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Systemic Risk between Cryptocurrencies and Real Currencies Using the Conditional Value at Risk Approach and Marginal Expected Shortfall

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ABSTRACT

The objective of this paper is to analyze and measure the systemic risk between cryptocurrencies and real currencies using a value approach in conditional risk exposure and expected marginal shortfall. Systemic risk in finance means the probability of a sudden crash of an entire financial system. This risk can lead to inconsistency or chaos in financial markets. Another important matter in the discussion of systemic risk is the contagion of risk, which is the probability of the spread of major economic changes in a country. In this research, statistical data of real and virtual currencies over the years 2015-2020 are used. For this purpose, the indices of systemic risk were calculated using CoVaR and MES, and then the correlation between the systemic risks of the evaluated currencies was created. In this analysis, the statistical data of the currencies of the exchange rate of the Pound to the Dollar, the exchange rate of the Yuan to the Dollar, the exchange rate of the Lira to the Dollar, the exchange rate of the euro to the Dollar, Bitcoin, Ethereum, Ripple, Litecoin and Ethereum Classic based on the daily price turnover of cryptocurrencies and real currencies are used. The result showed that there was a correlation between the systemic risk indices in relation to the studied currencies and virtual currencies had a lower systemic risk index than real currencies.

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1. Introduction

The current financial crises in the world, especially during the period 2007-2009, have attracted the attention of researchers, financial experts and policy makers to focus on and identify financial crises, the timing of their occurrence and the intensity to prevent their occurrence and recurrence. A systemic crisis in the financial system can have dramatic effects on the actual economy and economic welfare (D-Band and Hartman, 2000). After the financial crisis in 2007-2009, a lot of attention was paid to systemic risk as a large-scale risk that can affect the equilibrium of the entire financial system. During this period, it was found that the one-dimensional view of financial system monitoring institutions on the individual risks of each financial institution, including the value-at-risk, is not sufficiently suitable to prevent financial crises. Therefore, the forgotten sectors of financial risks, which are systemic or systematic risks of financial institutions should be given special attention in policy and legislation (Kent et al., 2010).

Systemic risk refers to the likelihood of the entire system collapsing due to a failure or crisis in some part or segment of the market. This risk arises from the simultaneous movement or correlation between sectors of the market; therefore, systemic risk occurs when there is an increased correlation between the risks and crises of different sectors of the market or when the risks of different sectors in one market segment or one country are linked and correlated with other segments and countries. It should be noted that the systemic risk is something completely different from the systematic risk, i.e. the simultaneous effect of general factors on the total price of existing securities in the financial market. Although systemic risk has been described as the linchpin of the recent financial crisis, there is no single definition or consensus for it. For example, according to a previous definition, a set of conditions that threaten the equilibrium, stability, and public confidence of the financial system is considered systemic risk (Billio et al., 2010).

In terms of systemic risk, a set of measures in the conditional risk is considered as one of the most important indicators. The indicator of conditional risk provides more useful data than indicators of unconditional risk. To evaluate the systemic risk, they proposed the conditional value-at-risk, which calculates the risk of the financial system only when institutions and markets are in a critical state. According to this, a firm's share of systemic risk creation is the difference between the conditional value-at-risk of the firm in critical and normal states. The index is even able to identify small entities that are important in terms of systemic risk (Adrian and Brunnermeier, 2011).

Researchers have considered various criteria for calculating systemic risk (Adarayan and Mier, 2011). They have developed the traditional value-at-risk criterion into the conditional value-at-risk criterion. The co stands for conditional, contagious and synchronous movement. The conditional value-at-risk calculates the loss of the entire financial system under the condition of helplessness of the specified financial institution. This indicator can be obtained as a bottom-up indicator because it measures the shock effects at the size of a firm on the whole system. They denote the share of financial institutions in systemic risk as the difference between the conditional risk value when the specified institution is in a state of distress and the conditional risk value when the specified institution is in a normal state. In fact, they used the ΔCoVaR indicator to show this difference. Acharya et al. (2017) developed and explained criteria such as marginal expected shortfall and systemic expected shortfall. The final share of a financial institution in systemic risk, through the marginal expected shortfall, is calculated as the historical average of the daily stock turnover of that institution. When the daily market turnover is 1% or 5% of its quarters, the recent criterion indicates the descending movement of an individual financial institution's risk in distress and market crisis.

