adjustment, thus reaching:

$$S_A = \frac{r_i}{\sigma_i} \cdot k \frac{V_i}{C_i} \quad (7)$$

Here the parameter k captures the risk appetite of the investor. The more risk-seeking the investor is, the lower the value of k, and thus – the higher the value of S_A. High values of S_A would imply a more desirable asset in terms of the risk-return tradeoff. Conversely, higher values of k, such as $k = 1$ lead to lower values of S_A, thus implying that the asset becomes more desirable as its liquidity risk decreases. The analyst may choose an appropriate adjustment for risk appetite but for illustrative purposes and simplicity here we retain the value of $k = 1$. In a similar vein to the Sharpe ratio, one may also adjust the VaR_α metric, thus reaching the following adjusted $VaR_\alpha{}^A$ (dropping indices for simplicity):

$$VaR_\alpha^A = VaR_\alpha \cdot \frac{C}{V} \quad (8)$$

This adjustment to the VaR metric effectively lowers the VaR whenever there is high liquidity, and increases it whenever there is low liquidity. As the fraction of market capitalization over volume traded approaches one, the adjusted VaR metric converges to the traditional one (eq. (4)). Thus, the adjustment allows the investor to have a more appropriate risk evaluation by strongly weighing in liquidity risk, and thus implying more conservative portfolio allocation choices. On the flipside, the adjusted VaR metric loses its usual interpretation – it is no longer the maximum expected loss in α% of the cases, and it should not be treated as such. It is rather a risk metric that can be more usefully utilized to compare alternative investments, and not obtain an absolute idea of possible losses. In a similar way, one may adjust the ETL metric ($ETL1_{1\text{-}\alpha}{}^A$), thus reaching:

$$ETL_{1-\alpha}^A = ETL_{1-\alpha}^A \cdot \frac{C}{V} \quad (9)$$

In a similar vein the adjusted ETL metric is no longer the average expected losses in 1 – α% of the cases, but rather this quantity adjusted by some probability of actually being able to realize it. Again, this should be used not as a measure of absolute losses but more as a way to compare alternative assets in overall portfolio optimization. It seems that of the proposed three metrics, the adjusted Sharpe ratio is the most straightforward one and thus less likely to lead to confusion and suboptimal decisions. At any rate, we have shown that adjusting risk management practices for liquidity risks is a crucial task in the optimal portfolio selection for cryptocurrencies. It may thus be useful to complement traditional risk-return measures with novel ones such as those proposed in eqs. (6), (7), (8), and (9). Essentially, this means earnestly moving into a 3-dimensional perspective for asset evaluation that includes not merely the mean-variance optimization but also liquidity considerations.

V. Application of Volume-Adjusted Risk Metrics

Calculating the proposed volume-adjusted metrics is a straightforward task as they rely on data that is widely available for exchange-traded assets – namely the price from which returns and risk metrics may be calculated, as well as trade volume and market capitalization. We calculate and visually present the adjusted Sharpe ratio S_A in Figure 8. This is the three-dimensional representation of the cryptocurrencies asset map. The figure clearly shows a large grouping of assets that are characterized by low levels of risk, return and trade volume near the origin. Ripple and Stellar stand out in this group as they provide better liquidity for a similar level of risk and return.

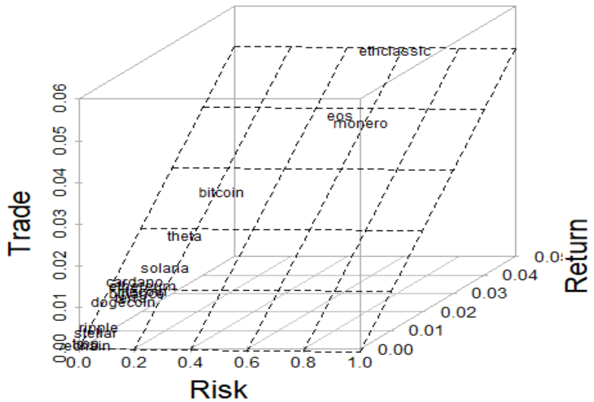

Figure 8: *Three-dimensional Risk Space for Cryptocurrencies*

As one moves up across all three dimensions, coins such as Solana and Theta seem to offer higher returns for comparable levels of risk and trade, thus making them more desirable to investors. Bitcoin stands out as historically a well-balanced cryptocurrency with relatively large amounts of trade that are combined with a good risk-return tradeoff. Finally, coins such as Eos and Monero exhibit a large amount or risk and similarly higher returns. Those tend to be dominated by Ethereum Classic that is in loosely the same risk group but offers higher returns with less liquidity risk. The adjusted Sharpe ratio, VaR, and ETL metrics are calculated for the cryptocurrencies under study and results are presented in Table 2.

