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Risk Seeking Behavior in Anticipation to Volatility Mean Reversal: A Case Study Using Bitcoin and SKEW

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The traditional finance approach to decision analysis, based on neo-classical economics, assumes self-interested, utility maximizing approach, and risk aversion. This essay points to a situation that investment in a risky asset (Bitcoin) is directly related to an increase in market risk, measured by SKEW index. This contradicts the traditional approach and aligns to several findings of behavioral finance. More specifically, it shows that investors may be risk seeking actors in anticipation to a belief that volatility will return to normal levels.

Keywords: risk aversion, Bitcoin, SKEW, risk seeking, risk, volatility

Introduction

The decision analysis, based on the traditional finance approach, is directly related to rationality and neo-classical economics. As it has been pointed by several researchers, these characteristics embed several restrictions and the real decision making is based upon different methods, as pointed by Raiffa (1997) as descriptive analysis. The development of the understanding about how choices are actually taken can be understood under the Behavioral Finance perspective.

On a chapter written by Pompian (2019), the Chartered Financial Analyst Institute (CFA) points that the standard body of knowledge in the field of finance, in terms of decision making, is centered on a utility maximization problem by individuals that are risk averse, self-interested, and rational. Raiffa (1959) goes further in analyzing Utility Theory. He points that it assumes that the individual is able to compute the probabilities of the all outcomes related to each alternative and can evaluate them in order to generate expected values, or utilities.

As described by Pompian (2019), rational decision making is constrained by two problems. Initially, the process may be seen under the bounded rationality situation, in which the individuals, when selecting among options, have computing and memory limitations that will lead to a choice that satisfice instead of optimize the problem. In this way, the cognitive errors displayed will lead to an only adequate solution related to believe perseverance and information processing biases. Additionally, rational decision is also constrained by mental state or emotions involved in making or acting upon a choice, such as fear, excitement, or greed. This is called emotional biases.

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In terms of risk taking, the normative risk averse assumption is challenged in works like Prospect Theory, from Kahneman and Tversky (1979), who prospects are framed before being chosen resulting in overreaction to small probability events and under reaction to less extreme higher probability events. Based on this finding, risk averse assumption was relaxed at least for a part of the utility function where the dominant framework is based on loss aversion. “For example, anyone who has ever purchased a lottery ticket has displayed risk-seeking behavior that is inconsistent with the rational risk-averse behavior assumed in traditional finance” (Pompian, 2019, p. 16).

Yaari (1987) proposes a theory in which risk aversion is represented by an equation *f*, convex shaped, that generates a “utility number”, when differentiated. This utility is the corrected mean of the preference and may imply that bad outcomes are heavily weighted in contrast with good outcomes, so the agent acts pessimistically.

Thaler, Tversky, Kahneman, and Schwartz (1997) observe that risk aversion profile is dependent on the time frame of the individual and also on the frequency in which the choice is checked. Loss aversion, then, affects directly the intent of assuming risk by individuals, in a different pattern than predicted by the utility theory.

This article will bring another evidence of behavior that can be categorized under risk seeking pattern. As it will be demonstrated, the demand of very risky and volatile financial crypto-assets demonstrates a non-expected pattern when analyzed under different market stress situations.

Crypto-Assets: Bitcoin as a High-Risk Asset

Among the universe of financial assets, crypto-currencies play a controversial role. Its auto-denominated currency status and the lack of control by regulators and financial system raised several concerns in governments and industry, has created several initiatives from different players in public, financial, and tech spheres, and has amazed investors by “abnormal returns”, especially in rallies like the end of 2017, the second quarter of 2019, and after September of 2020, amongst the widespread second wave coronavirus pandemic and recovery of stock markets (Figure 1).

Hougan and Lawant (2021) remark that as crypto-assets enter their second decade, combined market cap over 350 BUSD (as of September 2020) and the involvement of leading banking institutions dismissed an initial concern that it could disappear. Additionally, as the most important among more than 6,000 crypto-currencies, Bitcoin is the most important, with a market cap, as of October 2020, of 210.9 BUSD, almost 5 times higher than Ethereum, the second largest crypto-asset.

