WHAT INVESTMENT
OPPORTUNITIES DO
CRYPTOCURRENCIES PROVIDE?

by

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Abstract

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The study investigates the potential gains from considering crypto currencies as an investment opportunity. Specifically, we explore the ability of the most traded crypto tokens to be a strong hedge instrument against downfall movements in the traditional assets. Moreover, we quantify the potential gains to the global and local investors from including crypto currencies in its portfolio of traditional assets. Using maximum Sharpe ratio approach to build the optimal portfolio based on the CVaR as a coherent risk measure, paper suggests that the diversification of portfolio by crypto currencies is profitable both for global and Ukrainian investors. However, the difference of the wealth allocated to crypto market by global and local investors is ponderable, meaning clearly underdeveloped financial markets in Ukraine. While Ukrainians may allocate more than 90% of its wealth in the crypto market, it is crucial issue for Central Bank of Ukraine to create law regulation system for crypto.

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GLOSSARY

AR	Autoregressive model
BTC	Bitcoin
CVaR	Conditional Value at Risk
DASH	Dash
DCC	Dynamic Correlation Coefficients
ETH	Ethereum
FTSE 100	Financial Times Stock Exchange 100 Index
GARCH	General Autoregressive Conditional Heteroscedasticity model
LTC	Litecoin
MV	Mean-Variance approach
NEM	Nem
Nikkei 225	Japan stock market index
S&P 500	Standard and Poor's stock index
VaR	Value at Risk
XRP	Ripple

Chapter 1

INTRODUCTION

The recent rise of popularity of crypto currencies is an impressive phenomenon. Leading financial institutions keep an eye on digital currencies and have already incorporated its functionality in their payment systems. For instance, Citi Group developed its own Citi Coins to make transactions between countries manageable and less costly[1]. Leading Asian banks have already organized the trust thus making financial transactions between each other using Ripple coin[2]. Some large tech companies such as Microsoft, Dell, Expedia have started to accept digital payments.[3] Derivatives have been introduced for some crypto. For example, CBOE and CME exchanges made the announcement of Bitcoin forwards and futures from the 11th of December 2017. Crypto currencies are accepted as a legal payment in Japan.

The main question of my research is to verify potential gains for global investor, who has an access to the stocks, gold, crude oil and commodities markets, from including certain crypto currencies in its portfolio, considering their not mature state to be a financial asset. Except global trends about digital currencies, crypto currencies poses some additional value to the potential investor. Firstly, by adding a proper amount of risky asset, portfolio can potentially have higher returns (TIAA company analysis of portfolios from 1999 to 2013). Secondly, crypto currencies could serve as a strong hedge instrument for portfolio with traditional financial

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1 International Business Times ("Codename Citicoin", 2015)
2 CNBC ("Ripple develops blockchain-powered payment app with 61 banks to speed up transactions in Japan",2018). Banks of Korea enforce the update of Japan/Korea financial transaction alley.
3 International Journal of Economics and Management Engineering ("Analyzing the Effects of Adding Bitcoin to Portfolio", Vol:10, No:10, 2016)

assets, which we will investigate in the further chapters using the Dynamic Correlation Coefficients model (DCC model). In the very end, we inspect the opportunities with crypto market for Ukrainian investor and compare them to the global.

The beginning of crypto era started in 2008 year with announcing the first crypto currency Bitcoin by Satoshi Nakamoto. Bitcoin utilizes cryptography algorithms based on Blockchain. "Blockchain is an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way" (Iansiti, Marco, Lakhani, Karim, January 2017). Majority of the crypto currencies are based on Blockchain technology today. Peer-to-peer network is the main characteristic of the crypto tokens build on the block chain technology. There is no legal authority to be in charge of crypto transactions. Therefore, they function separately from the outside regulatory institutions. The absence of the regulatory third-party is a suitable circumstance for illicit activities and shadow economy. According to the Rob Wainwright, head of Europol, $5.5 billion is laundered annually through crypto currencies.[4]

Since the time of introducing Bitcoin, many others alternative coins have emerged. They attempt to introduce the improved financial payment technology and benefit potential users with faster and less expensive transactions. As of now, crypto market has more than 1000 various crypto tokens with the total market capitalization of more than 300 billion USD (source: coinmarketcap.com). While overcoming 300 billion cap by crypto market could serve as a good proxy for potential market rise, investors should be admonished by excessive number of ICO.

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4 cointelegraph.com/news/illicit-uses-of-cryptocurrency-gaining-attention-around-the-world-expert-take

While considering crypto tokens as a potential investment opportunity, it is essential to understand whether they possess any asset characteristic, e.g. do they hold any intrinsic value. When stock valuation are primary based on the discounted future cash flows generated by the company, what determines the price of crypto? One of the central reasons of why crypto currencies bring in so much attention from the mass media and financial institutions is its sky-rocket returns. However, at least partially it is caused by the speculation attractiveness of the market. Common schemes of pump and dump make the price fluctuate and overvalue crypto currency substantially. Majority of the investors are interested in the short or medium-terms gains, while not trying to enjoy the long-term utility of that technology. That is an indicator of the bubble market, which makes an investment in crypto currency risky enough.

The fundamental value of the complete crypto market lies within its technology characteristic to be a ledger and further important implications for the worldwide economy. Despite sceptics being sure about no fundamental value of crypto tokens, we will state the pros, which crypto market offers to its users. If a transaction is provided by fiat money, participants face the problem of the asymmetric information and adverse selection. It calls the necessity to have a credible third party to mitigate the fraud risk. Due to the safe block chain technology, where it is almost impossible to make a fake transaction, crypto currency are in some sense in front of the traditional payment system. Additionally, they require less transaction costs and much faster comparing to such monopolists on the financial payment systems like Visa. "Recent updates report that Ripple can now deal with a processing of 50,000 transactions per second in relation to VISA's 24,000 transactions per second"[5]. If PayPal suddenly decides that your account is used inappropriately, they could freeze it without any explanation. Since crypto

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5 https://globalcoinreport.com/how-ripple-xrp-outdid-the-transaction-speed-of-visa/

tends to be a substitute for the fiat money and gold, it is necessary to state the advantages of former against latter. During the great recession in 2008-2009 majority of EU governments together with US printed money as a main stimulus instrument to be competitive on the global economy. That means there were no constrained money supply. Opposed to the cash, majority of crypto currencies have fixed supply (for instance BTC has 21 million coin restriction, Ripple has 100 billion, etc.). Ceteris paribus, crypto are more probable to rise in its value if compare to the cash/gold. Moreover, there is a fresh trend in the crypto market, namely decentralized applications, which adds to the fundamental value of the crypto currencies. Emerging from the blockchain technology, they could bring positive externalities to the global economy. For instance, application based on the Etherium technology aims to manage identity of individuals on the highest level of trust. The other example is Eth-tweet, which is a decentralized blogging system, meaning that any published message could be deleted only by the publisher.

