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ANALYSIS OF RISK-RETURN TRADE-OFF IN CRYPTOCURRENCY MARKETS

KRİPTO PARA PİYASALARINDA RİSK-GETİRİ ETKİLEŞİMİNİN ANALİZİ

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ABSTRACT

A rational investor does not only focus on obtaining the maximum return while making the investment decision, but also tries to calculate the risk dimension of the investment. Risk and return are in close relationship with each other in the field of finance, just as they are in daily life. In this study, risk-return analysis was made on the top five cryptocurrencies with high transaction volume; "BTC, ETH, ADA, XRP, LTC" traded on crypto technology market exchanges. As it is known, digital currencies contain a lot of speculative movements. In this study, EGARCH-M model, which allows to measure the statistical connection between risk and return in the asset, which is one of the variable variance (GARCH) models, was used. Another feature of this model is that it measures whether there is an asymmetric effect in volatility. In the study, three different time periods are included: pre-pandemic period, pandemic period and the whole period.

As a result of the analysis, Cardano is the only cryptoasset in which the risk-return interaction was detected. A significant risk-return trade off, which was not detected before the pandemic period, emerged for Cardano with the pandemic and continued throughout the entire period.

In other analyzed cryptocurrencies; (Bitcoin, Ethereum, Ripple and Litecoin), no significant relationship was found in terms of risk-return tradeoff.
Keywords: Cryptocurrency, Risk-Return Trade-Off, GARCH models, Asymmetry
Jel Classification'': C5, C22, G11

ÖZET
Rasyonel bir yatırımcı, yatırım kararını verme aşamasında sadece maksimum getiri elde etmeye odaklanmaz, aynı zamanda yatırımın risk boyutunu da hesaplamaya çalışır. Risk ve getiri finans alanında da tıpkı gündelik hayatta olduğu gibi sıkı sıkıya bağlıdır. Bu çalışmada, kripto teknolojisi piyasası borsalarında işlem gören, işlem hacmi en yüksek beş kripto para üzerine ''BTC, ETH, ADA, XRP, LTC'' risk-getiri analizi yapılmıştır. Bilindiği üzere dijital para birimleri spekülatif hareketleri fazlasıyla barındırır. Çalışmada yöntem olarak değişen varyans (GARCH) modellerinden varlıkta risk ve getiri arasında istatistiki bağlantının ölçülmesine imkân tanıyan EGARCH-M modeli kullanılmıştır. Modelin bir başka özelliği ise volatilitede asimetrik etkinin olup olmadığını ölçmesidir. Çalışmada pandemi öncesi dönem, pandemi dönemi ve tüm dönem olmak üzere üç ayrı zaman periyoduna yer verilmiştir.
Analiz sonucunda risk-getiri etkileşiminin tespit edildiği tek kripto varlık Cardano'dur. Cardano için pandemi dönemi öncesinde saptanmayan anlamlı risk-getiri ilişkisi pandemi ile ortaya çıkmış ve tüm dönemde varlığını sürdürmüştür. Analiz edilen diğer kripto para birimlerinde ise (Bitcoin, Ethereum, Ripple ve Litecoin) risk getiri ilişkisi açısından anlamlı bir ilişki saptanmamıştır.
Anahtar Kelimeler: Kripto para, Risk iadesi takas, GARCH modelleri, asimetri

1. INTRODUCTION

The risk-return trade off indicates that how much risk we should take for a potential return. The higher the risk the return is likely to increase (Han, 2013).

Successful investors and traders have to be careful about buying and selling preferences of risky assets. Otherwise, they may run the risk of losing their capital. Therefore, they consider for alternative ways to achieve the highest potential gain as they hope to achieve, with the lowest potential risk. If one investment offers the same return as another, however with less risk, it may be a stronger option. While making an investment decision, the expectation of investor is to obtain the highest return with the lowest risk. Yet, this is practically impossible. Therefore, it is aimed to optimize risk and return. Different asset classes perform distinctively at dissimilar points in time. For instance, crude oil, real estate, gold, silver, etc. while it used to provide quite high returns, it has recently ceased to be attractive. The stock market has yielded great returns in the long term, but price-earnings ratios have risen considerably, so the risks have started to increase. On the other hand, risk-free investments such as fixed, fall into the low-risk, low-return category and unable to protect investors against inflation.

