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## Article

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# The Effect of Energy Cryptos on Efficient Portfolios of Key Energy Listed Companies in the S&P Composite 1500 Energy Index

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## ABSTRACT

This paper investigates if energy block chain based crypto currencies can help diversify equity portfolios consisting primarily of leading energy companies of the US S&P Composite 1500 energy index. Key contributions are in terms of assessing the importance of energy cryptos as alternative investments in portfolio management, and whether different volatility models such as autoregressive moving average – Generalized Autoregressive Heteroskedasticity (ARMA-GARCH) and machine learning (ML) can help investors make better investment decisions. The methodology utilizes the traditional Markowitz mean-variance framework to obtain optimized portfolio combinations. Volatility measures, derived from the Cornish-Fisher adjusted variance, ARMA family classes and ML models are used to compare efficient portfolios. The study also analyses the effect of adding cryptos to equity portfolios with non-positive excess returns. Different models are assessed using the Sharpe performance measure. Daily data is used, spanning from November 21, 2017 to January 31, 2019. Findings suggest that energy based cryptos do not have a significant impact on energy equity portfolios, despite the use of different risk measures. This is attributable to the relatively poor performance of energy cryptos which did not contribute in improving the excess return per unit of risk of efficient portfolios based on the leading US energy stocks.

**Keywords:** Equity Portfolios, Energy Cryptos, Performance Evaluation, Machine Learning, Volatility Measure

**JEL Classifications:** Q40, G11, G12

## 1. INTRODUCTION

Cryptocurrency portfolio management is already a reality with names like Blockfolio and Delta, allowing investors or traders to manage their portfolios of cryptocurrencies and altcoins using different tools like advanced charting, order books, and portfolio tracking. Despite the finance and banking sector being the leader when it comes to the amount invested in block chain technologies, other industries such as energy, healthcare, retailing, and manufacturing are unreservedly starting to adopt similar technological innovations. As of last year, the global energy sector was worth over two trillion US dollars (Cryptoverze, 2018) with the International Data Corporation predicting strong, double digit growth in the energy sector during 2016-2021. As reported by IBM (2017), the prevalent benefits of adopting block chain

technologies are associated with risk, time and cost savings. For example, countries such as Moldova, which imports more than 70% of its energy, will benefit from solar energy, through a crypto currency called solar coin, potentially reducing the reliance on imported fossil fuels such as natural gas and oil from Russia, with consumers also benefiting from lower prices (Tabary, 2018). Using smart contracts, nearly 20% of German firms have adopted block chain technologies in the energy sector (Witsch and Coester, 2018). Various startups in the US energy sector have raised nearly \$325 million in 2017 to implement block chain to energy related projects (Lacey, 2017). These projects range from facilitating peer to peer dealings without the necessity of a retail based energy provider or central utility, to tracking low carbon impact energy production. While block chain aims to introduce decentralized energy trading in various energy sectors like the electric power

sector, such sectors are commonly regulated in many countries. Nevertheless, policy makers have started to work on policy guidelines to gradually adapt to block chain technologies.

Central to the heart of this study, it is vital to understand how the energy industry is developing and the role block chain is or would eventually play. EIA (2018) forecasts the electric power sector to consume more energy than any other sectors, with the growth in renewable energy consumption being the firmest among other fuels. Natural gas consumption, is however, also expected to rise substantially due to development in the industrial sector, primarily for industrial heat and power, and liquefied natural gas produce. Even with natural gas production expected to account for nearly forty percent of US energy produce by 2050, wind and solar power generation leads the growth compared to other renewables. Gradually, traditional centralized power plants run by fossil fuels are facing competition from distributed power generation like solar panels and micro turbines. With numerous climate conscious policymakers which support clean energies, complemented with falling wind and solar power costs, renewable energy sources are expected to provide over ten per cent of global electricity supply over 2017-2022 (EIA, 2018). Despite the majority of renewable energies being deployable on large scale, solar energy has already been adopted on a smaller scale, where customers are managing their energy consumption through distributed energy resources.

During 2016, firms have globally incurred expenses of nearly fifty billion US dollars to promote existing digital electric power systems. Many established utilities in the electricity sector like E.ON in Germany have already embraced the potential advantages of block chain (Burger et al., 2016). In fact, utility related projects rank second in terms of block chain ventures (Livingston et al., 2018). Enerchain, a utility based project using block chain, is expected to sell electricity and gas to forty-five companies in Europe by the close of 2018 (Witsch and Coester, 2018). With a few of these firms being either involved in the distribution grids operations or wholesale production, the effect of these block chain related projects can be significant in the electricity market. For example, 4New, an energy producer, has been the first company to use waste to generate electricity to implement a block chain system (Keane, 2018). Other markets including oil are also involved with block chain related projects such as Intel Hyper ledger and Toyota, and the Energy Web Foundation partnership with Shell (Gratzke et al., 2017). US retail giants like walmart have lately been conferred a patent to develop an electric grid which will be powered by various crypto currencies (Alexandre, 2018). The block chained energy projects, being tokenized through energy crypto currencies, connect the customer or investor to renewable energy markets, where the latter gradually disconnect dependence on fossil fuel markets. While there is big potential for risk, time and cost savings from these groundbreaking systems, there are presently some issues with crypto currencies. For instance, in Canada, crypto miners have been consuming so much energy with their mining processes that the government had to intrude and stop further requests of power from these entities (Meyer, 2018). To avoid potential rate increases of energy supply, in a decentralized environment where the price would be determined by the forces of demand and supply, governments like the UK and Australia have

already contracted to develop initial guidelines for energy related block chains applications (Metalitsa, 2018).

Based on the above, with fossil fuel becoming relatively less consumed as we move towards a cheaper, cleaner and decentralized block chain technology, it is vital to evaluate if energy cryptos have a major role to play in portfolios which are aligned with top energy companies' activities. Alternatively stated, this study looks at whether the energy based block chain crypto can affect the leading US energy stocks based equity portfolios. With the cryptocurrency market, generally, exhibiting low correlations with other asset classes such as energy commodities (Author, 2018) and equities (Chen et al., 2016), it is interesting to pursue the prime question whether energy cryptos can help diversify away the risk of an equity portfolio, consisting principally of leading US energy stocks. This first question is yet to be examined.

A second, yet important question, which also arises is how, using different measures of risk from different models such as Cornish-Fisher (CF) expansion, autoregressive moving average – generalized autoregressive heteroskedasticity (ARMA-GARCH) and machine learning (ML), can help the investor or trader to make better informed decisions in how to allocate funds among the risky assets coming from different asset classes, and also how well the portfolio performed using the Sharpe performance measure. Four major energy cryptos are included into a portfolio which consists of the top ten US energy stocks. The analysis is initially conducted using the Markowitz mean-variance framework to determine the efficient portfolios, including the optimal risky portfolio combination. With other risk values coming from other models such as CF, ARIMA-GARCH, and ML, the efficient portfolios are compared using Sharpe performance measure, which is traditionally used to capture total risk. Due to the negative returns of cryptos, the study also analyzes the effect of adding energy cryptos into equity portfolios with non-positive excess returns. The rest of the paper provides some literature review, data, research methodology, and the research findings. Some conclusive remarks follow.

## 2. LITERATURE REVIEW

### 2.1. Modern Portfolio Theory

The ground breaking modern portfolio theory proposed by Markowitz (1952), continues to play a critical role in the field of portfolio management, where efficient portfolios depends on two population characteristics – the covariance and average of asset returns. For instance, Scala et al. (2019) adopted the Markowitz framework to propose a simplified strategy in managing portfolios of renewable energy sources. Similarly, Platanakis and Urquhart (2019) analyzed the effect of including cryptocurrencies, and found the Markowitz model to rank second after the Black-Litterman model. Platanakis et al. (2018) also found there is very little difference when choosing between an equally weighted portfolio and the optimal mean-variance portfolio. Given the covariance matrix and average returns, optimal risky portfolio weights can be computed, based on the preferred level of risk or targeted return values. However, in reality, the true parameters are not known, such that proxies are usually used. For instance, the sample mean

and sample covariance matrix are usually adopted which results in the “plug-in” portfolio (Ao et al., 2017). However, as reported by Michaud (1989) and Basak et al. (2009), the plug-in portfolio’s out of sample performance usually deteriorates as the number of assets increases. Some authors like Fastrich et al. (2015) and Fan et al. (2012) proposed the use of constraints in weights to improve the portfolio performance. However, as reported by Ao et al. (2017), these lead to suboptimal Sharpe ratios.