The crypto currency market is relatively new, implying scarce investigation by literature of feasible investors' award from including new assets into its portfolio. Those latest studies dedicated to the question of including crypto currencies in the investor's portfolio are mainly limited to the Bitcoin investigation, while omitting potential higher gains from altcoins investigations. We explore positive externalities from adding to portfolio the following tokens: Bitcoin, Ethereum, Ripple, Litecoin, Dash and Nem. The main criteria of choosing the mentioned currencies was its daily traded volume being higher than 100 000 000 USD. The coins like Bitcoin Cash, Bitcoin Diamond, Stellar, Etherium Classic were not considered due to them being recent forks of the most traded currencies. Except limited number of studies on crypto currencies, available literature in most cases propose not very precise methodology for investigations. Moreover, as was stated in a few empirical papers, ability of Bitcoin as a good diversifier may vary across different time horizons (see for example Bouri, Molnar, Azzi, Roubaud, 2016). We will test it on the data available until the March of 2018. While making rebalancing on the daily basis, we try to determine the weights of crypto currencies in the investor's portfolio.

The next sections in the paper is established in a following way: in the Literature Review part we will go through the most relevant works related to investing in crypto currencies and address its central pros and cons. Next, we will undergo the details of the methodology we use for verifying whether an asset could serve as a good hedge for traditional assets and methodology we use for constructing an efficient portfolio. Finally, the data description, investigation results and conclusions are presented.

Chapter 2

LITERATURE REVIEW

Despite the fact that the cryptos entered the financial market recently, they have managed to attract not only mass media and financial institutions worldwide, but also the attention of researchers. We will scrutinize through fundamental theoretical papers devoted to portfolio optimization. Afterwards we consider modern works related to making investor's right choice with digital currencies.

Harry Markovitz wrote the article that made the main contribution to the modern efficient portfolio theory in the 1991. He was first to state the variance to be a proxy for risk and solve the minimum variance problem given a certain amount of the expected revenue. After while, there were a list of papers, which criticized such an approach. The main drawbacks of the variance of an asset to be a risk measure is that it reflects fluctuations for both up and down sides of an asset price, while an optimizer is mainly interested in the potential drop of the asset. The first solution that may cross one's mind is using the semi variance as a proxy for risk what exactly did Markovitz, Todd, Xu, Yamane (1993, Springer). Still, such an approach assume a normal distribution of an assets returns (which is not the case for crypto currencies). Otherwise, it disrupts the optimal portfolio decision since variance and semi variance are likely to underestimate the possible lesion from extra tail-risk (see McNeil et al. (2005)). The literature poses a remedy for such a problem – concepts of Value at Risk and Conditional Value at Risk. The latter will be incorporated in our model, since the former has also its shortcomings when returns are not normally distributed. Furthermore, VaR does not specify the amount by which its quantile can be exceeded (for more details see Rockafellar and Uryasev, 2002). In the Methodology section, the definition and advantages of CVaR in details will be reveiled.

The main papers dedicated to crypto currencies (to Bitcoin in most) were published in 2015-2017 years. One of the most consistent and clear as by Trimborn, Li and Härdle (ISSN, July 7, 2017). Trimborn and Härdle developed the cryptocurrency index CRIX (hu.berlin/crix), which stands for total summary of the situation in the crypto currency market. It is based on the TOP 20 crypto currencies in terms of market capitalization. The index accounts for emission of new coins. Using Liquidity Constrained Investment Approach (LIBRO) to construct the optimal portfolio, the authors came to the result that crypto currencies are able to increase investor's return of a portfolio while controlling for a minimum volatility risk. While bringing the substantial input to the theoretical part of investigating a crypto attractiveness, the paper still suffers from several limitations. The global investor has an access to only three traditional financial assets - S&P 100 component stocks, DAX30 component stocks, stocks listed in Portugal Stock separately and 39 crypto currencies. Actually, global investor have an access to all world assets markets, including the market of commodities, bonds, real estate, gold, crude oil. Such a combination adds to the portfolio diversification opportunities and could bring higher returns. Furthermore, the authors use a simple minimum variance approach proposed by Markovitz, which is not precise in case of the crypto currencies. The daily log returns of crypto currencies do not follow the Normal distribution, which undermines one of the assumptions of the Market Portfolio Theory. Instead, we will be using Conditional Value at Risk, which accounts for the potential fat-tail problem and gives more précised results.

A tangible contribution to the literature was made by Kajtazi and Limited (October 30, 2017, SSRN). The authors explore positive externalities from adding bitcoin to an optimal portfolio in Chinese market using mean-CVaR technique with four different approaches for assets' weights - naïve, long only, unconstrained and semi-constrained. Based on the back testing researchers compare total revenue to investor's portfolio with and without Bitcoin. Results represent significant but weak correlation of cryptocurrency and different asset classes, implying more mature ecosystem for bitcoin in Chinese comparing to the west financial markets. Furthermore, authors state that enlarging bitcoin's share in the overall portfolio does not provide higher risk reward ratio consistently over time. While considering short positions, it appears bitcoin fail to produce additional benefits to investor if included to the portfolio over all periods. In addition, Bouri, Molnar, Azzi, Roubaund and Hagfors explore the same question mainly interested in Bitcoin role in the portfolio as not just a good diversifier (September, 2016, Elseveir). Authors investigate the role of Bitcoin as a safe-haven for traditional financial assets. They employ a Dynamic Conditional Correlation Model to show that Bitcoin role as a strong reliable hedge instruments varies across various time frames. This work is mainly valuable for my research since I will use the same approach for identifying qualitative hedge among raw of cryptos. Moreover, Gangwal (2016, International Journal of Economics and Management Engineering) had an extensive study on the effects of adding Bitcoin to the portfolio. Using time series data for Bitcoin and stocks, bonds, Baltic index, MXEF, gold, real estate and crude oil author explore variety of portfolio combinations with and without each component using naïve approach. All constructed portfolios give higher risk-reward ratio while including Bitcoin to it. Additionally, author removes the issue of potential hazard coming from future regulation by Central Banks worldwide, providing clear facts about acceptance and closest future of digital currency.