Based on analytical data obtained from the Quinn Matrix website, the correlation between Bitcoin and S&P500 has reached the highest level in history during the recent price drop in the market. This means that in the event of a price drop in the stock market, digital currencies will also experience a sharp drop in price. On the contrary, Quinn Matrix believes that the current correlation will not exist in the long term, and digital currency markets will also act independently of the global market in the near future. It should be noted that the price of gold fell by 30% in the first six months of the financial crisis of 2008 and subsequently rose to 150%.

Binance Research Group stated that Bitcoin and the US stock market had a correlation coefficient of 0.57 in 2020Q1. However, the good news for investors is that the current correlation will not last and digital currency markets will experience a different approach in the medium and long term. Accordingly, this research attempts to calculate the systemic risk of cryptocurrencies and real currencies based on common and reliable systemic risk measurement criteria, including conditional risk value measurement and marginal expected shortfall, and compares their results with each other. Then, a general index of systemic risk of the foreign exchange system was extracted from these criteria, so that this index can be used in the analysis, from the effects and effectiveness of other variables.

The remainder of this paper is organized as follows. In Section 2, we will discuss the research literature and have a review of the previous parts. Section 3 will discuss the research methodology. In Section 4, the research model will be presented. Finally, the conclusion will be given in Section 5.

2. Research Literature

2.1 Definition of Systemic Risk

Although systemic risk has been identified as the linchpin of the recent financial crisis, there is no single definition or consensus for it. For example, according to a previous definition, a set of conditions that threaten the equilibrium, stability, and public confidence in the financial system is called systemic risk (Billio et al., 2010). Nevertheless, the recent financial crisis is a complete case study of the definition of systemic risk, which shows how the emergence of a crisis in one of the financial sectors causes enormous financial imbalance and disrupts the activities of the real sector of the economy with its domain extension through the financial markets (Gaspar, 2012).

The recent financial crisis has shown that it can have irreparable effects on the financial and real sectors of the economy if no attention is paid to the systemic risk in the financial markets. Given that financial markets were at the heart of the recent financial crisis, the attention of surveillance institutions to these markets has become much more rigorous. Evidence of this surveillance includes the stringent Bal 3 laws, the Volcker rules, the and Dodd-Frank Act of the US, the Vickers and Bank Levy laws of England and the Liikanen proposals for Europe.

It is necessary to study the transmission of systemic risk from cryptocurrency markets to other various economic markets because it helps shareholders to have a better perceptual understanding of the existence of systemic risk posed by cryptocurrencies in financial and foreign exchange markets. Therefore, studying the transfer of cryptocurrencies helps policy makers and candidates to predict the looming systemic risk near them, in the foreign exchange markets, and accordingly helps them to better manage the risks of cryptocurrencies.

In the cryptocurrency market, rumors have a remarkable effect on it causes and will cause huge volatilities in this market. A large part of this society in the investment sector consists of an ignorant crowd. Being in this market is like being on a roller coaster that is constantly fluctuating. Many economic philosophers talk about the premiere years of the fourth industrial revolution in the world. A revolution that was based on new technologies such as artificial intelligence, Blockchain, vital technologies and so on and so forth. So, given the philosophy in economics, they say the globalized economy needs global capital.

2.2 Systemic Risk Measurement

The MES index was coined and used by Acharya et al. (2010) and Brownles and Engel (2012) to measure the systemic risk of the financial market. The conditional value at risk (CoVaR) index was developed by Adrian and Brunnermeier (2008) when the CoVaR index was calculated and measured by quantile regression method and then many CoVaR indices were used to calculate the systemic risk of different economies.

The two indices of MES and CoVaR differ in the way they analyze the systemic risk caused by individual financial markets. The index MES defines systemic risk as the expected turnover of shares of an individual financial institution when the financial market is in a critical state. The critical state of the financial market also varies depending on the characteristics of each economy, where in developed countries where the stock market has more fluctuations per day, a decline in the financial market of more than 2% is classified as a critical state. In contrast, the CoVaR index is defined as the conditional risk value of market turnover (e.g., the conditional risk value of market turnover with 95% probability) only when the individual financial institution is in a critical state (e.g., when the individual financial institution's stock turnover equals its one-day conditional risk value with 95% probability). Adrian and Brunnermeier (2011) proposed ΔCoVaR as the difference between the conditional Value-at-Risk of the market if the financial institution is in a critical state and the conditional Value-at-Risk of the market if the financial institution is in a normal state to measure systemic risk.