More importantly, some authors have proposed alternative measures of risk. For instance, Roy (1952) reported that the use of downside risk measures is geared towards the objective of maximizing the probability that the return of the portfolio is above a minimum acceptable level like the risk free rate. For instance, while Konno (1990) proposed the mean absolute deviation as a measure of dispersion, Speranza (1993) used the mean absolute value of negative deviations, and found that it is half of the mean absolute deviation from the mean. Lastly, but not least, although Markowitz (1959) introduced semi-variance in portfolio management, he recommended that the use of variance is computationally more manageable and provides the same information. Although we do not depart from the use of the traditional Markowitz model, our main contribution is to look into the implementation of alternative risk measures such as ML and generalized autoregressive conditional heteroskedasticity (GARCH) models, and analyze the performance of energy equity portfolios, under the mean-variance efficient frontier framework.

## 2.2. ARIMA GARCH Model

Since Engle (1982) estimated variability in U.K. inflation with the autoregressive conditional heteroskedasticity (ARCH), several empirical work made use of the ARCH model or some variations thereof. The main objective of using ARCH-type models is to examine the dynamic nature of the fluctuations in time series data. However, to capture all of the dependence in variance, the ARCH-type model requires a number of lags of the squared error ( $u_{t-1}^2$ ), which might result in an ARCH model that is not statistically desirable. Bollerslev (1986) developed the generalized autoregressive conditional heteroskedasticity (GARCH) model as a technique to capture the volatility clustering in financial time series data. The GARCH model also failed to take into account the asymmetric effect found by Black (1976). Nelson (1991) proposed the EGARCH model with the objective of including such effect and fitted into EGARCH model. While there is a significant number of empirical research work related to GARCH family models (Hammoudeh and Li, 2008; Wang and Moore, 2009; Elshareif et al., 2012; and Kang et al., 2009), many researchers such as Francq and Zako’ian (2004), Babu and Reddy (2015), Aknouche and Bibi (2009) and Xi (2013) have also applied and combined various ARMA models with ARCH processes, resulting in ARMA–GARCH hybrid models. The objective of these hybrid models is to stimulate the understanding and assessment of the dependence and the causal structure and provide much better accuracy of predictions.

## 2.3. ML

Nonparametric density estimation differs from parametric approach in that it does not require user specification of model

parameters. Therefore, nonparametric approach is a far more flexible option in simulating the density function of a variable. It is also not affected by the specification bias that is present in the parametric approach (Lehmann, 1990). Kernel density estimation is a nonparametric approach that is widely used in many fields of economics and engineering. Bouezmarni and Scaillet (2005) applied KDE to model the Brazilian income distribution, which is known to be highly skewed with an accumulation of observed points near the zero boundary. To this end, authors proposed the use of asymmetric kernel function with nonnegative support. They prove that asymmetric KDEs converge, in  $L_p$ , to the true probability density function. Renault and Scaillet (2004) successfully model recovery rates on defaulted bonds using KDE approach based on beta kernels. Beta kernel was adopted because the recovery rate values range between 0 and 1. The results of empirical tests on S&P’s database and Monte Carlo simulations demonstrated the validity of their approach.

Guerre et al. (2000) applied KDE to analyze auction data. In particular, the authors devised a procedure to model the distribution of bidder’s private values from observed bids based on kernel estimates. The authors show that their kernel estimators converge uniformly at the best possible rate. Jeon and Taylor (2012) used KDE in their work to produce density forecasts for wind power generation. The authors model wind power in terms of wind speed and wind direction. Conditional kernel density estimation is used to represent the stochastic relationship between the wind power and wind speed and direction. Post-sample density forecasting results showed that their approach was able to outperform the benchmark methods. Yavlinsky et al. (2005) used KDE in image annotation. The authors modeled the distribution of image features via nonparametric kernel smoothing. They showed image properties such as global color and texture distributions can be used effectively to annotate images. Test results based on Corel and Getty image archives produced results that are competitive with other similar methods.

## 2.4. Portfolio Performance

To evaluate the performance of portfolios and related benchmarks, performance measures such as Sharpe,  $M^2$ , Treynor, and Jensen’s alpha were developed and used in the investment arena. Alongside, asset-pricing models were developed to explore which aspect of a portfolio should lead to lower or higher expected returns. For instance, the capital asset pricing model (CAPM) introduced by Sharpe (1964) suggests that relying on such a model assumes the portfolio is exposed to market risk. While alpha proposed by (Jensen, 1968) is based on the difference between the actual returns and CAPM’s expected return, it does not control firm specific risk which could be important for investors (Fama, 1972). Equally, Treynor’s ratio proposed by Treynor (1965) considers only excess return per unit of systematic risk, which is analogous to Jensen’s alpha as discussed in Aragon and Ferson (2006). Sharpe (1966) introduced the Sharpe ratio which primarily captures the degree to which a portfolio is able to produce an excess return per unit of risk, where excess return is the difference between return and the risk-free rate. The Sharpe ratio is conventionally used for a portfolio compared to a single investment, since a portfolio excess risk and return consider the benefits of diversification, as opposed to the Sharpe of a single asset, where correlation cannot be calculated.



While various applications exist on the application of Sharpe (Author [2016] and Aragon and Ferson [2006] for an overview), the Sharpe ratio does not distinct between downside and upside risk. This is predominantly pertinent since cryptocurrency and energy markets tend to be non-normally distributed. Leland (1999) suggests the need to look into higher moments of distributions to capture investors' utility functions. For positively (negatively) skewed distributions, a portfolio would have a higher (lower) mean than for a normally distributed function, resulting in a relatively lower (higher) risk and higher (lower) excess return per unit of risk. To consider the issues related to distributions and Sharpe performance measure, Sortino and Van der Meer (1991) proposed the Sortino ratio that adjusts the Sharpe measure by looking at downside risk, where downside risk relates to returns falling below a defined target rate. Harry Markowitz, the founder of modern portfolio theory, also discussed the importance of downside risk in his seminal Markowitz (1959) paper, despite using standard deviation in his portfolio theory model.

## 2.5. Crypto and Energy Markets

It is vital to appreciate the factors affecting demand and supply in the energy crypto and energy commodity markets since the main purpose of the study is to evaluate whether energy cryptos can benefit portfolios consisting exclusively of leading energy stocks. While not studying solely energy block chain based crypto currencies and commodity energy markets, He et al. (2016) provides a decent synopsis of the currency characteristics of bitcoin and commodities, after summarizing findings of Calomiris (1988), Bordo (1981) and Redish (1993). As far as supply factors are concerned, both markets are decentralized in nature, with the source of supply being private under cryptos, and both private and public under commodity markets. Production costs are relatively high with cryptos owing to the amount of electricity required in crypto mining, and also high in commodity markets which involve mining. For commodity energy markets, the cost is gradually falling due to cheaper energy renewables. Regarding demand factors, both crypto currency and commodity markets can be used as a store of value, although the former is particularly susceptible to exchange rate risk and the latter to commodity price risk. Both can be used as a medium of exchange, although the crypto currency is still relatively new to the global financial arena. Although commodities have intrinsic values and can be used as units of account, cryptos have neither of these two features. Besides the demand and supply factors, it is also beneficial to understand how cryptocurrencies are affected by macroeconomic events. For instance, Author et al. (2019) analyzed major global announcements in US, UK and Europe, and found no specific news release during the structural breaks witnessed in crypto markets by late 2017. While Elendner et al. (2016) analyzed the top ten cryptos based on their market values and found them to be weakly correlated, Trimborn and Härdle (2016) found the CRIX to be more representative of the market than Bitcoin (BTC).

While some these studies attempt to explore the crypto and external world in areas like news announcements, energy futures markets, and crypto prices, they showed some lacking in some fundamental areas. For example, Author et al. (2019) analysis considered only news which were released without other news being simultaneously

released on the same day. This limits the scope of the findings when more than one news is released from different categories. Studies like Trimbor and Härdle (2016) and Elendner et al. (2016) either considered only the whole market index or top ten cryptos, such that generalization for key sectors like energy within the crypto markets are not made. Lastly, Chuen et al. (2018), despite using a Cornish Fisher framework along the traditional MPT theory, did not look into other measures of risk coming from different models like ARCH family classes or ML. Most noticeably, none of the studies mentioned looked specifically at the relationship between energy cryptos and energy equity, using a portfolio framework, where the diversification benefits of including energy cryptos into an energy equity based portfolio is assessed.