Important value to the literature brings paper of Chuen, Guo and Wang (June 2017, JEL). Authors raise the discussion about potential risks and gains from investing in new digital money reinforcing its arguments with Dynamic Conditional Correlation Model and Sentiment Analysis. The authors firstly examine the correlation between traditional assets and crypto currencies, declaring the big potential portfolio containing digital currency. CRIX substantially enlarge the efficient frontier of the traditional asset classes is the main finding from the paper.

Still, it suffers from its static model, not precise technical approach and omitting liquidity problem, which crypto currencies with low market capitalization possess. Seng, Silva and Saerbeck (2017) also considered crypto currency as a new investment opportunity. The study focus is on the three major digital currencies: Bitcoin, Ripple and Litecoin and three other asset classes – gold, stocks and bonds. Using DCC model the authors conclude that Bitcoin and Litecoin indicate the use as a hedge instrument, while Ripple serves mainly as a good diversifier and has significant positive correlation with other asset classes. While providing higher sharpe ratio, hedge effectiveness ratio proves that crypto currencies will always add to the total variance increasing portfolio risk. Considering only three crypto assets, the authors suggest including more currencies with time flaw for further research, which we will do in the next sections.

When making a research on optimal portfolio with crypto currencies it is vital to explore the interconnections between cryptocurrency market and traditional financial assets such as bonds, oil, gold and stocks. This theme was uncovered in the paper of Kurka (2017, EconStor). Using the method of spillover's indices and realized volatility measures proposed by Diebold and Yilmaz in 2009 and 2012, he concluded very low servitude of traditional assets and digital currencies, which was obviously from the Volume traded side. On the date when the study was conducted, the total volume traded on crypto market was not even equal to 1% Volume traded for example on American the stock market. Gold is the only one exception, which shocks are interconnected with volatility in crypto market. To conclude, the paper is valuable from the point of including gold and crypto currencies in the one portfolio.

Taking into account that we are going to build a dynamic portfolio with rebalancing each day, the paper of optimal dynamic portfolio selection by Li and Ng (1998) was important for consideration. The authors explore the theoretical model for the optimal multi-period portfolio selection in the mean-variance formulation. Furthermore, the paper suggests the analytical algorithm to find the efficient portfolio maximizing the utility function of the expected return. Yet, we will use the approach proposed by Trimborn, Li, Härdle in 2016 for dynamic portfolio construction with rebalancing on the daily basis.

Chapter 3

METHODOLOGY

We are interested in the property of the digital currencies to be a strong hedge instrument and its ability to enlarge the risk-reward ratio. The research consists of a three stages. In the first one, we are going to assess the ability of each crypto currency to be a strong hedge instrument for a traditional asset classes. The second stage is dedicated to constructing the optimal portfolio of traditional assets available for global investor and crypto currencies. We investigate which combination of each asset weights provides investor with the largest risk-reward ratio. In the very end, we construct an optimal portfolio for Ukrainian investor. We will assume that global investor possess some amount of wealth and seek to allocate his investment in the most efficient way. We are going to build dynamic portfolio with daily rebalancing. It could be helpful to verify consistency of each asset's weight over time and it is a common practice to revise portfolio constituents each day/month. Since crypto currencies volume traded is inferior to the traditional assets, it could be necessary to incorporate additional liquidity constraints on each cryptos based on its daily volume traded in case its weights higher than 20% threshold. Only Bitcoin and Ethereum are liquid enough, while other cryptos' weights should have additional constraints. Currently, Bitcoin total daily volume traded on average is more than 300 million in the top exchanges like BitMex, Binance, etc. For Ethereum this indicator is equal to the 150 million. It allows realizing any transaction within one-two hours maximum. Other crypto tokens do not possess such high liquidity level. Finally, owing to the presence of ambiguity about crypto currencies being a mature financial asset, we impose two scenarios for the future returns. With the 90% probability, we assume that historical returns of the crypto coins will be a good proxy for its future returns.

The second scenario with the 10% probability assume that there will be no opportunity in the future to gain wealth from the crypto tokens insuring from the risk of bubble market. The justification of the weights are due to the author's believes and arguments in favor of crypto currencies presented before.

3.1. HEDGE INSTRUMENT

For evaluating the extent to which each crypto currency could be a good safe haven for each traditional asset, we use the method, proposed by Ratner and Chiu (2013). This is a two-stage approach. In the first one, we extract the dynamic correlation coefficients from DCC model proposed by Engle (2002). The stated model capable to capture the dynamic correlation between returns of two different asset classes (Parhizgari and Cho, 2008). Therefore, we will use DCC approach as a principal one to explore hedging characteristic of Bitcoin, Etherium, Nem, Dash, Litecoin and Ripple against traditional asset classes. On the second stage of the model proposed by Ratner and Chiu, we will run a linear regression of the coefficients from the first stage on the extreme movements in the lower 10^{th}, 5^{th} and 1^{st} percentile of the distribution of the other asset. Depending on the statistical significance of the obtained coefficients, we could state the property of each digital currency to be a strong hedge instrument.

The Dynamic Correlation Coefficient model estimated in the following steps. In the first one, we specify the mean equation for each available to investor asset (Engle and Sheppard, 2001):

$$r_t = c_t + a\, r_{t-1} + \varepsilon_t \tag{1}$$

where r_t is the log-return of the asset; c_t is the conditional mean of the vector r_t and ε_t is the error term.