Overall, these two indices differ in their cause and effect on systemic risk. On the cause side, the MES index determines the crisis state for the financial market, while the CoVaR index determines the crisis state for the financial institution. On the effect side, the MES measures the impact rate of the financial institution on the critical state of the financial market through the average turnover under these conditions, while the CoVaR measures the impact rate on the financial market when each financial institution is in a critical state through the conditional value in market risk.

3. Literature Review

Handika et al. (2019) conducted a research titled "does the risk of cryptocurrencies expand to Asian financial markets". They used the three methods developed by Forbes and Rigobon et al. (2003) and Longstaff (2010). Their results of using the first model showed that the correlation ratio (unadjusted) between the five virtual currencies and the thirteen Asian financial markets was low in both high and low variance periods. However, after adjusting for the bias in the correlation ratio, there were no significant changes in the degree of multiplication of the expansion mechanism from the five virtual currencies to the stock markets and Asian stock exchanges. The second expansion test using the multinomial logit analysis of simultaneous marginal returns found that virtual currencies were not statistically significant determinants of both positive and negative marginal returns. Third, the use of expansion analysis and a higher conditional value-at-risk framework showed that cryptocurrencies were not statistically significant determinants in explaining the change in current variables in the Asian financial market. The results of the conditional value-at-risk system are also compatible after monitoring the daily, weekly and monthly effects. These results suggested that virtual currencies did not pose a threat to Asian financial systems.

Eivazlou and Rameshg (2019) studied systemic risk using the final expected fractional method of MES and compared it with the conditional value-at-risk method of COVaR using the dynamic conditional volatility model between commercial and exchange banks in Iran. In this research, financial institutions were ranked based on these two criteria and a threshold value was set for modelling the crisis in the financial system with the use of threshold autocorrelation models. At the end, the relationship between the systemic risk and the fundamental factors of financial institutions and macroeconomic factors is verified using a data panel. The obtained results show that the two methods MES and CoVAR provided similar results. Moreover, the method proposed in this research, which was a combination of oscillatory models and dynamic conditional correlation with Monte Carlo simulations, resulted in a lower error.

Rahmani et al. (2019) evaluated the systematic risk of banks operating in the capital market based on ΔCoVaR, MES, SRISK with the use of multivariate GARCH models of DCC and then the effect of intrinsic bank variables and macroeconomic variables on these indicators was calculated. The results showed that large banks do not necessarily have higher systemic risk, and perhaps smaller banks play a role in the occurrence of this risk. Also, the leverage ratio of banks does not have a significant impact on systemic risk. Nevertheless, with an improvement in economic growth MES will decrease and with an increase in inflation ΔCoVaR will increase.

Mohammad Salehifar (2018) studied the return and risk behavior of Bitcoin BTC compared to gold, currency and stock markets using the approach of GJR_GARCH and T-GARCH models. For this purpose, he has collected the data related to daily price of Bitcoin, Tehran Stock Exchange index, free market rate of USD/Rial, free market rate of Euro / Rial, Azadi Spring Coin and future gold contracts for a period of five years (from 19/09/2013 to 18/09/2018). He examined the research hypotheses, with the use of Dickey Fuller root unit test, the univariate model of GJR–GARCH, TGARCH and Spearman Correlation coefficient. The research findings suggested that although the return and risk of bitcoin was significantly higher than other investment options such as currency, gold, coins and stock exchanges in the country, its behavior could not be associated with competing markets in terms of risk and return. Moreover, unlike other assets, the impact of positive news is higher than negative news in bitcoin transactions. In the end, Dyhrberg (2016)'s research that Bitcoin is something between gold and currency is not acknowledged.

Karim Ali and Nimox (2018) estimated the systemic risk of 46 European banks based on the CoVar index using Copula functions. They then examined the impact of macroeconomic factors and specific banking factors, such as scale, leverage ratio, and capital-equity beta, on systemic risk. Their results revealed that the volatilities of macroeconomic variables held some share in the systematic risk.

Qiang Jie et al. (2018) studied the "dynamic coherence and integration in the cryptocurrency/virtual currency market". This research showed a series of developed indices by Diebold and Yilmaz (2012-2016) to investigate the connectedness through return and volatility spillovers of six digital cryptocurrencies that were put into operation from August 7, 2018 to February 22, 2018. Despite the return shocks, the results showed that Litecoin was at the center of the return networks, followed by Bitcoin, the largest cryptocurrency or digital currency. This data showed that the return shocks, due to these two cryptocurrencies, had the most impact on other cryptocurrencies. Further analysis showed that connectedness over negative returns was usually higher than over positive returns. Ripple and Ethereum generate increased connectedness via negative returns, while Ethereum and Dash generate very weak connectedness via positive returns. Based on volatilities in expansion, Bitcoin is considered the most influential, and, after that, LiteCoin and Dash have minimal connectedness. Thus, tools are being provided to protect opportunities and create diversification in the cryptocurrency market. With these in mind, the results indicated that each of the cryptocurrencies in return and connectedness was not necessarily associated with market scale. Further analysis suggested that the size of transactions and the global financial system and indistinctive effects, such as the effect of alternative investments, were the determinants of net sided expansion.