Alternatively stated, this study bridges the gap in the prevailing literature on three grounds. First, it is the first, to test whether leading energy stocks and energy cryptos can be combined together within one optimal risky portfolio and assess their performance using the Sharpe performance measure. While it is expected that when energy prices rise, this would allow, *ceteris paribus*, renewable energy based crypto prices to increase, by acting as substitutes from traditional fossil based energy companies, and vice versa, it has also been observed that alternative investments like cryptos and commodities share low correlations, as reported previously in literature. An increase (decrease) in the prices of energy products, passed through higher (lower) equity prices in the energy sector, can lead to a significant (insignificant) change to energy crypto prices, which can potentially affect the risk and return of energy equity portfolios with (without) energy based cryptos. Since the decoupling of crude oil and natural gas prices which occurred around 2008, the demand for oil to produce electricity has plunged greatly, due to aged petroleum assets being gradually retired, lower natural gas prices, and better awareness on the environmental impact of the relatively high sulfur component of oil. While a negative correlation between different assets would decrease portfolio risk, a negative correlation between specific energy companies, say the top ten energy companies of S&P1500 energy index, and energy cryptos can help later identify which energy cryptos can be mixed to a portfolio of energy stocks and vice versa.

Second, this study is the first one which introduces different measures of risk. The paper expands on the traditional modern portfolio theory model introduced by Markowitz (1952), by including alternative measures of risk based on the Cornish Fisher expansion model, the ARIMA-GARCH optimized model and a ML. This enables different approximations of risk to be used to reach the optimal risky portfolio, under an efficient frontier framework. Last, but not least, due to the negative returns observed in the last few years, the study also analyzes the effect of adding energy cryptos into equity portfolios with non-positive excess returns. This allows us to observe the impact of negative crypto returns onto an energy based portfolio made up of only zero or negative returns. This creates a scenario where all returns in both the energy equity and crypto currency markets are negative or zero, and analyzes whether mixing the new alternative asset class with traditionally based equity portfolios help in reducing portfolio risk, characterized by a scenario of downside risk, as proposed by Sortino and Van der Meer (1991) and Markowitz (1959).

### 3. RESEARCH METHODOLOGY AND DATA

The daily percentage return,  $R_p$ , is based calculated as the logarithm of the return at time  $t$  over the return at time  $t-1$  (ignoring dividends). The use of logarithmic as opposed to simple returns is supported by the heightened volatility exhibited in crypto and commodity markets and supported by Hudson and Gregoriou (2015) who found higher volatility tend to reduce expected returns upon using logarithmic returns. Further, due to portfolios usually being constructed and held over medium to long investment horizons, logarithmic returns are preferred to simple returns, where Dissanaik (1994) and Roll (1983) found the latter to yield unsatisfactory results. The volatility measures across models differ as follows:

#### 3.1. Markowitz Mean-variance Framework

As reported by Markowitz (1952), the modern portfolio theory (MPT) is based on individual asset's standard deviation,  $\sigma$ , as a

measure of risk where  $\sigma = \sqrt{\frac{\sum (R_i - \bar{R})^2}{n-1}}$ . Under the assumption

that investors are mostly risk averse with a preference in convex utility curves being positioned on the north west end of a risk and return map, and a normal distribution in the asset returns, a portfolio is constructed with the aim of reaching a maximum portfolio return while minimizing standard deviation. The portfolio variance and portfolio return are decomposed as follows:

$$R_p = \sum_{i=1}^n \omega_i R_i \quad (1)$$

$$\sigma_p^2 = \sum_{a=1}^n \sum_{b=1}^n \omega_a \omega_b \sigma_{ab} \quad (2)$$

Where  $\omega_i$  represent the weights of different assets within the risky portfolio and  $\sigma_{ab}$  is the covariance between two assets. MPT optimizes portfolio combinations by maximizing a possible expected portfolio return and minimizing portfolio risk, subject to the constraint that  $\sum_{i=1}^n \omega_i$  resulting in the efficient frontier. For

the purpose of this study, we assume only long positions for all assets, such that no negative weight is allowed in the optimal portfolio construction. To take into account the different risk appetite of investors, a risk aversion coefficient was introduced in the optimization process as:

$$\max_{p \in R_p} \left\{ \phi \sum_{i=1}^n \omega_i R_i - \sum_{a=1}^n \sum_{b=1}^n \omega_a \omega_b \sigma_{ab} \right\} \quad (3)$$

where  $\phi$  represents the risk aversion of the investor. With investors assumed to be risk averse,  $\phi$  would take a positive value, where an investor seeking higher return is expected to bear or invest in a riskier portfolio. The mean-variance model, however, is subject to some criticism when it comes to the normal distribution assumption. In line with Chuen et al. (2018) who found cryptocurrencies returns were highly non normal, a Cornish-Fisher expansion (CF) is also adopted to include higher moments of returns, i.e., skewness and kurtosis into the Markowitz mean-variance model. While other expansions like Gram-Charlier and Edgeworth expansions (Leon et al., 2009), the CF expansion provides a relatively straightforward relation between kurtosis, skewness and the second moments in the distribution of asset

returns, as supported by Cao et al. (2010) and Fabozzi et al. (2013). Proposed by Cornish and Fisher (1938), CF provides an explicit expansion for any standardized quantile of the true distribution as a function of the corresponding quantile of the normal approximation, such that it is then a simple polynomial function of the corresponding unit normal quantile, where the coefficients of each resulting term are functions of the moments of the true distribution. Alternatively stated, the CF quantile can be stated as:

$$q_{CF,\alpha} = \mu + Z_{CF,\alpha} \sigma_{CF} \quad (4)$$

Where  $q_{cf,\alpha}$  is the CF quantile function and  $Z_{CF,\alpha}$  is the normalized quantile and is calculated as:

$$Z_{CF,\alpha} = a_0 + a_1 z + a_2 z^2 + a_3 z^3 \quad (5)$$

Where  $a_0 = -s$ ;  $a_1 = 1 - 3k + 5k^2$ ;  $a_2 = s$ ;  $a_3 = k - 2s^2$ .  $k = \frac{K}{24}$  and  $s = \frac{S}{24}$ .

and S are the kurtosis and skewness parameters. Z represents the Gaussian normal distribution with a mean value of 0 and variance of 1. While the relationship between the Gaussian and CF quantile can be explained further as reported in Amédée-Manesme et al. (2018), our interest resides more on Maillard (2018) who reports the standard deviation,  $\sigma_{CF}$ , of the Cornish Fisher expansion model as follows:

$$\sigma_{CF} = \frac{\sigma}{\sqrt{1 + \frac{1}{96} K^2 + \frac{25}{1296} S^4 - \frac{1}{36} K S^2}} \quad (6)$$

A recent application of the Cornish Fisher expansion model in portfolio includes Chuen et al. (2018) who found that the traditional Markowitz approach of using standard deviation resulted in an underestimated measure of risk compared with the Cornish Fisher expansion.

#### 3.2. ARIMA GARCH Model Specification

Following Bollerslev (1986), Nelson's (1991) and Babu and Reddy (2015), we examine and model the behavior of daily returns of ten top energy stocks and 4 cryptos. Two distinct groups have been identified, the first group follows GARCH models and it consists of nine indices namely (KMI, CVX, XOM, EOG, OXY, MPC, VLO, SNC, TSL). The other group, on the other hand tends to follow ARMA-GARCH Models which includes COP, SLB, POWR and GRID.

The standard GARCH (1, 1) model used can be expressed as follows:

$$y_t = \pi_t \theta + \varepsilon_t \quad (7)$$

$$\sigma_t^2 = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (8)$$

Where  $\pi_t$  is a set of exogenous variables capturing past information and  $\varepsilon_t \sim N(0, \sigma_t^2)$   $\omega_0, \alpha_1$ , and  $\beta$  are the parameters to be estimated.

In the ARMA-GARCH model, we will include the AR (1) or MA (1) in the standard GARCH (1, 1) model - conditional mean

equation. This inclusion of ARMA depends on evidence generated from our daily returns series. For example if some return series show evidence of autocorrelation, then AR (1) will be combined with GARCH (1,1) model and estimated accordingly. Hence, following Babu and Reddy (2015) and Wang and Moore (2009), the specification of ARMA-GARCH model is stated as follows:

$$r_t = \mu + e_t, e_t | I_{t-1} \sim N(0, \sigma_t) \quad (9)$$

$$\sigma_t^2 = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (10)$$

where  $\mu = \phi_1 r_{t-1} + \theta_1 e_{t-1}$ .  $N$  represents the conditional normal density with mean zero and variance  $\sigma_t$ .  $I_{t-1}$  is the information available at  $t-1$ .  $\alpha_1, \beta, \phi$  and  $\theta$  are the parameters to be estimated.