In the second stage we implement GARCH(1,1) process using residuals from the equation (1) to estimate the parameters in the variance model:

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2 \tag{2}$$

$$\varepsilon_t = \sigma_t\, \nu_t\,, \nu_t \sim \mathrm{N}(0,1) \tag{3}$$

where σ_t^2 is a conditional variance, ω is an intercept, α is a coefficient that demonstrate the impact of the shocks in the previous period, β is a coefficient that transmits the GARCH(1,1) effect and ν_t is a standardized normally distributed residual returns with mean 0 and variance 1.

In the final step of the DCC model the correlation coefficients between two assets i and j in the time period t obtained using equation:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\,\sqrt{q_{jj,t}}} \tag{4}$$

where $\rho_{ij,t}$ are conditional correlation of two assets in period t , $q_{ij,t}$ is the conditional covariance of the two assets i and j respectively, $q_{ii,t}$ and $q_{jj,t}$ are the conditional variances for the assets i and j.

Using obtained on the second step standardized residuals ν_t we can compute the covariance matrix θ_t, which of the following form:

$$\theta_t = \begin{pmatrix} q_{11,t} & \cdots & q_{1n,t} \\ \vdots & \ddots & \vdots \\ q_{n1,t} & \cdots & q_{nn,t} \end{pmatrix} \quad (5)$$

The θ_t matrix follows the DCC(1,1) where we assume that it follows an AR(1) model and computed in the next equation:

$$\theta_t = (1 - \gamma - \tau)\,\bar{\theta} + \gamma\, \nu_{t-1}\, {\nu_{t-1}}^T + \tau\, \theta_{t-1} \quad (6)$$

where $\bar{\theta}$ is unconditional correlation matrix, γ and τ are coefficients that state for the previous shocks and DCC in the previous period on the DCC in the current period.

After extracting dynamic correlation coefficients from the DCC model, we regress it on the extreme movements in the lower 10th, 5th and 1st percentile of the distribution of the other asset incorporating approach using by Ratner and Chiu (2013):

$$DCC_t = h_0 + h_1 D\left(r_{other\ asset;t(q10)}\right) + h_2 D\left(r_{other\ asset;t(q5)}\right) + h_1 D\left(r_{other\ asset;t(q1)}\right) + \xi_t \quad (7)$$

where $r_{other\ asset;t}$ is the return of each traditional asset under study, D stands for dummy if the return of an asset falls into corresponding lowest value, ξ_t is an error term.

As stated in the Ratner and Chiu study, the crypto currency asset is a weak hedge against downward fluctuations of the other asset if the h_0 is not statistically different from 0 and strong hedge if h_0 is statistically significant and less than 0. Additionally, the crypto currency asset is a weak safe heaven against movements in the other asset if coefficients h_1, h_2, h_3 are not significantly different from 0 or it could be a strong safe haven if this coefficients are negative and statistically significant.

3.2. PORTFOLIO OPTIMIZATION

Classical CAPM suggests considering mean-variance approach to find the optimal wealth allocation among N different assets for one-period equilibrium model. There were conducted a list of studies incorporating mentioned approach dedicated to portfolio optimization with Bitcoin as alternative asset class (see for ex. Trimborn, Li and Hardle, 2016). However, the variance serves as a weak proxy for risk measure since it is likely to underestimate the probable losses arising from the significant part of returns distribution cluster in the tails. Log-returns of crypto currencies possess fat-tail property, meaning that utilizing standard portfolio optimization approach proposed by Markovitz is not appropriate in our case. As an alternative, we incorporate the model based on the linear programming with Conditional Value at Risk (expected shortfall) as a main error functional to be minimized. The concept was introduced in a series of papers presented by Uryasev and Rockfellar starting from the 1999 and currently is widely exploitable by investors. Given measure is a coherent risk measure contrasting to the simple variance or Value at Risk. It captures the amount by which the lowest quintile of the portfolio could be exceeded.

Let us state the formal definition of CVaR and linear programming model to be solved. Define the cumulative distribution function $\Psi(\omega, \zeta)$ of a loss $z = f(\omega, y)$:

$$\Psi(\omega,\zeta) = P\{ y \,|\, f(\omega,y) \leq \zeta \} \tag{8}$$

where ω – is a vector of weights of N assets included in the portfolio, ζ – is a specified level of potential losses, y – is uncertainties the has an impact on the loss function.

On this, the Value at Risk for a predetermined level of confidence α (ζ_α) is determined as:

$$\zeta_\alpha(w) = \min\{ \zeta \,|\, \Psi(\omega, \zeta) \geq \alpha\} \tag{9}$$

The Conditional Value at Risk (CVaR) is now the expected value of the loss, given that the loss is weakly exceeding the Value at Risk $\zeta_\alpha(\omega)$:

$$\mathrm{CVaR}_\alpha(\omega) = \frac{1}{1-\alpha} * \int_{f(\omega,y) > \zeta_\alpha(\omega)} f(\omega,y) * p(y)dy \tag{10}$$

To construct an optimal portfolio we further maximize risk-reward ratio with respect to weights vector ω conditionally on the following constraints:

$$\omega^T \hat{\mu} = \bar{r} \tag{11}$$

$$\omega^T \mathbf{1} = 1 \tag{12}$$

where ω is the vector of asset's weights, $\hat{\mu}$ – expected return of each asset, $\bar{r}$ – predetermined level of expected return of the portfolio. Additionally to the constraints (11) and (12) liquidity constraints based on the daily volume traded could be added in case if needed.

To evaluate whether a crypto assets should be included we will use a risk-return ratio as a risk-return efficiency of the portfolio. The confidence level for the CVaR will be chosen at the level of 90%, which is the most common among investors. The higher the risk-return ratio the better off the investor.

With an attempt to evaluate whether crypto assets should be included into the portfolio of traditional asset classes we construct the optimal portfolio with CVaR minimization. We use the first year data to evaluate the optimal wealth allocation among assets. The rest of the time series is used to check the robustness of the choosing weights incorporating back-testing using daily rolling basis. Besides, we compare the portfolio returns for a global minimum-variance portfolio against minimum CVaR portfolio. Due to its ability to capture low level fluctuations in the returns of the portfolio, the latter expectedly brings higher returns over rolling periods.