The fact that Bitcoin is the crypto-asset with the highest liquidity should theoretically lead to more efficient pricing. For this reason, Bitcoin will be used to evaluate quantitative and qualitative aspects of crypto-currency as an asset class and more broadly as a proxy of a risky asset class.

Warren (2020) calls to the attention that despite the increase in importance, it is still less than all 15 largest banks in total assets.

According to Bohme, Christin, Edelman, and Moore (2015), the lack of a centralized authority to control the money raises transactional burden related to a system that needs to keep scarcity. The procedure defined to cope with this issue is the creation of virtual wallets where users participate in verifiable transaction log, or blockchain, that uses cryptography as security feature and is updated by users that solve mathematical problems based on the transactions, in a process called mining.

Early adopters consisted of players that needed "greater anonymity and the absence of rules concerning what could be bought or sold" (Bohme et al., 2015, p. 222), most importantly in drug trafficking. Even though regular "investors" are using Bitcoins, Warren (2020) points out for the continuing illicit profile of the asset and the developments in regulation.

In terms of volatility, Hougan and Lawant (2021) demonstrate the high-risk profile of the asset class by comparing annualized 90-day standard deviations of returns with major asset classes including stocks, corporate bonds, commodities, and emerging market currencies. In addition, it is pointed out that fact that long bear markets are recurrent.