### 3.3. ML Model Specification

Nonparametric density estimation is an important tool in statistical data analysis. It is used to model the distribution of a variable based on a random sample. The resulting density function can be utilized to investigate various properties of the variable. Among the nonparametric methods kernel density estimation (KDE) is the most popular approach in the current literature (Fan, 2005; Silverman, 2018; Simonoff, 1996). It is a well-established technique both within the statistical and ML communities (Botev et al., 2010; Kim and Scott, 2012; Liu et al., 2011).

Let  $\{x_1, x_2, \dots, x_n\}$  be an i.i.d. sample drawn from an unknown probability density function  $f$ . Then the kernel density estimate of  $f$  is given by:

$$\tilde{f}(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \quad (11)$$

Where  $K$  is the kernel function and  $h$  is the bandwidth parameter. Intuitively, the true value of  $f(x)$  is estimated as the average distance of  $x$  from the sample data points  $x_i$ . The “distance” between  $x$  and  $x_i$  is calculated via a kernel function  $K(t)$ . There exists a number of kernel functions that can be used for this purpose including Epanechnikov, exponential, tophat, linear and cosine. However, the most popular kernel function is the Gaussian function i.e.,  $K(t) = \phi(t)$ , where  $\phi$  is the standard normal density function. Given that daily stock return values are approximately symmetrical and have a theoretically unbounded support with diminishing tails we also employ  $\phi$  as our kernel function in our calculations. The bandwidth parameter  $h$  controls the smoothness of the density function estimate as well as the tradeoff between the bias and variance. A large value of  $h$  results in a very smooth (i.e., low variance), but high bias density distribution. A small value of  $h$  leads to an unsmooth (high variance), but low bias density distribution.

The rule of thumb for optimal bandwidth value is stated as follows:

$$h = \left(\frac{4s^5}{3n}\right)^{0.2} \quad (12)$$

Where  $s$  is the sample standard deviation (Silverman, 2018). We use the same bandwidth value as in equation 1 to perform our calculations. In particular, we used the scikit-learn ML library

and its implementation of KDE to model the probability density functions of daily returns for individual stocks and cryptos. KDE in scikit-learn is implemented in the `sklearn.neighbors`. Kernel density estimator, which uses the ball tree or KD tree for efficient queries<sup>1</sup>.

### 3.4. Portfolio Performance Measure

As part of evaluating the performance of the efficient portfolios, including the optimal portfolio combination, the Sharpe performance measure is used. The Sharpe ratio is the excess return per unit of risk, and assumes total risk (downside and upside) is considered. In line with Sortino and Van der Meer (1991), who captured downside risk through the Sortino ratio, we also looked into non-positive returns, by calculating the excess return as  $R_A - MAR_A$ , where  $MAR_A$  represents the minimum acceptable return. If  $(R_A - MAR_A) > 0$ , the resulting value is substituted to zero, otherwise, the value is set as  $RA - MAR_A$ . This guarantees that the model captures only downside risk. For the purpose of this study, the minimum acceptable return is set as the risk-free rate which is based on an average of the 3 month US Treasury bill rates.

For the purpose of this study, the top ten energy stocks are selected from S&P Composite 1500 energy index, which captures the performance of publicly listed companies which are members of the Global Industry Classification Standard energy sector. Launched in December 2005, the index has ninety-two constituents with a maximum market capitalization value of \$310,254 million and mean capitalization value of \$14,712 million, as at January 31, 2019. The top ten stocks were selected based on their relative index weight to the index, and are classified as follows:

The energy crypto currencies selected are SunContract (SNC), power ledger (POWR), energo labs (TSL) and GRID+(GRID). Although energy coin (ENRG) prices were available for the time under analysis, it was disregarded to the gap in the crypto dataset from October 2018 to January 2019. Other energy based cryptos like KWHCoin, Energi, 4NEW and Energi Mine were also excluded since they were first released only between June 2018 and August 2018. The daily data sample is set from November 21, 2017 to January 31, 2019. While the Chicago Mercantile Exchange allows electronic trading of energy contracts from Sunday to Friday, and pit trading is from Monday to Friday, the crypto market never closes. The daily closing prices of crypto currencies are gathered from Coinmarketcap. The daily stock prices for the top energy stocks were collected from Factset.

## 4. RESEARCH FINDINGS

### 4.1. Descriptive Statistics

Before pursuing any analysis, it is useful to capture the historical performance of the energy stocks and energy cryptos. As reported in Figure 1, the four energy cryptos exhibited a relatively similar trend, with a noticeable peak reached in December 2017, before trending significantly downwards since then. While GRID had a relatively higher price of 2.86 compared to other cryptos, energy cryptos shared strongly positive correlation coefficients

<sup>1</sup> The Nearest Neighbors module documentation in scikit-learn for further details



ranging from 0.75 to 0.92. This is similar to Author (2019) who finds positive correlations between 0.72 and 0.9 among energy cryptos over the period 2017-2018. Figure 2 displays the energy stock prices for the top ten constituents listed under the S&P Composite 1500 energy index. As observed, the prices tend to behave in a similar fashion during the 2017-2019 period. Except for COP and SLB which shared a negative correlation of  $-0.1$ , all other energy stocks shared positive correlations among themselves, ranging from 0.21 to 0.96. The positive correlation pairs among the risky assets point to a low level of diversification in such a portfolio, since all the stocks originate from the same asset class. Although not reported here, correlation coefficients between energy stocks and energy cryptos were mixed in values, with each energy stock having between two and five negative correlation values with energy cryptos. These ranged from  $-0.5$  to  $-0.59$ , thereby increasing the expectation that the inclusion of energy cryptos in the energy equity portfolio can potentially reduce the portfolio risk as a benefit of diversification across different asset classes.

Figure 1 represents the daily prices for select energy block chain based cryptos over the period November 2017–January 2019. The entities (trading symbols) are SunContract, power ledger, energo labs and GRID+(GRID). Closing prices are the latest data for each day (UTC time).

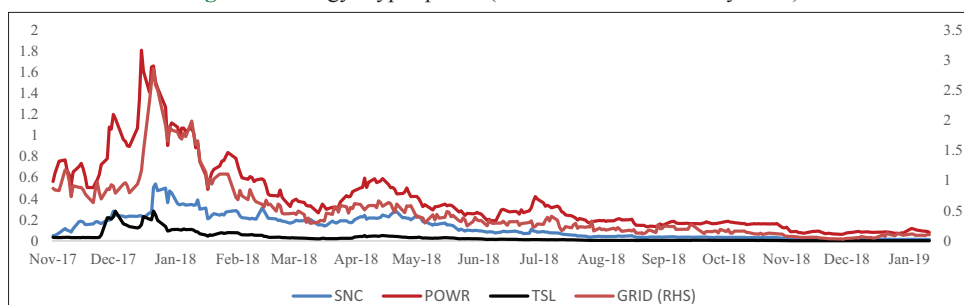
Figure 2 shows the daily stock prices, at close, for the ten energy companies, which are all listed as leading constituents under the S&P1500 Composite 1500 energy index. The companies (trading symbols) include Exxon Mobil, Chevron corp, ConocoPhillips, Schlumberger Ltd, EOG Resources, Occidental Petroleum, Marathon Petroleum Corp, Phillips 66 (PSX), Valero Energy

Group and Kinder Morgan Inc. Asset specification details are provided in Table 1.

In Figures 3 and 4, we present histograms of daily logarithmic returns of ten stocks and four cryptos along with respective KDE graphs for the ML based model. In line with Sortino and Van der Meer (1991) who proposed the Sortino ratio which captures downside side, we modeled the probability density function, using negative or zero excess returns, where excess returns were calculated as the difference between actual returns and an average of the 3 month US treasury bill rates. We dubbed the adjusted returns as Sortino returns. The probability density function for the Sortino returns are reported in Figure 4. A comparison of the standard deviations for all assets between the two probability density functions shows that there is a substantial difference in the standard deviations using the normal returns compared to Sortino returns. The greatest difference is observed among the energy stocks. The standard deviations based on normal returns for energy stocks are much lower compared to Sortino based returns. It is also worth observing that the standard deviations based on Sortino returns are relatively consistent among the energy stocks and the cryptos. On the other hand, the standard deviations based on normal returns are much higher for cryptos compared to energy stocks.