C h a p t e r 4

DATA DESCRIPTION

The data set for research consists of traditional asset classes – S&P stock index, Nikkei 225 index, the Financial Times Stock Exchange 100 Index, Brent oil, gold, Risk Weighted Enhanced Commodity TR index, Global Developed Markets Real Estate and 6 crypto currencies (Bitcoin, Etherium, Litecoin, Ripple, Nem and Dash),which were selected based on the volume traded, available for at least two-three years exchange dynamics and the broadest differentiating in technology used for each crypto currency. We excluded various forks of the main cryptos like Bitcoin Diamond, Bitcoin Cash, Etherium Classic and Stellar. The data for each of the chosen crypto currencies lie in the following range: Bitcoin – from 04/2013 till 03/2018, Etherium – from 08/2015 till 03/2018, Ripple – from 08/2013 till 03/2018, Nem – from 04/2015 till 03/2018, Litecoin – from 04/2013 till 03/2018, Monero – from 05/2014 till 03/2018. The data was obtained Each time series were fully used for the first stage of the methodology to determine the ability to be a safe haven for the traditional asset classes. For constructing an optimal portfolio we cramped all time series to the shortest individual time period available – from 7/08/2015 till the 20/02/2018. In the final analysis we obtained 592 observations of 7 series of traditional assets and 6 series of crypto currencies. The summary statistics are presented in the tables below.

Table 1. Summary statistics for the daily log-returns of the crypto currencies

Statistic	N	Mean	St. Dev.	Min	Max
log_returns_BTC	929	0.400	4.103	-20.753	22.512
log_returns_ETH	929	0.622	8.486	-130.211	41.234
log_returns_Dash	929	0.567	6.161	-24.323	43.775
log_returns_LTC	929	0.436	6.011	-39.515	51.035
log_returns_NEM	929	0.876	9.739	-36.145	99.558
log_returns_XRP	929	0.529	8.098	-61.627	102.73

Table 2. Summary statistics for the daily log-returns of traditional asset classes

Statistic	N	Mean	St. Dev.	Min	Max
log_returns_S&P	592	0.039	0.834	-4.184	3.829
log_returns_Nikkei	592	0.017	1.377	-8.253	7.426
log_returns_oil	592	0.059	2.312	-8.857	10.416
log_return_FTSE	592	0.007	0.409	-2.076	1.526
log_returns_gold	592	0.021	0.520	-2.383	2.933
log_returns_commodity	592	0.010	0.286	-0.968	1.103
log_returns_real_estate	592	0.002	0.390	-1.790	1.075

The data for digital currency was obtained from the coinmarketcap.com (daily close price and daily volume traded). Time series for the traditional assets were obtained from investimg.com and the data were taken for the same time as the newest crypto currency (in our case it is Ethereum).

To ensure that proposed portfolio optimization method with CVaR being an appropriate risk measure should be incorporated, we suggest take a closer look on the densities of the logarithms of returns of each digital currency. They possess fat-tail characteristic, especially Ethereum and Nem. In this case, the appropriate risk measure is that one, which could count downside asset fluctuations better.

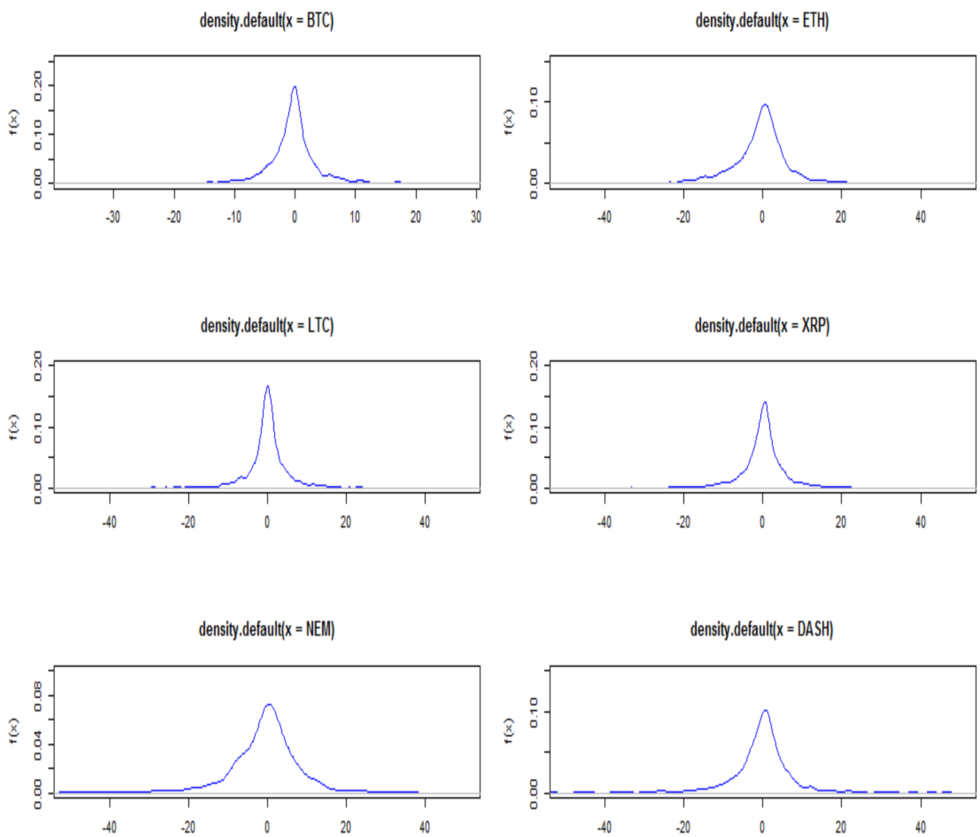

Figure 1. Distribution of the daily log-returns of each crypto token

It is important to mention that as a proxy for a global exchange of each cryptos the data from the Binance exchange was used since it accounts for the highest volume traded worldwide for the crypto currencies cited in the research (source: coinmarketcap.com). In the next chapter we will describe in details obtained results for global and local investors. Additionally, we will answer the question whether crypto currencies could serve as a strong hedge instruments against fluctuations in traditional asset classes.