In an eight pages article written by a mysterious individual named Satoshi Nakamoto in 2008, illegally promoted Bitcoin is an unregulated digital currency (Nakamoto, 2008).

In recent years, with increasing media influence and transaction volumes, Bitcoin and other cryptocurrencies have experienced large capital gains and losses with high volatility. Interestingly, the returns of Bitcoin and other crypto assets show very low correlations with other investment units "stocks, bonds" or traditional investment assets such as gold and oil. The number of cryptocurrencies is also increasing day by day and its use is becoming more and more widespread. Although Bitcoin did not appeal much attention in the first years, it started to draw attention with the rapid increase in its price in the following years and became the most popular cryptocurrency (Antony, Maina & Omari, 2019).

This study try to shed light on the risk-return trade-off of an investment made in the top 5 cryptocurrencies traded in the crypto markets and with the highest trading volume.

2. LITERATURE

Research on volatility, risk, and return of cryptocurrencies have drawn the attention of media, governments, and investors. Many scholars used different methodological approaches for Bitcoin and other cryptocurrencies.

Wang (2021) analyzed the Bitcoin volatility with GARCH models using Bitcoin daily closing prices between October 1, 2013 and July 31, 2020. It was revealed that Bitcoin can protect investors against financial risks during an economic depression and it has a revised asymmetric effect between positive and negative shocks, thus making Bitcoin a suitable asset for investors to add their portfolios as a safe-haven characteristic.

Troster et al. (2019) used GARCH and GAS models to predict returns and risks for Bitcoin. The study utilized daily price data for the period of June19, 2010 and April 16, 2018. Logarithmic return and Value-at-Risk variables were used. Findings showed that heavy-tailed GAS models provide more successful results for Bitcoin return and risk in terms of goodness-of-fit and predictive performance.

Kahraman et al. (2019) tested the most suitable model by using single volatility models such as ARCH, GARCH, T-GARCH, GARCH-M, E-GARCH, and I-GARCH and long memory models such as AP-GARCH and C-GARCH for prices of Bitcoin, Ethereum and Ripple which had the highest market value for the period between August 24, 2016 and May 7, 2018. It was found that effect of shocks on volatility in Bitcoin and Ethereum was permanent and effect of positive shocks is greater than the effect of negative shocks, while the volatility effect of shocks in Ripple is temporary and short-term.

Baur et al. (2018) examined the relationship between Bitcoin, gold and USD with the GARCH, EGARCH and GJR-GARCH models. However, unlike Dyhrberg's academic research, the findings showed that Bitcoin is distinctive from gold and other currencies. The findings also showed that Bitcoin has unique risk-return characteristics, following a different volatility process compared to other assets, and does not have a relationship with other assets.

Naimy and Hayek (2018) investigated the volatility of Bitcoin with GARCH, EWMA and EGARCH models using USD-indexed 1093-day prices of Bitcoin between April 1, 2015 and March 31, 2016. They found that EGARCH was the best model for measuring volatility. They suggested that Bitcoin's price behavior is uniquely different from other traditional currencies.

Chu et al. (2017) examined volatility of daily global price indexes of the most popular cryptocurrencies consisting of Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple data between June 22, 2014 and May 17, 2017 by using SGARCH, EGARCH, GJRGARCH, APARCH, IGARCH, CSGARCH, GARCH, TGARCH, AVGARCH, NGARCH, NAGARCH, and ALLGARCH models. Results showed that IGARCH and GJRGARCH were the most compatible models and all cryptocurrencies, especially Bitcoin, Ethereum and Litecoin, exhibit extreme volatility.

Dyhrberg (2016) used GARCH model to reveal the capabilities of Bitcoin as a financial instrument and to explain the relationship between Bitcoin, gold and dollar. Findings showed that Bitcoin is similar to gold and dollar in many ways. Bitcoin and gold responded to similar variables in the GARCH model, had similar hedging capabilities, and reacted similarly to positive and negative shocks.