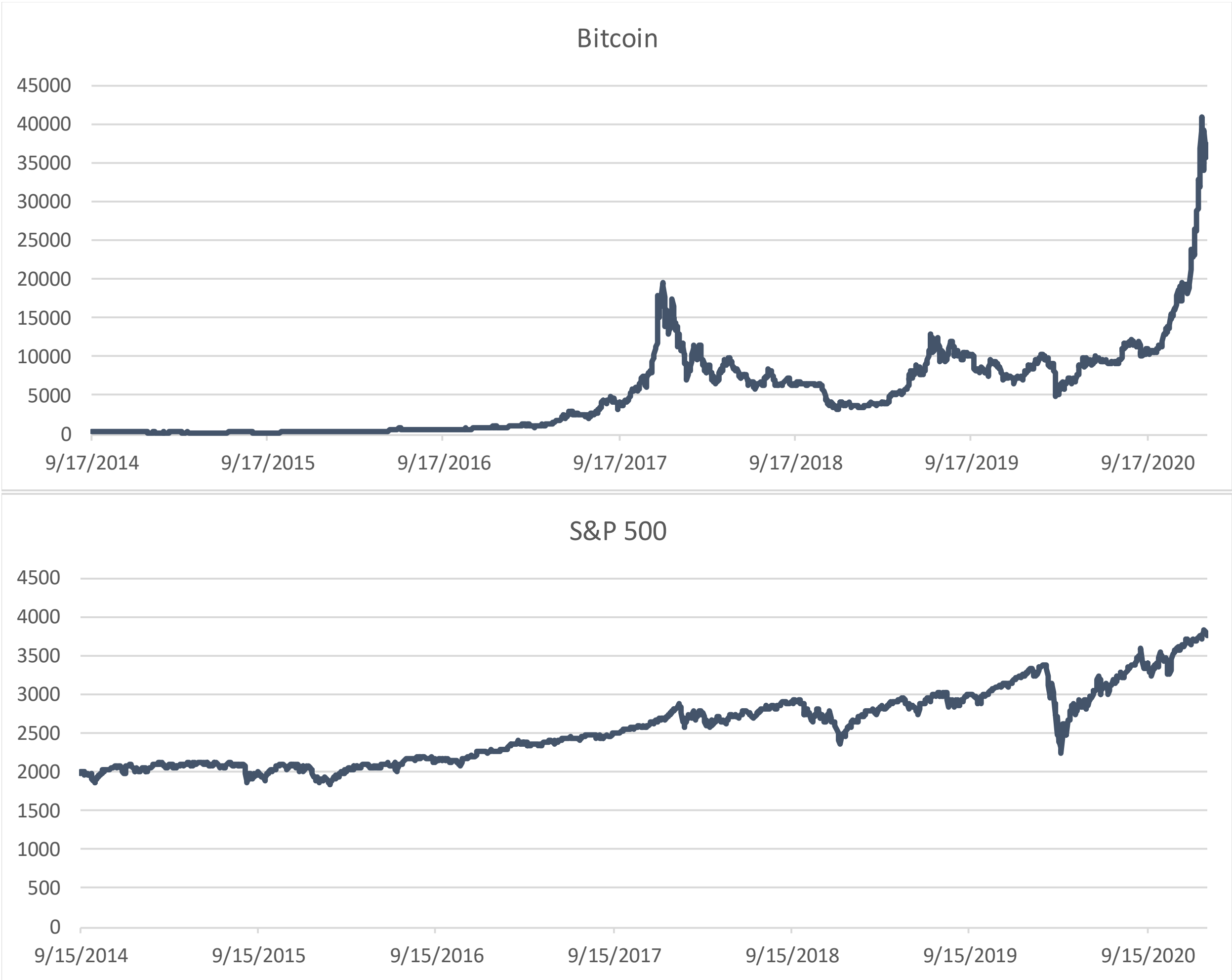

Figure 1. Adjusted closing—Bitcoin (in USD) and S&P 500 (in points). Source: Yahoo Finance (2021).

Iwamura, Kitamura, Matsumoto, and Saito (2020) argue that this volatility, from an economic perspective, is the result of a dual instability stance based on the combination of a fixed supply (in a LM model analysis) and sustainability of the mining process.

As a risky asset, Bitcoin should be subjected to the effects of risk aversion, moderated by portfolio implications, as defined by Markowitz. In this way, as the market scenario becomes more stressed, allocation to this kind of asset should decrease as investors should look for "fly to safety" strategies. Before getting into the expected behavior, it's crucial to making an analysis on the measures of market stress.

Market Risk Measurement and Expected Behavior

There are many approaches for evaluating and measuring risk in financial markets. Maybe the most basic and intuitive is based on the computation of descriptive statistics of time-series returns on a specific financial asset or index or asset class. Such measures as range, quartile, percentile, variance, standard deviation, and coefficient of variation are extensively covered by statistics text books, like Defusco, Mcleavey, Pinto, and Runkle (2007).

As discussed by Mayhew (1995), despite the controversy on weather historical measures are efficient, most of the body of research points to a bias in this kind of estimators of future volatility expectation, raising need to find other methods to forecast future volatility.

Hull (2014) explains the Nobel Prize winner Black, Scholes, and Merton model (BSM) which is a risk neutral approach to a hedged position consisting of an option and the underlying asset. This portfolio is valued under a no-arbitrage argument, where riskless portfolios must yield risk-free rates. The formula derived by the authors is able to make the valuation of european options under certain features of the underlying asset and option, such as strike price, time to maturity, and volatility.

By looking at the problem of defining expected volatility in financial markets, and considering that market prices of traded options are available, BSM can be used to generate the implied probabilities in the market. Carr and Wu (2006) recognize that although subjected to constraints, this approach is consistent for forecasting subsequent realized volatility and represents "accurate approximation of the conditional risk-neutral expectation of the return volatility" (p.15).

In 1993, the Chicago Board Options Exchange (CBOE) launched an index to track implied volatility for the S&P 100 stock index, which became the "premier benchmark for stock market volatility" (CBOE, 2019, p. 3). Carr and Wu (2006) describe this index as the average of BSM implied volatility on eight near the money options at the two nearest maturities, using an artificial conversion to trading days in order to generate the index. Some of the main constraints of that model are that BSM model considers volatility as constant and non-stochastic parameter, what could reduce the economic motivation of following up the index and that payoffs were still difficult to replicate, what have a direct implication on the arbitrage argument.

CBOE (2019) discuss the methodology change in the index in 2003, creating the VIX, aimed on measuring the implied volatility of S&P 500, aggregating weighted prices of puts and calls on the index over a wide range of strike prices. According to Carr and Wu (2006), the motivation behind this change on the VIX is related to the lack of real economic meaning of the former index unless under a monotonic transformation of option prices, its investable capacity, and the elimination of the upward bias in the old methodology.

Besides that, as VIX can replicate the Variance swap payoff, not only the economic substance but also the "produtification" of that index was enhanced, as investors can use these new products to hedge or take directional bets on the market. As part of this effort, CBOE launched a series of indexes trying to measure different aspects of the volatility in the market.