Kleinow et al. (2017) began by comparing the experimental results of a popular and useful criterion for systemic risk using data from US financial institutions from 2005 to 2014. The four criteria they used in their work are: the final expected proportion, correlation risk, conditional risk value, and low sequence dependence. In their work, they calculated alternative criteria in different time periods and for different financial institutions using data from US financial institutions. Their discoveries indicated that the four criteria had different outcomes based on market data. The differences in the present results were found between different financial sectors as well as between the components of the sectors. The results showed that different systemic risk criteria can lead to different risk scores for different financial institutions. Moreover, they concluded that the risk assessment of financial institutions based on one criterion should be used with great care and caution.

Mohammadi Aghdam et al. (2017) calculated the systemic risk of a currency shock in Iranian financial markets that financial markets have been exposed to various uncertainties such as financial crises, oil shocks, changes in foreign exchange policies and similar cases in recent years. The occurrence of a shock, which is a mild stage of a crisis, is always accompanied by macro and micro level effects, which are not limited to the target market but may spread to other markets. Consequently, it is crucial to study the intensity and direction of the spread of fluctuations from one market to another. The aim of this study was to calculate the impact of a currency shock and the intensity of systemic risk in foreign exchange, capital and insurance markets.

Bury and Nicola (2017) examined the "systemic risk of local currencies in emerging markets". Emerging markets are increasingly issuing local currency sovereign bonds, and the share of foreign investors is moderately increasing in this market. By issuing local currency debt, emerging markets can eliminate exchange rate risk, which is cited as an example of foreign currency debt. Foreign investors can expand the diversity of their financial securities and gain exposure to fast-growing economies by investing in local currency debt. Nevertheless, foreign investors can act as a channel of shock expansion, both at the global level and in emerging markets. For example, following the rise in interest rates in developed markets, foreign investors are likely to withdraw their savings from emerging market sovereign debt, thereby lowering the price of bonds. In this research, attention has been paid to the increase in sequence risk. In the first step, the vulnerability of emerging markets to the systemic risk in the sovereign debt market is assessed by using the reduced CoVaR risk scale explained by Adrian and Brunnermeier (2016). They considered CoVaR assessed using quantitative conditional regressions and controlling for global variables, and found that countries' vulnerabilities differed across time periods and there were various differences across countries. In addition, the share of local currency debt available to foreign investors affects countries' vulnerability to systemic risk in the local currency sovereign debt market. These results showed interesting implications for governments and financial institutions in terms of optimal debt currency and risk management. In addition, the results pointed to the need to contain volatility in the allocation of securities to foreign investors, for example, by controlling capital or taxes to reduce the cost of sudden capital surpluses/outflows.

Giglio et al. (2016) examined how systemic risk and financial market crises affected the propagation of shocks to the real sector of the economy. This paper examined 19 different developed systemic risk criteria in Europe and the US. Moreover, the estimators proposed the cross-sectional criteria for constructing a systemic risk index and showed their compatibility in the model structure. Experimentally, systemic risk criteria have provided first-rate data for predicting examples of future external macroeconomic shocks. They used financial data for financial institutions with the two-digit code SIC 60 to construct the variables related to the US index. They also calculated stock returns from CSRP and COMPUSTAT data for US financial institutions.

Adrian and Brunnermeier (2011) introduced a new method for calculating systemic risk known as CoVaR. CoVaR refers to the conditional risk value of the financial system under the assumption that the financial institution is in distress. They fitted the associated dynamics of stock returns of individual financial institutions to the financial system using the quantile regression approach. For this purpose, they described the contribution to systemic risk of each financial institution by recognizing the difference between CoVaR under critical condition of individual financial institution and CoVaR under normal condition of individual financial institution. The difference between these two CoVaRs was explained by the ΔCoVaR. When measuring systemic risk using ΔCoVaR, Adrian and Brunnermeier found that in the time series dimension, there was a very strong relationship between the conditional value-at-risk of each financial institution and the ΔCoVaR related to that institution, while in the cross-sectional dimension, the relationship between these two variables was estimated to be weak.