3. DATA SET AND METHODOLOGY

The study examined three different periods of pandemic for better comparison of effects of it: (1) Pre-pandemic, (2) pandemic period and the entire period. Data set included five crypto assets with high transaction volume which are presented in Table 5. Data series were formed by using daily frequencies.

Pandemic period was officially started when the World Health Organization (WHO) declared the epidemic as a "pandemic", and it was terminated at the beginning of 2022 Russian invasion of Ukraine to avoid the effects of this process. Initial date of observations for pre-pandemic period were determined according to the pandemic period to obtain equal number of observations.

Table 1: Data Series for Five Cryptocurrencies

CryptoCurrency	Pre-Pandemic Period	Pandemic Period	Overall Period	Reference
Bitcoin (BTC) Ethereum (ETH) Ripple (XRP) Litecoin (LTC) Cardano (ADA)	3/27/2018- 3/10/2020 (715 Observations)	3/11/2020- 2/23/2022 (715 Observations)	3/27/2018- 9/30/2022 (1649 Observations)	https://tr.investing.com/

The risk-return tradeoff constituting basic structure of several finance theories can be tested with the ARCH in mean (ARCH-M - Autoregressive Conditionally Heteroscedastic) model which introduced to literature by Engle, Lilien and Robins (1987). In this model, conditional variance or standard deviation as a risk measure was added to the mean equation as an explanatory variable. The estimated expected risk coefficient ω is a measure of the risk-return tradeoff. The ARCH-M model is obtained by showing the conditional variance equation in the form of GARCH model. Specification of the model is as below (Kayalıdere, 2013):

$$r_t = b + \alpha_1 r_{n-1} + \omega\sigma_n^2 + u_n^2, \qquad u_n^2 \sim (0, \sigma_n^2) \qquad (3.1)$$

$$\sigma_n^2 = c + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2 \qquad (3.2)$$

In equations 3.1 and 3.2, r_t and σ_n^2 denote the return and the variance equations, respectively, whereas ω is the risk parameter.

Standard GARCH model developed by Bollersev (1986) assumed that positive and negative shocks in a market create a symmetrical effect on volatility. In other words, positive and negative news have the same effect on volatility in GARCH model (Akel, 2011: 28). In EGARCH model developed by Nelson (1991), the effects of positive and negative shocks on volatility can be examined by an asymmetrical structure (Güneş & Saltoğlu, 1998).

In EGARCH model developed by Nelson (1991), the conditional variance equation is addressed as follows:

$$\ln(\sigma_n^2) = a_0 + a_1 \ln(\sigma_{n-1}^2) + a_2 \frac{u_{n-1}}{\sqrt{\sigma_{n-1}^2}} + a_3 \left[\frac{|u_{n-1}|}{\sqrt{\sigma_{n-1}^2}} - \frac{\sqrt{2}}{\pi}\right] \qquad (3.2)$$

EGARCH model has two important advantages over the standard GARCH method. First, since the logarithm of conditional variance $\ln(\sigma_n^2)$ is modeled on the left side of equation, conditional variance (σ_n^2) always takes a positive value, even if the parameters are negative. Thus, there is no need to specify artificial limitations to ensure non-negative condition of the parameters in the model. Since the relationship between volatility and return is negative, (a_2) will be negative. In this case, it is concluded that negative news across the market creates higher volatility than positive news (Akel, 2011).

As described in this section, EGARCH-M model which involves the characteristics of both volatility models (GARCH-M and EGARCH) was used in this study. For this method, conditional variance process in Equation 3.2 was used together with the average return shown in Equation 3.1.

4. FINDINGS

The logarithmic differences for price series in the analysis are converted into return series, and the descriptive statistics and unit root test results of these return series are shown in Table 2 for each period.