One that is specifically interesting for the theoretical goal of this essay is the SKEW index. CBOE (2011) notices the asymmetry in volatility towards the put side in a way that "the curve of S&P 500 implied volatilities no longer smiles" (p. 3) as a result of tail risk. Hull (2014) offers explanations for this phenomenon related to leverage in lower stock prices and the fear of a crash, which is particularly important when behavioral biases are evaluated. In this way, SKEW Index may be specifically interesting in the understanding of behavioral patterns as the movement from smile to skew in volatility function can be attributable to aversion to tail risk.

According to CBOE (2011), SKEW index is calculated from a tradable portfolio of out-of-the-money S&P 500 options, constituting an exposure to the fat tail feature of return probability distribution. The index can be interpreted as the skewness of the S&P 500 return probability distribution, where 100 means a normal distribution, and a higher probability of tail risk being associated with higher number, as shown in Table 1.

As a result, SKEW is an indicator of the fear related to a very sharp decline in prices, above two or three standard deviations, and, can be seen as an useful measure of the perception of likelihood of tail risk. More specifically, "perceived tail risk increases when market participants increase their probability of a catastrophic market decline, what has come to be called a 'black swan'" (CBOE, 2011, p. 8).

Table 1
Estimated Probabilities of S&P 500 Tail Risk Events

SKEW	2 Std. dev. below mean	3 Std. dev. below mean
100	2.30%	0.15%
105	3.65%	0.45%
110	5.00%	0.74%
115	6.35%	1.04%
120	7.70%	1.33%
125	9.05%	1.63%
130	10.40%	1.92%
135	11.75%	2.22%
140	13.10%	2.51%
145	14.45%	2.81%

Note. Source: CBOE (2011).

As a measure of perception of risk, or fear, increased SKEW should be linked to a reduction in risk taking by market participants, including asset classes with higher volatility. The model developed will evaluate this hypothesis and seek to provide explanations on the behavioral implications of the results.

Model and Variables Description

The aim of the model is to compute differences in Bitcoin demand at distinct perceived market risk levels and understand behavioral trends from the analysis. The hypothesis, based on neo-classical economics and normative behavior, is that demand for risky assets will be adversely affected by the increased perception of risk or, in simplistic terms, by fear.

The asset who demand will be evaluated will be the Bitcoin. Daily closing prices will be used in order to evaluate price movements from demand and supply forces. As explained, the high volatility associated with this asset configures the high-risk allocation that should be avoided in moments when the riskiness of the market increases. As a potential weakness of this approach, any conclusion shall always take into consideration that, in some moments, a sort of trade-frenzy occurs, distorting rational demand patterns. This is especially true for Bitcoin, used mainly by young individuals as an investment alternative.

In terms of market riskiness, the SKEW index will be used, as it reflects the perception of tail risk in the distribution of market returns. Calculated based on out-of-the money options, it provides a better view of future volatility than ex-post data and its level implies that investors are changing the shape of the implied distributions of market returns on the left tail.

The data set consists of 1568 days of trading information from Sep./17/2014 to Jan./15/2021, extracted from www.finance.yahoo.com on Jan./19/2021. Days without trading information for all variables were excluded from the sample. Variables collected were Bitcoin in USD (code BTC-USD in the source), S&P 500 in points (code ^GSPC in the source), VIX in points (code ^VIX in the source), and SKEW (code ^SKEW in the source). For calculation of daily returns, adjusted closing prices were used. Main statistics derived from the data are shown in Table 2.

Table 2

Sample Statistics of Variables in the Data Set

	Bitcoin	Bitcoin return	S&P 500	S&P 500 return	VIX	VIX change	SKEW	SKEW change
Sample size	1,568	1,567	1,568	1,567	1,568	1,567	1,568	1,567
Average	5,123.82	0.38%	2,560.95	0.05%	17.46	0.41%	129.55	0.05%
Median	3,908.72	0.23%	2,547.74	0.06%	14.88	-0.72%	128.65	0.00%
Standard deviation	5,427.61	4.53%	467.36	1.17%	8.12	9.07%	8.42	3.12%
Correlation to Bitcoin return		1.000		0.139		(0.092)		(0.049)

Note. Source: model calculations.