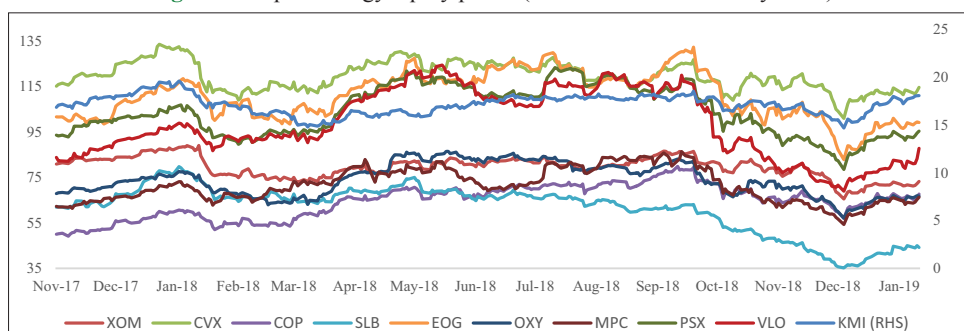
Figure 3 displays the probability density function for all the selected energy equities and energy cryptos' logarithmic daily returns over the period November 2017–January 2019. Equities include Exxon Mobil, Chevron Corp, ConocoPhillips, Schlumberger Ltd, EOG Resources, Occidental Petroleum, Marathon Petroleum Corp, Phillips 66 (PSX), Valero Energy Group and Kinder Morgan Inc. Energy cryptos are SunContract, Power Ledger, Energo Labs (TSL) and GRID+(GRID).

**Figure 1:** Energy crypto prices (November 2017–January 2019)



Source: Coinmarketcap (2019). GRID is displayed on the right hand side vertical axis

**Figure 2:** Top 10 energy equity prices (November 2017–January 2019)



Source: Factset, S&P500 Dow Jones Indices. KMI is displayed on the right hand side vertical axis



Figure 4 displays the probability density function for all the selected energy equities and energy cryptos' adjusted logarithmic daily returns. The adjusted returns are calculated after taking the difference between actual logarithmic returns and an average of the 3 month treasury bill rates over the period November 2017–January 2019. All positive returns are substituted as zero returns to capture only downside risk. Equities include Exxon Mobil, Chevron Corp, ConocoPhillips, Schlumberger Ltd, EOG Resources, Occidental Petroleum, Marathon Petroleum Corp, Phillips 66, Valero Energy Group and Kinder Morgan Inc.

Resources, Occidental Petroleum, Marathon Petroleum Corp, Phillips 66 (PSX), Valero Energy Group and Kinder Morgan Inc. Energy cryptos are SunContract, Power Ledger, Energo Labs (TSL) and GRID+(GRID).

## 4.2. Analysis

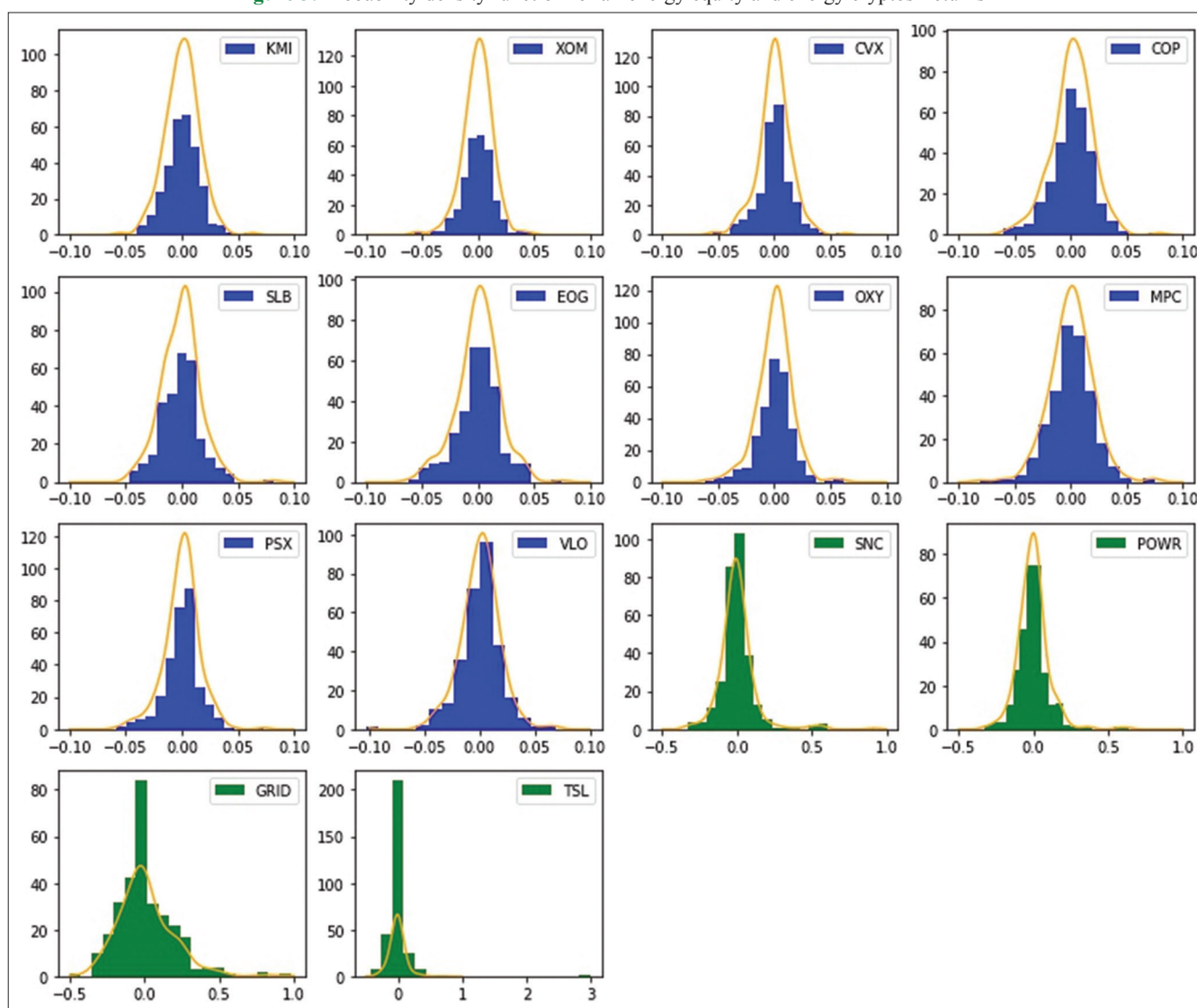
Before analyzing the impact of the different measures of risk on the energy portfolios, it is vital to depict the behavior of the different risk