Table 2: Descriptive Statistics and Unit Root Test Results

PRE-PANDEMIC PERIOD					
Descriptive Statistics	**BTC**	**ETH**	**XRP**	**LTC**	**ADA**
Mean	0.000016	-0.00113	-0.00139	-0.00138	-0.00183
Maximum	0.158967	0.176031	0.32104	0.258175	0.263961
Minimum	-0.147200	-0.22037	-0.1995	-0.18814	-0.21667
Standard Deviation	0.035374	0.047796	0.048001	0.049026	0.054074
Skewness	-0.078794	-0.42139	0.726603	0.190418	0.047314
Kurtosis	6.277018	5.7902	8.96818	5.872942	5.157047
Jarque-Bera	320.219	234.65	1122.497	249.8653	138.6888
(Prob.)	*[0.000]	*[0.000]	*[0.000]	*[0.000]	*[0.000]
Unit Root Test (ADF)	-28.1193	-28.6494	-27.2186	-27.9215	-28.2276
(Prob.)	*[0.000]	*[0.000]	*[0.000]	*[0.000]	*[0.000]
PANDEMIC PERIOD					
Descriptive Statistics	**BTC**	**ETH**	**XRP**	**LTC**	**ADA**
Mean	0.002165	0.003619	0.001691	0.001086	0.004314
Maximum	0.177424	0.230772	0.448991	0.256413	0.286973
Minimum	-0.49728	-0.58964	-0.54102	-0.48678	-0.5372
Standard Deviation	0.042582	0.055703	0.071359	0.059301	0.064786
Skewness	-2.17775	-1.85068	-0.15122	-1.45556	-0.46591
Kurtosis	29.99964	23.15688	15.73435	15.1787	11.14506
Jarque-Bera	22246.26	12494.99	4827.09	4664.662	2097.621
(Prob.)	*[0.000]	*[0.000]	*[0.000]	*[0.000]	*[0.000]
Unit Root Test (ADF)	-32.8361	-32.9497	-28.434	-31.2554	-31.0927
(Prob.)	*[0.000]	*[0.000]	*[0.000]	*[0.000]	*[0.000]
OVERALL PERIOD					
Descriptive Statistics	**BTC**	**ETH**	**XRP**	**LTC**	**ADA**
Mean	0.000553	0.000569	-0.00011	-0.00056	0.000633
Maximum	0.177424	0.230772	0.448991	0.258175	0.286973
Minimum	0.497278	-0.58964	-0.54102	-0.48678	-0.5372
Standard Deviation	0.038807	0.051469	0.058837	0.053477	0.058778
Skewness	-1.30282	-1.16092	0.083786	-0.8405	-0.25795
Kurtosis	21.15161	15.83464	16.7137	12.03594	9.218906
Jarque-Bera	23090.56	11681.51	12915.76	5800.544	2673.945
(Prob.)	*[0.000]	*[0.000]	*[0.000]	*[0.000]	*[0.000]
Unit Root Test (ADF)	-43.8965	-27.7792	42.18188	-44.3705	-27.8424
(Prob.)	*[0.000]	*[0.000]	*[0.000]	*[0.000]	*[0.000]

* represents significance at the 0.01 level. Values in square brackets are probability values.

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Skewness and kurtosis values of descriptive statistics and the results of Jarque-Bera test suggested that there was not a normal distribution for all series. Therefore, the EGARCHM model was estimated with Student's t distribution assumption.

Before GARCH model estimation, the ARMA process followed by each series was determined. Afterwards, compatibility of ARCH structure in the models was tested for different lag periods which is presented in Table 3. Results showed that ARCH effect was not determined in two periods for Bitcoin and one period for Ethereum and Litecoin. Hence, these periods were excluded from analysis.