Bitcoin return averages are them computed for each state of riskiness, for the effect of comparison. Six blocks of risk were defined (SKEW less than 130, SKEW between 130 and 140, SKEW above 140, all of them divided on SKEW Change greater than zero and lower than zero) and daily data were computed based on this classification and presented in Figure 2.

In addition, risk levels were evaluated considering a Value at Risk (VaR) approach. Defusco et al. (2007) explain VaR as a measure of the minimum loss expected at a certain level of probability, that could be calculated using a normal distribution. As SKEW indicates a deviation from normal distribution, an adjustment can be made to the minimum loss considering the fat tail profile defined by a higher SKEW.

In this way, the model calculates a proxy of VaR considering the mean S&P 500 Annual Expected Return (12.64%, geometrically linked from the result presented in Table 2 for 252 days) and the volatility represented by the average daily VIX level for that specific risk block (as VIX is already an annualized measure). SKEW is then used to model the shape of probability distribution using the following formula, derived from Table 1 (that holds a linear relation):

$$\text{Prob. 2 Std. Dev. Bellow Mean} = 0.0027 \times \text{SKEW} - 0.247$$

Accordingly, VaR measurement is based on the probability of losing more than two standard deviations from the mean, and a minimum estimated loss computes the average severity that would at least occur in cases of tail events, by multiplying the probability of events below two standard deviations and the minimum loss that would result in these events. The higher the minimum estimated loss, the higher the risk level of the situation.

SKEW INDEX CHANGE DURING DAILY SESSION	LESS THAN 130	BETWEEN 130 AND 140	MORE THAN 140
INCREASING SKEW	27.12% of Total Sample Avg. Bitcoin Return 0.172% Avg. VIX Level 18.41 Avg. SKEW Level 123.94 VaR Analysis 8.76% probability of losing at least 24.18% annualized Minimum Estimated Loss of 2.12%	16.98% of Total Sample Avg. Bitcoin Return 0.233% Avg. VIX Level 16.82 Avg. SKEW Level 134.78 VaR Analysis 11.69% probability of losing at least 21.00% annualized Minimum Estimated Loss of 2.45%	7.72% of Total Sample Avg. Bitcoin Return 0.613% Avg. VIX Level 16.37 Avg. SKEW Level 145.04 VaR Analysis 14.46% probability of losing at least 20.11% annualized Minimum Estimated Loss of 2.91%
DECREASING SKEW	29.16% of Total Sample Avg. Bitcoin Return 0.185% Avg. VIX Level 17.99 Avg. SKEW Level 123.04 VaR Analysis 8.52% probability of losing at least 23.35% annualized Minimum Estimated Loss of 1.99%	14.87% of Total Sample Avg. Bitcoin Return 1.165% Avg. VIX Level 16.38 Avg. SKEW Level 134.53 VaR Analysis 11.62% probability of losing at least 20.13% annualized Minimum Estimated Loss of 2.34%	4.15% of Total Sample Avg. Bitcoin Return 0.549% Avg. VIX Level 16.04 Avg. SKEW Level 143.86 VaR Analysis 14.14% probability of losing at least 19.45% annualized Minimum Estimated Loss of 2.75%

SKEW INDEX LEVEL AT COSING OF DAILY SESSION

Figure 2. Model results. In Figure 2, each box includes the results calculated in the respective state of riskiness and the variation of the risk. Average Bitcoin return and risk levels are presented (both VIX and SKEW), as well as the VaR calculation. Source: model calculations.

Conclusions and Behavioral Findings

The evaluation of the data allows for the rejection of the hypothesis that investors follow the neo-classical economic assumptions, specifically in terms of risk averse behavior. The greatest demand for Bitcoin (risky asset) occurs in the intermediary risk level when volatility is reducing. This SKEW level is already above the average for the total sample, indicating that the highest demand occurs when risk is still high but reducing.