C h a p t e 5

RESULTS

5.1. HEDGE PROPERTIES

We firstly investigated the property of each crypto currency to be a good safe haven for the traditional asset classes. We considered all possible pairwise time series where the first series chosen from the list of traditional asset classes and second one is from the list of digital crypto currencies. The justification for considering pairwise DCC models is traditional assets' correlation (Table3). All except gold are positively correlated, but gold itself have a small weight in the final portfolio for global investor.

Table 3. Correlation between log returns of the traditional assets

	S&P	Nikkei	Br. Oil	FTSE	Commodity	Real Estate
S&P	1	0.19	0.4	0.55	0.35	0.65
Nikkei225	0.19	1	0.11	0.33	0.16	0.19
Brent Oil	0.4	0.11	1	0.39	0.69	0.28
FTSE	0.55	0.33	0.39	1	0.41	0.46
Commodity	0.35	0.16	0.69	0.41	1	0.31
R. Estate	0.65	0.19	0.28	0.46	0.31	1

In the first stage, we excluded the dynamic correlation coefficients for each pair of time series using DCC model proposed by Lucas. Summary information of the most volatile dynamic correlation coefficients of crypto-currency asset combination presented in the Table4.

Table 4. Summary statistics of crypto-asset pair DCC

Statistic	N	Mean	St. Dev.	Min	Max
ETH/S&P	603	-0.064	0.06	-0.313	0.218
ETH/Oil	603	-0.001	0.032	-0.08	0.09
LTC/S&P	1,143	0.019	0.028	-0.057	0.168

On the second stage, we run obtained coefficients on the lowest 10-th, 5-th and 1-st percentile of the corresponding traditional asset. The results on Bitcoin is consistent with the previous literature. It serves neither as good nor bad hedge instrument. Rather it could be a strong diversifier. All regression results presented in Appendix A.

The results on the properties of each crypto currency to be a strong hedge instrument for traditional assets partially confirm the previous studies. Namely, the Bitcoin could not serve as a strong hedge against downward fluctuations in the traditional asset classes (see Appendix A and methodology). Moreover, Ethereum, Nem and Litecoin could serve as hedge instrument only for fluctuations in S&P index., Preferable digital asset for investor who is going to dilute his portfolio with new crypto currency will be Ripple. Notice, that due to the low variability of dynamic correlation coefficients in some asset pairs, it was hard to measure the hedge property for some crypto currencies.

5.2. CASE OF GLOBAL INVESTOR

Using the proposed CVaR approach to construct the optimal portfolio we vindicate the importance of the crypto currencies assets as a potential investment opportunity. Aiming to obtain robustness estimations we built the dynamic portfolio with the scrolling time window of 75 percent from the overall time series. Such an approach is a widely used in practice for out-of-sample back testing.

The central question of the study was to verify the potential under diversification of the portfolio of traditional assets without digital money. Therefore, we investigated two options of including and not including crypto currencies to the traditional assets portfolio. The comparison based on the portfolio return and risk-return ratio. Figure2 presents the comparisons of the returns of two different portfolios. The higher returns in the case of portfolio with both asset's classes together with the higher daily risk-reward ratio (Table 5) gives a strong sign in favor of digital currencies.

Figure 2. Compound returns in the portfolio with and without crypto assets

Table 5. Summary of the key comparison portfolio metrics

Portfolio Optimization Framework	CVaR	Risk Return Ratio
Traditional assets with crypto currencies	1.306%	0.0224
Traditional assets without crypto currencies	0.5937%	0.0074

We also provide the comparison of dynamic portfolios by verifying the difference in returns (Appendix B) based on the two different approaches – Mean-variance approach and CVaR approach. Since the variance is not a coherent risk measure and consequently is not capable to catch the fat-tail problem of crypto currencies, it was expected to obtain on average higher returns for the portfolio, which is optimized using Conditional Value at Risk. Illustration presented in the Figure 3.

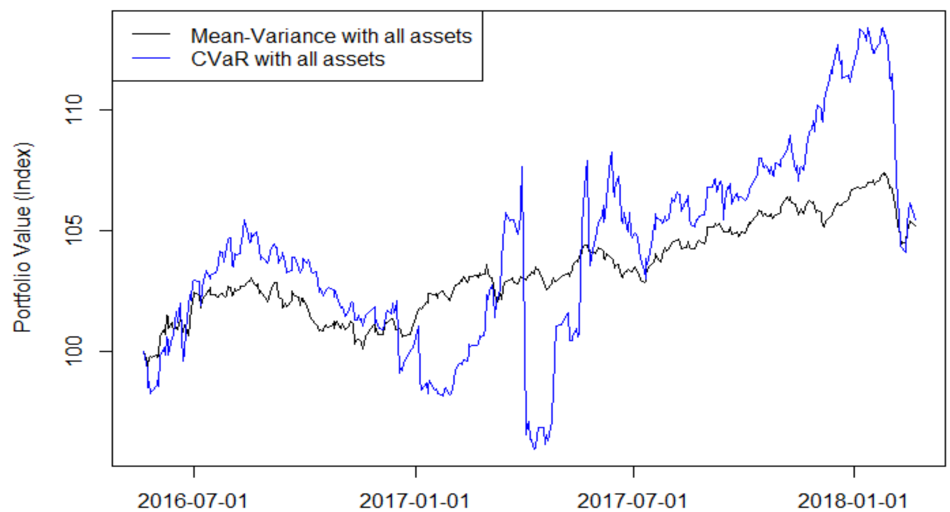

Figure 3. Compound returns on the dynamic portfolios based on the CVaR and MV

One more issue that is important is the crypto currencies share in the total portfolio (Table 6). On average, all crypto currency has 8% share in the optimal portfolio. This insures investors from the highly volatile nature of digital money, while giving the opportunity to partially enjoy the sky-rocket returns of crypto currencies. Furthermore, particular results do not demand putting additional liquidity constraints on the crypto currencies.