The adjusted Sharpe ratio may guide risk management efforts. Its interpretation closely follows that of the traditional one (eq. (1)). Higher values of S_A indicate better risk-return tradeoff given volume traded. The highest ratios among the currencies under study are for Bitcoin Cash (0.362), Polkadot (0.113) and Filecoin (0.012), and thus those currencies provide optimal risk-return-liquidity tradeoff for the risk-averse investor. The worst tradeoff is found with the Tron, Vechain, and Stellar coins that all feature extremely low values of the adjusted Sharpe. Similarly, the adjusted VaR and ETL metrics for Bitcoin Cash (-0.08 and -0.10), Polkadot (-0.30 and -0.37), and Filecoin (-2.24 and -2.79) register the highest values across the sample pointing that these exhibit the lowest risk. On the opposite end of the spectrum, one finds Vechain, Tron and Stellar.

All three types of volume adjusted metric show remarkable internal consistency, with all of them identifying the same assets as low-risk or high-risk ones. Furthermore, the indications given by volume-adjusted metrics are broadly consistent with traditional ones for the groups that have the highest risk and lowest risk. Nuances and differences tend to appear for mid-risk coins.

As an alternative way to peruse the volume-adjusted matric, the analyst may choose to look at the risk ranks of crypto assets. These preserve the ordering of riskiness of the cryptocurrencies under study but instead collapse the measures into an ordinal scale. On the one hand this provides for a direct comparison of risk rankings for alternative assets that may be useful in situations of discrete choices. On the other hand, this minimizes the risk of misinterpretation of the newly proposed volume-adjusted risk metrics and thus enlarges the scope of their applications. This naturally comes at the price of an information loss but even those risk ranking improve upon a method that largely disregards the issues of volume and capitalization as proxies for liquidity risk. The application of such risk metrics has served to illustrate a few relevant facts for the management of crypto portfolios.

Table 2: Volume Adjusted Risk Metrics for 20 Selected Cryptocurrencies, 2016-2021

Coin	Sharpe Ratio	Adjusted Sharpe Ratio	Adjusted VaR (95%)	Adjusted ETL (5%)	Risk Rank by Adj. Sharpe	Risk Rank by Adj. VaR	Risk Rank by Adj. ETL
Bitcoin Cash	4.057	0.362	-0.08	-0.10	1	1	1
Binance Coin	0.009	0.001	-30.47	-38.05	13	16	16
Bitcoin	0.026	0.003	-9.72	-12.15	6	8	8
Cardano	0.011	0.002	-17.08	-21.45	10	10	10
Dogecoin	0.008	0.001	-22.26	-27.91	15	12	12
EOS	0.039	0.003	-5.37	-6.70	7	6	6
Ethereum Classic	0.050	0.004	-4.42	-5.53	5	5	5
Ethereum	0.011	0.001	-25.85	-32.47	12	15	15
Filecoin	0.184	0.012	-2.24	-2.79	3	3	3
Litecoin	0.010	0.001	-24.32	-30.40	16	14	14
Monero	0.036	0.003	-6.28	-7.84	8	7	7
Neo	0.100	0.011	-3.07	-3.84	4	4	4
Polkadot	1.302	0.113	-0.30	-0.37	2	2	2
Solana	0.014	0.001	-23.58	-29.78	11	13	13
Stellar	0.003	0.000	-58.31	-73.45	18	18	18
Terra	0.009	0.001	-21.30	-26.80	14	11	11
Theta	0.019	0.002	-13.05	-16.43	9	9	9
Tron	0.001	<0.005	-111.38	-139.45	19	19	19
Vechain	0.001	<0.005	-230.67	-290.40	20	20	20
Ripple	0.003	<0.005	-34.09	-42.84	17	17	17

Source: Author's calculations

First, the amount of trade that is associated with a given cryptocurrency is an important determinant of its risk profile. While the investor may tend to focus on a risk-return optimization, they should keep in mind that the ability to close positions or liquidate assets is a crucial part of the investment process in emerging crypto assets. Cryptocurrency time series have clearly indicated episodes where trading activity plummets as prices fall, thus exerting additional pressure on this downward spiral. It may be therefore of some utility to expand traditional metrics into volume-adjusted ones.