**Table 1: Asset specification details**

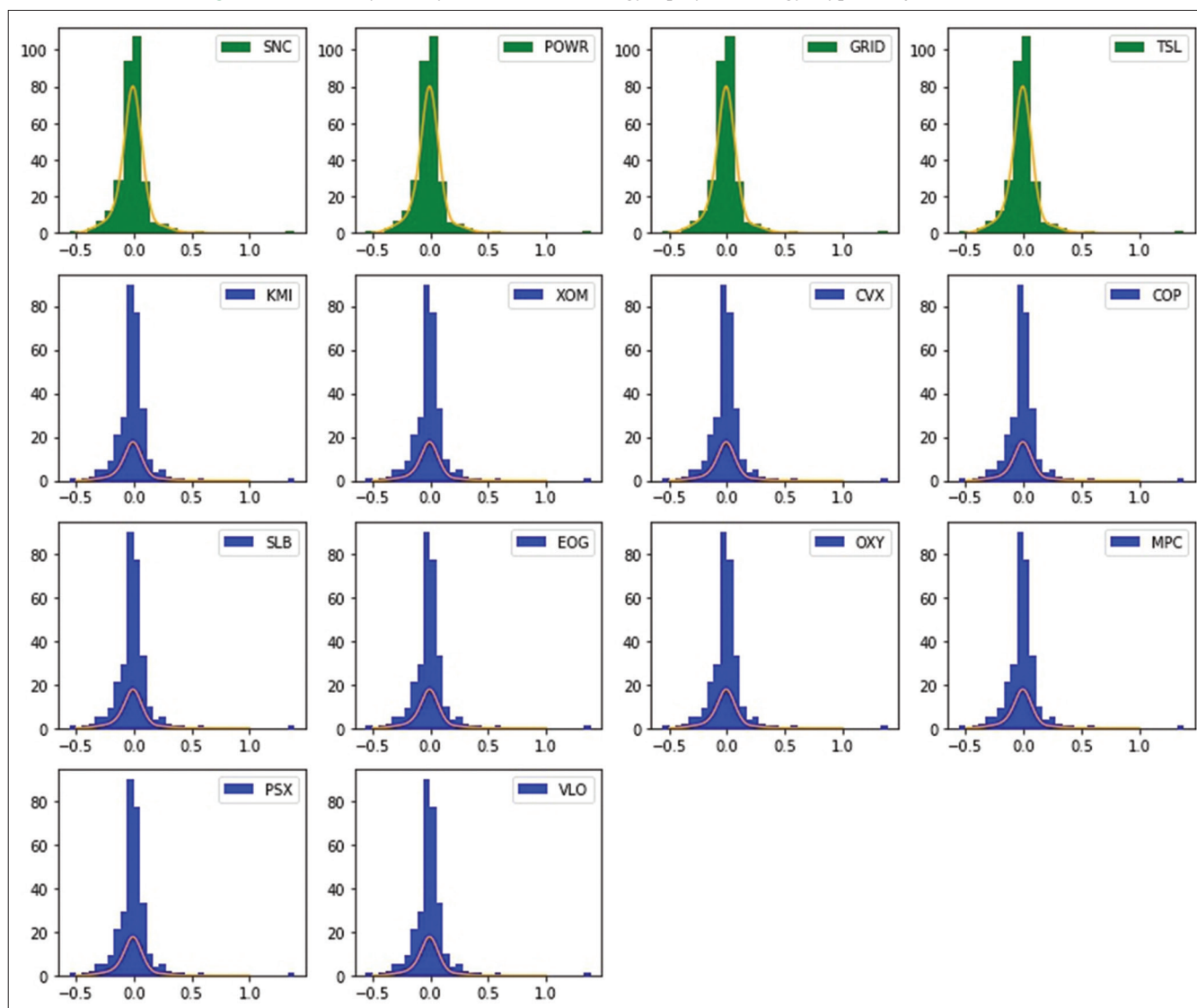
Company	Trading symbol	Sector	Industry	Sub industry
Exxon mobil	XOM	Energy	Oil, gas and consumable fuels	Oil and gas exploration and production
Chevron corp.	CVX		Oil, gas and consumable fuels	Integrated oil and gas
Conoco phillips	COP		Oil, gas and consumable fuels	Oil and gas exploration and production
Schlumberger Ltd.	SLB		Energy equipment and services	Oil and gas equipment and services
EOG resources	EOG		Oil, gas and consumable fuels	Oil and gas exploration and production
Occidental petroleum	OXY		Oil, gas and consumable fuels	Oil and gas exploration and production
Marathon petroleum corp.	MPC		Oil, gas and consumable fuels	Oil and gas refining and marketing
Phillips 66	PSX		Oil, gas and consumable fuels	Oil and gas refining and marketing
Valero energy group	VLO		Oil, gas and consumable fuels	Oil and gas refining and marketing
Kinder Morgan Inc.	KMI		Oil, gas and consumable fuels	Oil and gas storage and transportation

Source: Factset, S&P500 Dow Jones Indices

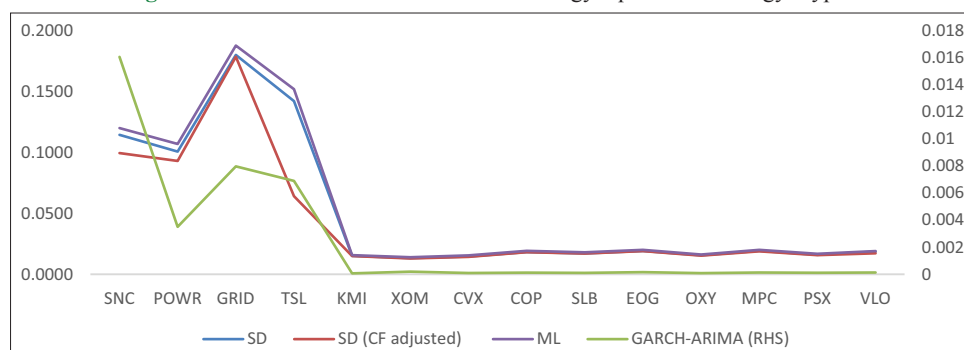
**Figure 3: Probability density function for all energy equity and energy cryptos' returns**



**Figure 4:** Probability density function for all energy equity and energy cryptos' adjusted returns



**Figure 5:** Behavior of risk models for the energy equities and energy cryptos



models over the energy cryptos and energy equities. As observed in Figure 5, the risk values for all the energy stocks, under all the four models, shared mostly the same relationships, with the GARCH-ARIMA model showcasing the lowest risk values compared to the standard deviation, CF risk adjusted model and the ML model. While the latter three models also appear to be positively correlated with each other for the four energy cryptos, the GARCH-ARIMA model departs from this analogy, with much lower risk values.

SD refers to standard deviation; SD (CF adjusted) is the standard deviation from the Cornish Fisher risk adjusted model; ML is the risk from the ML based model; and GARCH-ARIMA is the optimal risk from ARIMA-GARCH family class models. Equities include Exxon Mobil, Chevron Corp, ConocoPhillips, Schlumberger Ltd, EOG Resources, Occidental Petroleum, Marathon Petroleum Corp, Phillips 66 (PSX), Valero Energy Group and Kinder Morgan Inc. Energy cryptos are SunContract, Power Ledger, Energo

Labs (TSL) and GRID+(GRID). The GARCH-ARIMA graph is displayed on the right hand side vertical axis.

#### 4.2.1. Efficient portfolios under the Markowitz framework

As a well-established model in portfolio management, it is imperative to construct efficient portfolios consisting of solely of energy stocks, and also assess the impact of including different asset classes such as energy cryptos on the portfolio's risk and return. Figure 6 reports efficient portfolio combinations include mostly energy stocks such as KMI, XOM, CVX, COP, SLB and PSX. No influence of the cryptos on the energy equity based portfolios. As we move from the minimum variance portfolio to the right of the efficient frontier, the weight of COP increased steadily, caused primarily due to the stock having the highest return compared to all other constituents. A portfolio which includes energy cryptos with equal weights resulted in a negative portfolio return of -0.2% with a risk of 2.89%. Comparatively, a portfolio with only energy stocks had a return of 0.01% with a portfolio risk of 1.36%. The difference in the portfolio risk and return is partly due to the negative performance of all individual cryptos, which had relatively larger losses compared to the individual energy stocks. Although not reported here, the inclusion of energy cryptos did not result in any significant change to the efficient frontier of the portfolio, despite the individual stocks and energy cryptos' risk were adjusted with the Cornish Fisher model. Major constituents of the efficient portfolios, with or without cryptos, consisted of KMI, XOM, COP, PSX and VLO, with a gradual increase in the weight of COP as we move towards the optimal risky portfolio. The optimal portfolio

return of 0.10158% yielded a Sharpe value of 0.0519 under both portfolios, with insignificant differences observed for portfolio combinations which were below the minimum variance portfolio. This can be explained by the poor performance of energy cryptos which pulled down the return of the portfolio for non-efficient portfolio combinations.

#### 4.2.2. Efficient portfolios without cryptos using Markowitz, Markowitz CF portfolio and ML

Figure 7 displays the risk and return of portfolios consisting only of energy equities, where risk is measured as standard deviation, Cornish-Fisher risk adjusted standard deviation and ML based risk measure. The Cornish Fisher adjustment to the Markowitz Portfolio (with no cryptos) resulted in a slight improvement in the return per unit of risk. For example, for a portfolio comprising of 98% COP and 2% KMI, the Sharpe value increased from 0.0511 to 0.0515. The optimal portfolio return of 0.10158% yielded a higher Sharpe of 0.0519 for both the traditional and the Cornish Fisher adjusted model. The effect of the CF adjustment was more evident near the minimum variance portfolio, where the same return could be achieved with a slightly lower risk than the traditional Markowitz model. The ML model however resulted in higher risk values for the same returns, compared to the Markowitz and Markowitz CF adjusted model. The Sharpe of the optimal risky portfolio was the highest with the CF model at 0.0519, followed by the Markowitz model at 0.0514, and the ML yielding 0.0489 respectively.