Table 6. Weights' summary of each crypto currency in the optimal portfolio

Weights	N	Mean(%)	Median(%)	Max(%)	Min(%)
BTC	413	0.66	0.00	14	0.00
ETH	413	2.73	1.32	2.1	0.00
Dash	413	2.69	1.22	10.19	0.00
LTC	413	>0.01	0.00	>0.01	0.00
NEM	413	1.32	1.06	6.51	0.00
XRP	413	0.43	0.01	16.83	0.00

Table 7. Weights' of each traditional asset class in the optimal portfolio

Weights	N	Mean(%)	Median(%)	Max(%)	Min(%)
S&P	413	1.72	0.00	24.32	0.00
Nikkei225	413	3.07	0.00	14.08	0.00
Brent oil	413	0.00	0.00	0.00	0.00
FTSE	413	23.31	24.41	46.73	6.4
Gold	413	12.27	10.14	31.9	1.00
Commodities	413	38.44	40.58	66.49	0.00
Real estate	413	19.7	33.47	33.47	0.00

5.3. CASE OF UKRAINIAN INVESTOR

In this section, we study a hypothetical scenario of an investor who has access to crypto markets and to the Ukrainian stock market. The idea is to model an investor who has funds in Ukraine, is subject to capital controls and cannot move the funds out of the country, and therefore is confined to the Ukrainian markets. Of course, an investor might try to circumvent capital controls and move the funds out of the country to invest into international markets. In our hypothetical scenario we shut down this motive. We also exclude fixed income from the analysis by classifying it as a risk-free. While this assumption is open to debate, we do not have sufficient date on the probability of default of the Ukrainian government or the domestic companies to use these assets in our analysis.

Thus, we study an investor who is optimizing a portfolio of assets that include crypto currencies and the Ukrainian stocks. This is a purely theoretical exercise, which is nonetheless is interesting. We expect the investor to put a substantively larger share into the crypto due to low performance of the Ukrainian stocks. We would like to quantify this effect by comparing the results of the same model applied for a global investor and for a constrained investor operating in Ukraine. The results will essentially tell us whether the Ukrainian stocks have some value for such an investor or whether he/she would like to flee the Ukrainian market fully investing into crypto. If the optimal amount of investment into the Ukrainian stocks is 0, it would suggest that the Ukrainian stock market has no economic value and does not perform its functions of allocating the capital, but possibly serves some other purpose such as tax optimization or evasions or schemes of acquisition of companies.

So, we include in the portfolio the same set of crypto assets and five constituents of the Ukrainian UX index. Of course, we exclude the global stock indexes and commodities (as it was for global investor). The dynamic returns for two portfolio options presented in the Figure 4.

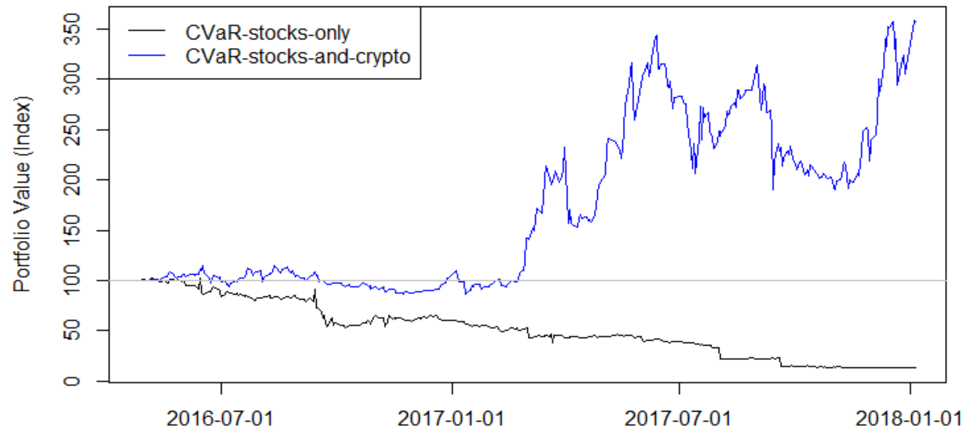

Figure 4: Compound returns on the dynamic portfolios with and without crypto currencies for Ukrainian investor

During last 2 years constituents of the Ukraine UX index experience serious downfall. As a result, the portfolio built on only five Ukrainian stocks gives substantially negative returns and it is optimal to consider crypto currencies as a potential investment. The surprise here is that the optimal share of investment into the Ukrainian stocks is not 0. This means that the Ukrainian stocks provide some risk-sharing opportunities for the investor and do not fall fast enough to make these opportunities useless. In addition, while almost obvious, we can infer that a Ukrainian investor who cannot move the capital out of country and does not have private investment opportunities in Ukraine would move almost all of his/her wealth into crypto. This is very alarming. It tells us that capital markets in Ukraine do not function and that the investors will move their funds into unregulated areas, given an opportunity, exposing economy to additional risks and shocks.

Table 8. Weights' of each crypto currency in the Ukrainian portfolio

Statistic	N	Mean	St. Dev.	Min	Max
BTC	413	15.26	5.13	83.91	0.00
ETH	413	27.44	22.9	1.00	0.00
Dash	413	31.12	31.8	90.09	0.00
LTC	413	0.62	0.00	17.45	0.00
NEM	413	3.173	0.00	25.1	0.00
XRP	413	5.817	2.17	16.83	0.00

Chapter 6

CONCLUSIONS

We study the optimal allocation of investor's wealth between stocks and crypto assets. We find that the optimal share of crypto assets in a portfolio of global investor on average reaches 8%. Using DCC approach, we verify the hedge properties for each crypto token against traditional asset classes. We demonstrate that Litecoin is the only crypto asset that can be used for hedging traditional assets. Other crypto tokens could serve as diversifiers. Additionally, we explore the question of whether it is necessary to include the crypto currencies to the portfolio of traditional assets based on the CVaR approach. As was expected, despite the high volatility of the crypto, its skyrocket returns compensate it with total increasing of portfolio gains. Based on the most tradable and liquid currencies, we can conclude that crypto market looks attractive to the potential investors, however still possess the risk of being bubble. Partially we tried to take into account this fact considering two scenarios of crypto future development. Therefore, despite the obtained empirical results, a word of caution is warranted about persistent fluctuations on the crypto currencies market. A lot attention from the speculators around the world to BTC and other tokens creates the market being far away from equilibrium. Investors should be aware of all cons of potential bear crypto market and regulation from the side of Central Banks of the most powerful countries, which could substantially shake the market. Billions of USD are daily traded in crypto exchanges, so regulators cannot stay aside. Crypto market is a fuel for shadow economy worldwide, demanding imposing some restrictions.