Table 3: Test Results of ARCH Effect in ARMA Models

Pre-pandemic Period					
Arch Test	**BTC (MA 2)**	**ETH (AR 2)**	**XRP (ARMA 3,3)**	**LTC (ARMA 1,1)**	**ADA (ARMA 4,2)**
L-1	4.7868	0.3671	40.2205	1.3666	2.4408
Prob	**[0.0287]	[0.5446]	*[0.0000]	0.2422	[0.1182]
L-3	11.5701	2.0971	44.4741	2.5421	3.2601
Prob	*[0.0090]	[0.5525]	*[0.0000]	0.4677	**[0.0211]
L-5	17.7084	5.9724	45.3391	2.7981	3.1975
Prob	*[0.0033]	[0.3089]	*[0.0000]	0.7311	*[0.0073]
Pandemic Period					
Arch Test	**BTC (ARMA 3,2)**	**ETH (ARMA 3,4)**	**XRP (ARMA 2,2)**	**LTC (ARMA 1,1)**	**ADA (ARMA 1,1)**
L-1	1.9997	3.616	14.5947	5.8319	13.363
Prob	[0.1573]	***[0.0573]	*[0.0001]	**[0.0157	*[0.0003]
L-3	0.3944	6.7163	26.3453	2.6647	16.0811
Prob	[0.9414]	***[0.0815]	*[0.0000]	[0.4462	*[0.0011]
L-5	3.4163	13.9519	31.3379	16.6952	30.5924
Prob	[0.6361]	**[0.0159]	*[0.0000]	*[0.0051]	*[0.0000]
Overall Period					
Arch Test	**BTC (ARMA 4,2)**	**ETH (AR 2)**	**XRP (AR 1)**	**LTC (ARMA 1,1)**	**ADA (ARMA 2,2)**
L-1	2.8152	5.6071	36.8191	10.3037	15.2545
Prob	***[0.0934]	**[0.0179]	*[0.0000]	*[0.0013]	*[0.0013]
L-3	2.8259	5.6806	62.7501	11.1735	16.6664
Prob	[0.4192]	***[0.0584]	*[0.0000]	**[0.0108]	*[0.0008]
L-5	6.3823	23.1526	72.0363	33.6846	32.3851
Prob	[0.2708]	*[0.0003]	*[0.0000]	*[0.0000]	*[0.0000]
*, ** and *** represent significances at the 0.01, 0.05 and 0.1 levels, respectively. Values in square brackets are probability values.					

Table 4: Results of EGARCH-M Model for Bitcoin

Parameters	Pre-pandemic period
Return Equation	
Constant	0.00023[0.9182]
Risk Parameter	-0.00031[0.9958]
Equation of Variance	
Constant	-0.164**[0.0218]
ARCH	0.25211*[0.0003]
GARCH	0.99508*[0.0000]
Asymmetry	0.00492[0.8693]
Log Likelihood	1490.446
AIC	-4.149707
SIC	-4.092091

* and ** represent significances at the 0.05 and 0.01 levels, respectively. Values in square brackets are probability values.
SIC: Schwarz Information Criterion
AIC: Akaike Information Criterion

Risk parameter for Bitcoin was negative in the pre-pandemic period. However, this coefficient was not statistically significant. Similarly, the parameter showing the asymmetry effect of positive and negative shocks was not statistically significant.

Table 5: Results of EGARCH-M Model for Ethereum

Parameters	Pandemic Period	Overall Period
Return Equation		
Constant	-0.01544[0.7918]	-0.00743[0.2302]
Risk Parameter	0.53915***[0.0663]	0.18034[0.1410]
Equation of Variance		
Constant	-1.24933**[0.0237]	-0.5481*[0.0011]
ARCH	0.209183**[0.0136]	0.18931*[0.0000]
GARCH	0.817594*[0.0000]	0.92889*[0.0000]
Asymmetry	-0.06905[0.1557]	-0.01891[0.4040]
Log Likelihood	1173.335	2758.478
AIC	-3.26292	-3.33878
SIC	-3.16647	-3.29275

* and ** represent significances at the 0.05 and 0.01 levels, respectively. Values in square brackets are probability values.

Although coefficient of the risk parameter is positive in both periods for Ethereum, it was not statistically significant. However, the asymmetry parameter is negative but statistically not significant in these periods.

Table 6: Results of EGARCH-M Model for Ripple

Parameters	Pre-pandemic period	Pandemic Period	Overall Period
Return Equation			
Constant	-0.00151[0.6924]	0.00043[0.8863]	-0.00232[0.3081]
Risk Parameter	-0.00705[0.9182]	0.01329[0.8147]	0.03005[0.4788]
Equation of Variance			
Constant	-0.91371*[0.0015]	-0.32369*[0.0000]	-0.4328*[0.0000]
ARCH	0.52616*[0.0042]	0.29327*[0.0000]	0.35525*[0.0000]
GARCH	0.88141*[0.0000]	0.97226*[0.0000]	0.95822*[0.0000]
Asymmetry	0.03892[0.5451]	0.0659***[0.0672	0.03388[0.2278]
Log Likelihood	1290.324	1134.767	2802.875
AIC	-3.59304	-3.15427	-3.3939
SIC	-3.50954	-3.05782	-3.36764

* and ** represent significances at the 0.05 and 0.01 levels, respectively. Values in square brackets are probability values.