#### 4.2.3. Efficient portfolios under ML

As shown in Figure 8, major constituents for the ML based portfolio, with and without the inclusion of energy cryptos, were KMI, XOM, CVX, COP, OXY and PSX. The inclusion of the crypto in the ML based model did not result in any noticeable change in the Sharpe values of efficient portfolio combinations. Similar to the Markowitz and Markowitz CF adjusted based models, higher return per unit of risk was achieved with efficient portfolios consisting primarily of COP. This can be explained due to the energy stock having the highest returns among all other constituents. The Sharpe of the optimal portfolio with ML model remained at 0.0489. The relatively poor performance of the energy cryptos, coupled with the low positive correlation values did not help to reduce the risk of the optimal risky portfolios. The only discernable difference was observed for efficient portfolios around the minimum variance portfolio. For instance, a portfolio based

Figure 6: Markowitz portfolio model

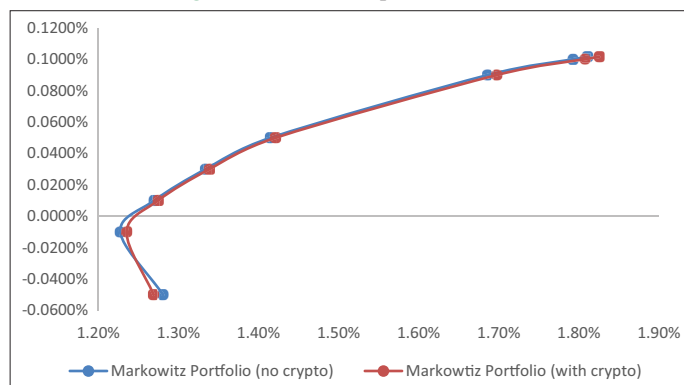
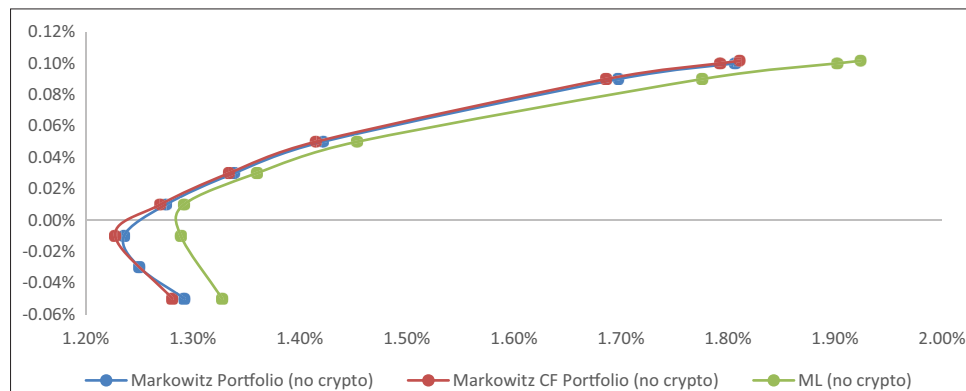


Figure 7: Efficient portfolios (with no cryptos)



wholly on equity portfolios with a return of  $-0.05\%$  had a risk of  $1.33\%$ , compared to a portfolio with stocks and cryptos, which reported the same return with a slightly lower risk of  $1.30\%$ . For negative portfolio returns, the inclusion of crypto in the equity portfolio, resulted in lower risk with the same return as in a portfolio holding only energy stocks. This suggests, that during an economic downturn, including a crypto in an equity based portfolio would tend to reduce the risk levels for a given return. However, the differences between the two portfolios disappear as we approached the optimal risky portfolio combination, with a higher risk and return.

#### 4.2.4. Efficient portfolios with cryptos using Markowitz, Markowitz CF and ML models

While section 5.2.2 shows the risk and return of efficient portfolios, which consist only of energy stocks, it is vital to similarly analyze

the impact of using different risk measures onto portfolios which include the four selected energy cryptos. As reported in Figure 9, the inclusion of the energy cryptos in the efficient portfolios resulted in the lowest excess return per unit of risk for the ML model, compared to the other two models. While the use of cryptos slightly improved the Sharpe value of the optimal portfolio for the Markowitz model from  $0.0514$  to  $0.0515$ , the Sharpe value decreased from  $0.0519$  to  $0.0515$  under the CF adjusted model. The Sharpe value did not change under the ML model i.e., remain at  $0.0489$ .

#### 4.3. Risk Adjusted Returns and Efficient Portfolios

Due to the negative performance of cryptos, the study also analyses the effect of adding cryptos to equity portfolios with non-positive excess returns. This allows us to capture the impact of negative cryptos returns onto the equity based portfolios. Alternatively stated, the use of zero or negative excess returns, allows us to capture the downside risk of mixing different asset classes together in an efficient portfolio framework. As observed in section 5.1, the standard deviations based on Sortino returns were relatively consistent among the energy stocks and the cryptos, compared to the standard deviations based on normal returns which were much higher for cryptos relative to energy stocks. Figure 10 shows the portfolio risk and return of the efficient portfolios. Both the Markowitz and Markowitz CF adjusted Portfolio model resulted in Sharpe values of  $-0.5969$  and  $-0.6077$  respectively. Comparatively, the ML based model yielded a Sharpe value of  $-0.033$ . In all the three models, equity portfolio combinations with a proportionally higher weight in XOM, on the efficient frontier,

Figure 8: Machine leaning based efficient portfolios

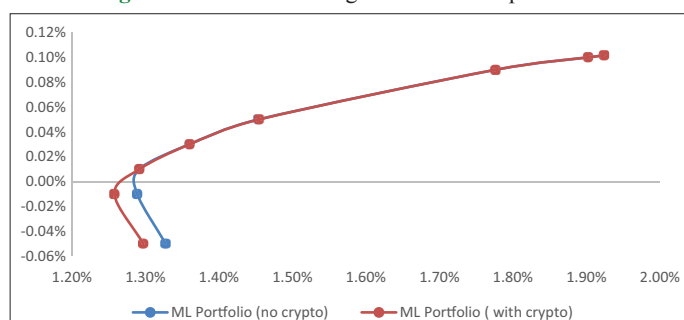


Figure 9: Efficient portfolios with cryptos

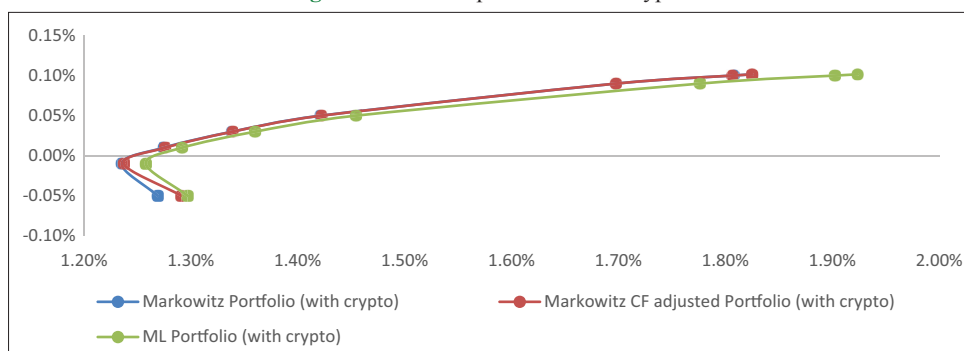
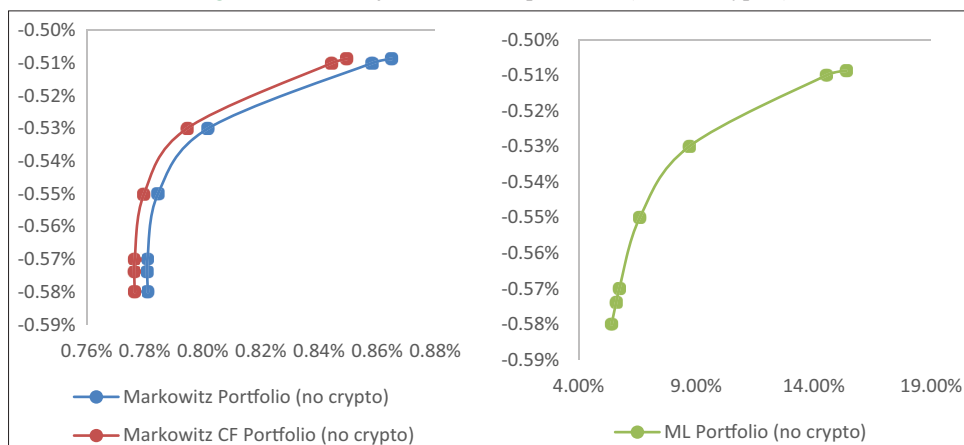
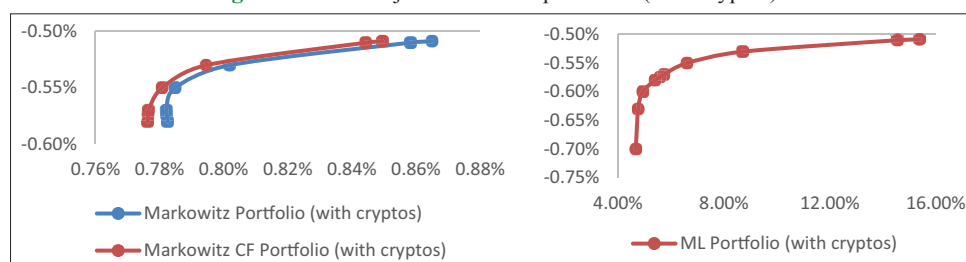


Figure 10: Risk-adjusted efficient portfolios (with no cryptos)





**Figure 11:** Risk-adjusted efficient portfolios (with cryptos)



yielded higher excess return per unit of risk. Compared with the Markowitz and Markowitz CF adjusted model, the optimal risky portfolio under the ML model had a higher portfolio risk. This can be explained due to the individual risk values of the ten energy stocks ranging from a minimum risk value of 14.45% for MPC and a maximum risk value of 15.38% for XOM. This can be compared with the other two models, where standard deviations values ranged only between 0.86% (XOM) and 1.22% (EOG) under the Markowitz model, and between 0.85% (XOM) and 1.19% (EOG) under the Markowitz CF portfolio model.