Second, the move from the traditional 2D mean-variance optimization framework for asset allocation and into a 3D framework that incorporates trade volume, enables the investor to take a richer perspective on the asset map. The efficient asset plane shows which assets are strictly dominated by other ones in terms of one of the three dimensions and focuses the investor's attention on more optimal ones. Among the set of non-dominated assets, an optimal selection of cryptocurrencies can be made given well-defined risk preferences. Even in the absence of such preferences or other relevant measure of the risk appetite, the investor will still be better off by avoiding all dominated assets.

Third, the proposed metrics are but a straightforward extension of standard risk management metrics that aim to enhance and not replace traditional approaches. With assets that are characterized by large trade volumes, the adjusted Sharpe, VaR and ETL metrics provide the same qualitative conclusions since volume traded is less relevant here. In fact, as the volume traded approaches market capitalization (i.e., the fraction between them approaches unity), then volume-adjusted metrics converge to the non-adjusted ones. On the other hand, highest risk assets exhibit high volatility, driven by few transactions which is reflected in non-adjusted and adjusted metrics alike. Volume-adjusted metrics are clearly superior in the case of medium amounts of trade where they can differentiate between seemingly similar risk profiles of cryptocurrencies. In short, volume-adjusted metrics are applicable across all types of risk profiles and enable a richer understanding of risk throughout. They will be even more useful as most assets move to midmarket and finer differentiation between them is needed.

Conclusion

The proliferation of novel digital assets also spells the need for more sophisticated and rigorous risk management methods. Cryptocurrencies in particular have gained significant traction and are now attracting not only technology enthusiasts and amateur investors but also professional and institutional ones. Thus, an enhanced understanding of their price behavior and risk profiles holds the key to improving asset allocation and portfolio management decisions. An improved understanding of the relevant risks would enable a large set of investors to properly evaluate the strengths and weaknesses for different financial operations ranging from payment, through short-term hedging all the way into long-term investment. This is likely to result in the deeper integration of crypto assets in the global financial system, thus easing payments and providing diversification opportunities. A further benefit would be the emergence of closed ecosystems based on the blockchain. The current trend of NFTs that can be purchased exclusively with cryptocurrencies is but one example. Thus, better risk management has the potential to increase market efficiency, investment opportunity and overall welfare.

The paper has focused on integrating a key risk component – liquidity risk –

into the overall portfolio management process for cryptocurrencies. We have studied the behavior of the twenty largest cryptocurrencies by market capitalization over a period of up to seven years and marked the significant association between market depth (as proxied by trade volume) and volatility and price dynamics. Given their emergent nature, most coins are characterized by exponential price rises, followed by deep collapses amid significant volatility. While impervious to overall macroeconomic trends and traditional asset returns, crypto assets are highly sensitive to changing conditions on crypto exchanges and to the profile and sentiment of the nice investors that trade in them. Incorporating the amount of trade serves to better understand these dynamics and improve asset allocation decisions.

Essentially this allows the investors to move from a traditional 2-Dimensional mean-variance optimization and incorporate market depth into a 3-Dimensional framework that illustrates the traditional risk-return tradeoff but also include trade volume. This 3D asset map clearly shows clusters of dominated assets and outlines potentially attractive investment opportunities. Together with a clear set of risk preferences, the 3D asset map may be used to optimally select personalized portfolios or individual assets, effectively serving as an expanded three-dimensional version of the well-known Markov efficient frontier and its associated optimization. In this spirit we have also proposed a set of volume-adjusted risk metrics – the adjusted Sharpe ratio, VaR, and ETL measures. Such volume adjustment can be easily applied to a wider set of risk metric of choice such as the beta of the asset. Alternatively, the analyst may opt to only consider assets within given trade volume constraints as an alternative way to proxy market depth. At any rate, results have underlined the importance of including liquidity risk in crypto risk management. The adjusted metrics we proposed are calculated for a period of five years and are shown to be useful guides for making informed risk management decisions. In conclusion, this article has aimed to propose a possible enhancement to traditional risk management approaches, which makes them more useful for the brave new world of crypto assets. While presented results may be somewhat preliminary, they are in consonance with extant literature, and we hope that they will spark a critical discussion and further enquiry into this important topic.

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