More importantly, it's noticeable that Bitcoin returns increase much before risk starts to drop. Average returns in situations when SKEW is higher than 140 are more than three times higher than in the moments the SKEW is lower than its average. It indicates that as long risk aversion cannot be ruled out, a risk seeking moment occurs where investors act on a mean reversal expectation, exposed to what Pompian (2019) calls Gamblers Fallacy.

This anticipation movement can be highlighted by the analysis of SKEW historic pattern, as shown in Figure 3. It shows strong cyclicality, mean reversion, stationarity, and homoscedasticity trend. Based on it, the conclusion of a risk seeking behavior in anticipation to a risk drop movement is reinforced. Again, it conflicts with traditional risk aversion profile.

This conclusion is also corroborated by the evaluation of the minimum estimated loss. Bitcoin returns improve when this indicator increases. As risk is increasing, return is more than three times higher when minimum loss jumps 37% from 2.12% to 2.91%, showing that investors are buying Bitcoins as market risk piles.

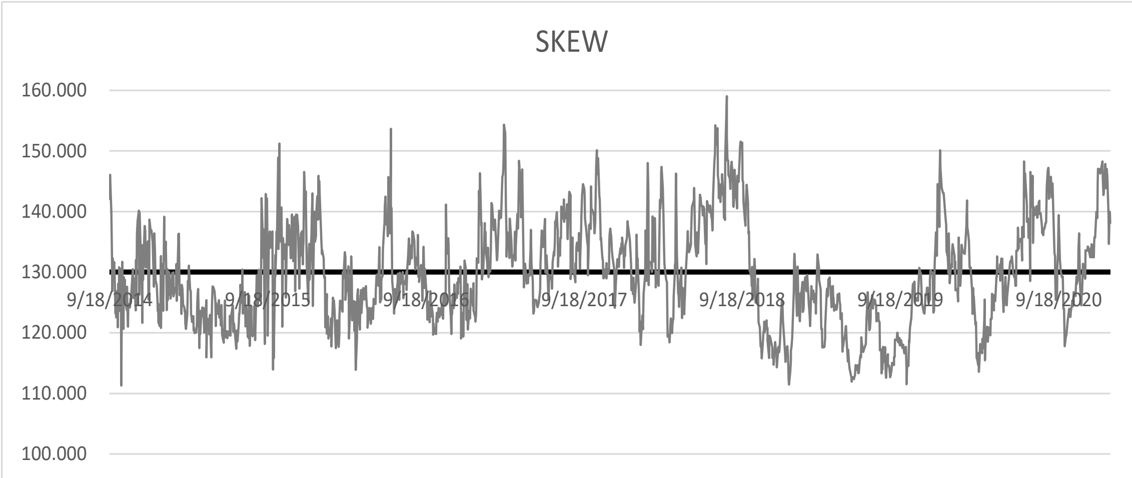

Figure 3. Adjusted closing—SKEW (in points). Source: Yahoo Finance (2021).

Another two final concerns must be analyzed. Initially, Bitcoin is understood as dominated by young individual investors, despite the fact that, more recently, institutions started to get on Bitcoin arena for portfolio diversification and allocation to clients. Risk appetite for the young investor segment may not be representative of the total market, aligned with common portfolio design heuristics. As gains in Bitcoins became widely discussed in social media forums and traditional media outlets, a trade-frenzy tends to occur and returns may not be analyzed as independent in temporal terms. This effect may enhance the anticipation effect described.

Lastly, even though Bitcoin and SKEW are used as proxies for risky asset and market risk, it is important to notice that returns on Bitcoin are not directly reflective of the riskiness in the stock market. The general idea is that risk in market segments is not disconnected from the risk in the whole market, emphatically the strong traded stock market. As risk increases, it is expected that lower risk securities, like fixed income or ultimately gold, increase in prices, and not a risky asset class as cryptocurrencies. In any case, the low correlation of returns between the S&P 500 and Bitcoin could indicate that some sort of diversification is pursued in times of higher risk. In this case, investors would be "super-rational" in pursuing this allocation. Still, risk seeking pattern in anticipation of a future risk drop seems more reasonable as the "super-rational" behavior would require the average investor to be able to articulate the diversification effect, based on Markowitz Portfolio Theory, implying high degree of sophistication that seems unlike for normal investors.

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