Although not reported here, the use of the Cornish Fisher adjusted model for portfolios with and without cryptos, reveals that the inclusion of energy cryptos did not result in any significant change to the efficient frontier of the portfolio, despite the individual stocks and energy cryptos' risk were adjusted with the Cornish Fisher model. The highest excess return per unit of risk among all efficient portfolios was  $-0.6078$  with a portfolio risk of  $0.85\%$  and return of  $-0.51\%$ . The inclusion of energy cryptos did not benefit the equity portfolio due to the proportionally more negative returns observed for all individual cryptos. Most of the efficient portfolios consisted predominantly of equity companies such as KMI, XOM and VLO. As we move from the minimum variance portfolio towards the optimal risky portfolio, the weight of XOM increased gradually, due to the stock having the highest return of  $-0.51\%$ . Similarly, the use of the ML based model for portfolios with and without cryptos, supports that the inclusion of the crypto in the ML based model did not result in any noticeable change in the Sharpe values of efficient portfolio combinations. The Sharpe of the optimal portfolio remains at  $-0.0336$ , with higher excess return per unit of risk observed as efficient portfolios consist more of the XOM energy stock. The relatively poor performance of the energy cryptos, coupled with the low positive correlation values did not help to reduce the risk of the optimal risky portfolios. Under portfolios comprising solely of energy stocks, portfolios with lower returns than the minimum variance portfolio returns had relatively higher risk as denoted in the graph. Comparatively, for the same portfolio return, energy equity portfolios which also included cryptos did not witness an increase in risk. This is attributed to the relatively lower returns levels for each of the energy cryptos, compared to the energy stocks.

Moreover, our study looks at the impact of including energy cryptos in existing energy equity portfolios, using risk adjusted returns. As reported in Figure 11, the inclusion of the energy cryptos in the efficient portfolios resulted in the lowest excess return per unit of risk for the ML model, compared to the other two models. While the use of cryptos slightly improved the

Sharpe value of the optimal portfolio for the Markowitz model from  $0.0514$  to  $0.0515$ , the Sharpe value decreased from  $0.0519$  to  $0.0515$  under the CF adjusted model. The Sharpe value did not change under the ML model.

The highest excess return per unit of risk was observed under the ML model without cryptos at  $-0.0336$ . The Markowitz portfolio model produced a Sharpe value of  $-0.5969$  for the optimal risky portfolio, where the inclusion of cryptos within the portfolio did not make any significant impact. The same remark was made with the Markowitz Cornish Fisher adjusted model, where the energy cryptos did not contribute to the performance of the portfolio. The ML model had a proportionately high decrease in its Sharpe value, after having included cryptos into the portfolio construction. This could be explained by the relatively lower returns in the new alternative asset class such as crypto currencies compared to energy equities. Overall, the inclusion of cryptos did not affect the performance of energy equity based portfolios, with the exception of the ML based model.

#### 4.4. Portfolio Performance Evaluation

While the use of different risk models in the construction of the efficient portfolios (with and without cryptos) is important, it is even more imperative to evaluate the portfolio performance of the different models. The Sharpe values of the optimal risky portfolios, under each risk model, are calculated. Both the Sharpe values of using all returns and risk adjusted returns are provided in Table 2:

For portfolios, which included the use of all returns, positive and negative, the inclusion of the energy cryptos in the efficient portfolios resulted in the lowest excess return per unit of risk for the ML model, compared to the other two models. While the use of cryptos slightly improved the Sharpe value of the optimal portfolio for the Markowitz model from  $0.0514$  to  $0.0515$ , the Sharpe value decreased from  $0.0519$  to  $0.0515$  under the CF adjusted model. The Sharpe value did not change under the ML model. Comparatively, for zero and non-positive excess returns' based efficient portfolios, the highest excess return per unit of risk was observed under the ML model without cryptos at  $-0.0336$ . The Markowitz portfolio model produced a Sharpe value of  $-0.5969$  for the optimal risky portfolio, where the inclusion of cryptos within the portfolio did not make any significant impact. The same remark was made with the Markowitz Cornish Fisher adjusted model, where the energy cryptos did not contribute to the performance of the portfolio. The ML model had a proportionately high decrease in its Sharpe value, after having included cryptos into the portfolio construction. This could be explained by the relatively lower returns in the new alternative asset class (crypto currencies) compared to equities.

**Table 2: Portfolio performance evaluation**

Sharpe	All returns		Risk-adjusted returns	
	(with cryptos)	(without crypto)	(with cryptos)	(without crypto)
Markowitz	0.051488	0.051362	-0.596923	-0.596923
CF	0.051487	0.051893	-0.607786	-0.607786
Machine learning	0.048847	0.048847	-0.596923	-0.033565

Overall, the inclusion of cryptos did not affect the performance of energy equity based portfolios, with the exception of the ML based model.

## 5. CONCLUSION

While energy commodities such as crude oil and natural gas affect not only other commodities but also other alternative assets such as equities, energy policy makers are gradually getting more concerned with renewable energy sources and technologies such as block chain which are behind those cleaner energy products. The introduction of the new alternative asset class dubbed as crypto currencies, has motivated recent work, where researchers not only looked into what can potentially determine the value of crypto currencies but also into conceivable relationships of crypto currencies with other financial assets. This study fills the gap by being the first to evaluate whether energy based block chain cryptos can affect energy equity portfolios which consists of the leading US energy stocks. Our study is also the first to dwell into how different measures of risk, derived from the Markowitz Cornish-Fisher (CF) expansion, ARMA – generalized autoregressive heteroskedasticity (GARCH) and ML models, can help the investor make better informed decisions in how to allocate funds among the risky assets coming from different asset classes, and also how well the portfolio performed using the Sharpe performance measure. Last, but not least, the study analyzes whether mixing the new alternative asset class with traditionally based equity portfolios help in reducing portfolio risk, in a scenario which captures downside risk.

While the positive correlations among energy stocks suggest a low level of diversification in existing energy equity portfolios, negative correlations between energy stocks and energy cryptos suggest initially that the inclusion of energy cryptos can reduce portfolio risk. Risk values for all energy stocks, under the Markowitz, Cornish-Fisher Markowitz adjusted, Machine-Learning and ARIMA-GARCH models shared mostly the same relationship, with the ARIMA-GARCH model having the lowest risk values. Risk values of energy stocks under the ARIMA-GARCH model also departed from the positively correlation observed among other risk models' values. The inclusion of energy cryptos did not significantly impact the efficient portfolio frontier, under both the Markowitz and Markowitz Cornish Fisher adjusted risk models. A similar observation was found upon using the ML based risk values, where higher excess return per unit of risk was achieved with efficient portfolio consisting primarily of COP. The relatively poor performance of energy cryptos with low positive correlation values did not help to reduce the optimal risky portfolio risk. This was also evidenced when analyzing the impact of including energy cryptos onto energy equity portfolios consisting

only of negative or zero returns. Last, but not least, findings of the portfolio performance evaluation support that the inclusion of energy cryptos in efficient portfolios did not significantly impact the excess return per unit of risk. Overall, findings suggest that traditional Markowitz based and ML models can be used to capture risk, while not materially affecting the portfolio performance evaluation. Further, the findings provide portfolio managers further light that energy cryptos do not significantly impact the efficient frontier, while they are actively aiming to construct optimal risky portfolios with the highest possible Sharpe values. A future research avenue can tap into investigating how regulatory bodies such as the International Energy Agency put forward policies for the energy industry to benefit from the digitization of energy, through technologies such as energy based block chain cryptos.

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