Risk coefficient was negative in pre-pandemic period and positive in the pandemic and overall periods for Ripple. However, these coefficients were not statistically significant. Although the asymmetry parameter was significant only in the pandemic period, it was determined that there was no asymmetric effect due to positive coefficient.

Table 7: Results of EGARCH-M Model for Litecoin

Parameters	Pandemic Period	Overall Period
Return Equation		
Constant	0.00337[0.5622]	-0.00716[0.1958]
Risk Parameter	-0.0117[0.9216]	0.14317[0.1807]
Equation of Variance		
Constant	-0.14191[0.2310]	-0.3805*[0.0009]
ARCH	0.11022*[0.0009]	0.17049*[0.0000]
GARCH	0.98901*[0.0000]	0.95492*[0.0000]
Asymmetry	0.08238*[0.0004]	0.00538[0.7822]
Log Likelihood	1143.872	2686.877
AIC	-3.18337	-3.25091
SIC	-3.12569	-3.20821

* and ** represent significances at the 0.05 and 0.01 levels, respectively. Values in square brackets are probability values.

Risk coefficient was negative in the pandemic period and positive in overall period for Litecoin. Coefficients were not statistically significant for both periods. Asymmetry parameter is positive and statistically significant during the pandemic period. Positive value indicates that there is no asymmetric effect during the pandemic period.

Table 8: Results of EGARCH-M Model for Cardano

Parameters	Pre-pandemic period	Pandemic Period	Overall Period
Return Equation			
Constant	-0.01188[0.2541]	0.00834**[0.0164]	-0.0130**[0.0172]
Risk Parameter	0.18974[0.3337]	0.38243**[0.0127]	0.22955**[0.0223]
Equation of Variance			
Constant	-0.59084**[0.0364]	-0.92613*[0.0011]	-0.85649*[0.0000]
ARCH	0.20141*[0.0053]	0.33212*[0.0002]	0.30721*[0.0000]
GARCH	0.92286*[0.0000]	0.87808*[0.0000]	0.887554*[0.0000]
Asymmetry	0.00126[0.9703]	0.01394[0.7434]	0.01292[0.6473]
Log Likelihood	1118.645	1049.145	2514.879
AIC	-3.11449	-2.9118	-3.04238
SIC	-3.0309	-2.82188	-3.00625

* and ** represent significances at the 0.05 and 0.01 levels, respectively. Values in square brackets are probability values.

The risk parameter was positive in all three periods for Cardano. During the pandemic and overall periods, these tradeoffs were statistically significant at the 0.05 level. The parameter showing the asymmetry effect of positive and negative shocks was not statistically significant.

6. CONCLUSION AND RECOMMENDATIONS

Rapid development of financial markets across the globe and the emergence of different assets in these markets may lead investors to prefer various alternatives. A rational investor desires to obtain the highest return among these alternatives. Each return opportunity includes its risk within itself. In this context, investor's preference is determined by reasonable concurrence of risk and return.

In this study, Cardano was the only crypto asset in which risk-return tradeoff was found. For Cardano, a significant risk-return trade-off , which was not determined pre-pandemic period, emerged with the pandemic and continued throughout the entire period. In terms of Bitcoin, Ethereum, Ripple and Litecoin, presence of a risk-return tradeoff was not determined. Classical financial theories assume that investor has the opportunity and knowledge to make rational decisions. On the other hand, increasing potential of the behavioral effect in investment preferences is a factor that directly affects investor preferences. This effect is undoubtedly stronger on crypto assets with higher volatility, especially compared to classical financial instruments. The fact that risk-return tradeoff which is one of the basic principles of finance could not determined for four of the five cryptocurrencies included in the research can be understood within the scope of this effect.

It might be useful for future studies to use alternative volatility models that allow risk-return tradeoff at intra-day frequency interval on cryptocurrencies with different characteristics.

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