We also find significant difference in investment opportunities abroad and within Ukraine. Owing to the absence of a strong investment market in Ukraine, crypto currencies become engaging option to put a prevail part of the Ukrainians' wealth in it. Regulation issues concerning crypto market are especially notable comparing to the global situation and need to be solved by Central Bank of Ukraine in the shortest time. While 2017 was a year of substantial crypto market growth, 2018 should become a year of superposition control under digital money.

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APPENDIX A

Table 9. Regression results for BTC DCC models

	Dependent variable		
Quantile	Real estate	Nikkei	Brent Oil
quantile_10	0.004	-0.007*	0.000
	(0.004)	(0.004)	(0.000)
quantile_5	0.000	-0.002	0.000
	(0.007)	(0.005)	(0.000)
quantile_1	0.036**	-0.010	0.000
	(0.011)	(0.009)	(0.000)
Constant	-0.01***	0.025***	0.026***
	(0.001)	(0.001)	(0.001)
Observations	638	1143	1143
R2	0.018	0.012	0.002
F Statistic (df = 3; 1139)	3.983***	4.494***	0.830
Note	*p<0.1	**p<0.05	***p<0.01

Table 10. Regression results for LTC DCC models

	Dependent variable		
Quintile	S&P	Nikkei	Brent Oil
quantile_10	-0.0002	0.003	0.004
	(0.001)	(0.004)	(0.004)
quantile_5	0.001	-0.013**	-0.0131
	(0.002)	(0.006)	(0.006)
quantile_1	-0.002	-0.0002	-0.0002
	(0.003)	(0.009)	(0.009)
Constant	-0.013***	0.019***	0.02***
	(0.0003)	(0.001)	(0.001)
Observations	1143	1143	1143
R^2	0.001	0.006	0.007
F Statistic (df = 3; 1139)	0.235	2.195*	2.105*
Note	*p<0.1	**p<0.05	***p<0.01

Table 11. Regression results for NEM DCC models

	Dependent variable		
Quintile	S&P	Nikkei	Brent Oil
quantile_10	0.00001	0.00001	0.00001
	(0.000)	(0.000)	(0.000)
quantile_5	0.00001	-0.00001*	0.00001
	(0.000)	(0.000)	(0.000)
quantile_1	0.00001	0.000	0.00001
	(0.000)	(0.000)	(0.000)
Constant	-0.054***	-0.053***	-0.054***
	(0.000)	(0.001)	(0.001)
Observations	687	687	687
R2	0.005	0.005	0.001
F Statistic (df = 3; 1139)	1.075	1.613	0.272
Note	*p<0.1	**p<0.05	***p<0.01

Table 12. Regression results for XRP DCC models

	Dependent variable		
Quintile	S&P	Nikkei	Brent Oil
quantile_10	0.000001	0.000001	0.000001
	(0.000)	(0.000)	(0.000)
quantile_5	0.000001	0.000001	0.00001
	(0.000001)	(0.000)	(0.000)
quantile_1	0.000001	0.000001	0.000001
	(0.000001)	(0.000)	(0.000)
Constant	-0.032***	-0.032***	-0.032***
	(0.000001)	(0.000)	(0.000)
Observations	1,079	1,079	1,079
R2	0.012	0.004	0.004
F Statistic (df = 3; 1139)	1.296	1.529	1.072
Note	*p<0.1	**p<0.05	***p<0.01

Table 13. Regression results for ETH DCC models

Quintile	Dependent variable		
	Real estate	Commodities	Brent Oil
quantile_10	-0.0043	0.00	0.005
	(0.005)	(0.00)	(0.006)
quantile_5	0.003	0.00	-0.0005
	(0.008)	(0.00)	(0.009)
quantile_1	-0.01	0.00	-0.021
	(0.026)	(0.00)	(0.014)
Constant	-0.014***	0.026***	-0.001
	(0.0012)	(0.00)	(0.001)
Observations	639	639	639
R2	0.003	0.015	0.01
F Statistic (df = 3; 1139)	0.735	2.125**	1.996
Note	*p<0.1	**p<0.05	***p<0.01

APPENDIX B

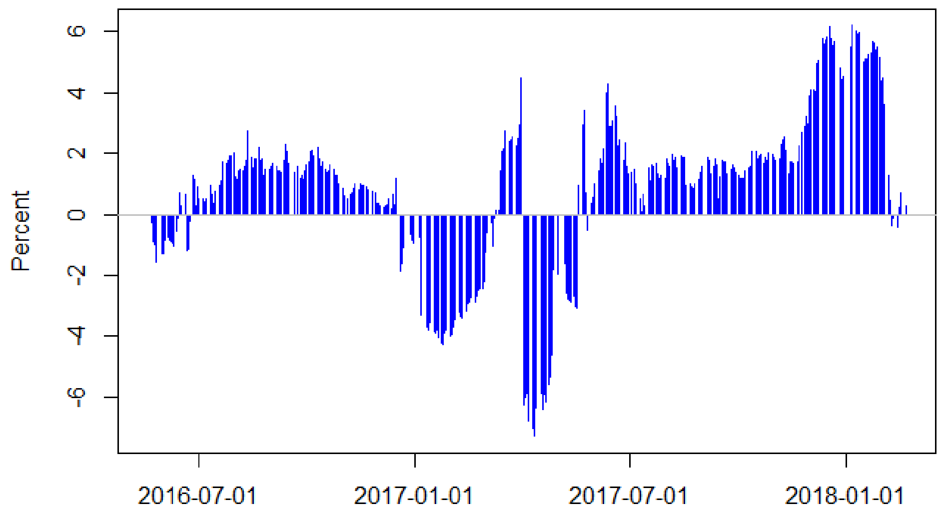

Figure 5. Relative out-performance of CVaR portfolio for all assets versus only traditional (global investor)