Following Adrian and Brunnermeier (2010) and using the CoVaR criteria, Drakos and Kouretas (2013) examined systemic risk in three emerging market areas within Latin America, Central and Eastern Europe and Southeast Asia. In this work, they looked at the shares of banking, insurance and other financial services sectors in systemic risk. The surveys were conducted using weekly data over the period 1995:11 to 2013:2 within Mexico, Czech Republic, Hungary, Poland, Romania, Turkey, Hong Kong, Indonesia, Korea, Malaysia, Philippines, Singapore and Thailand. The main findings, based on the 1% and 50% multiple regression estimates, showed that return on equity was a major factor in the emergence of systemic risk. There was also evidence that changes in the overall index (systemic variable), liquidity margins, and quarterly interest rate volatilities had weak effects. Moreover, in Mexico, Czech Republic, Hungary, Romania, Hong Kong, Indonesia, the Philippines, and Thailand, the banking sector tends to be a strong contributor to systemic risk. In Malaysia, the insurance sector has the largest share of systemic risk, while in Poland, Turkey, Korea and Singapore, the highest percentage share of systemic risk is contributed by other financial institutions. Based on the results of the conditional value-at-risk criteria estimation, the share of each financial industry in systemic risk increased after the crisis for all emerging market economies, both before and after 2008.

In this aspect, by choosing the scale of conditional value-at-risk, differential risk and evaluating it using a quantitative regression model, an estimate of systemic risk was given based on seasonal frequency from the second quarter of 2000 to the fourth quarter of 2020. The results of the first stage confirmed the hypothesis of the impact of the currency shock on different increases in risk in all three markets, and the second stage, i.e. the scale of systemic risk, also showed that the financial market was exposed to a high level of expansion fluctuations compared to the other two markets, and the intensity of expansion fluctuations in the capital market and money market were placed in the next ranks. In accordance with the results, policy makers should prevent the occurrence of financial crises or reduce the impact of fluctuations and their expansion by creating a comprehensive program and applying an appropriate strategy.

The present research is innovative as it uses statistical models (dynamic conditional correlation pattern) and marginal shortfall expected approach and conditional value at risk to estimate systemic risk in cryptocurrencies and real currencies.

4. Research Methodology

In this research, we use the conditional value-at-risk approach and MES, to study, analyze and calculate the systemic risk between cryptocurrencies and real currencies. To measure both defined systemic risk criteria, dynamic conditional correlation (DCC) models developed by Engel (2002) as one of the multivariate types of GARCH are used. Multivariate GARCH models have the advantage that they can be considered as the time-varying measure of systemic risk for a financial institution or market.

The following criteria were applied to assess the systemic risk between cryptocurrencies or virtual currencies and real currencies; it should be noted that the data used in this research is the return of the currencies used. The MES criterion is calculated based on the criterion developed by Brownles and Engel (2012). The MES criterion used as a benchmark for calculating the share of each currency in the total portfolio of real and virtual currency is given in Equation (1):

$$MES_{i,t}(C) = E\left[R_{i,t} | R_{m,t} < C\right] \tag{1}$$

In Equation (1), Rm,t and Ri,t are respectively the daily returns of the financial market (just like the daily returns of the foreign exchange market) and the daily returns of the virtual currency *i* on day *t*. C is also a threshold value that indicates the occurrence of a systemic event. This value was studied equal to -2% in the research of Engel (2012).

It should be noted that in order to evaluate MES, one can use the autoregressive conditional heteroskedasticity model (ARCH), the multivariate conditional heterogeneous variance model or the multivariate GARCH and DCC model developed further by Engel (2012) to model the dynamics of conditional fluctuations in volatility. Then, considering the volatility and conditional correlations, MES can be calculated for each day as follows.

To assess systemic risk using CoVaR, we use the model of Gerardi and Ergon (2013), which is an evolved form of the earlier model of Adrian and Brunnermeier (2011). In general, the level of value at risk of virtual currency i is calculated according to equation (2):

$$pr\left(R_{i,t} \leq VaR_{q,t}^{i}\right)=\mathrm{q} \tag{2}$$

Therefore, the exposure value (Gerardi and Ergon, 2013) is calculated as Equation (3):

$$pr\left(R_{m,t} \leq CoVaR_{q,t}^{m|i} \leq VaR_{q,t}^{i}\right)=\mathrm{q} \tag{3}$$

The difference between Equation (3) and Adrian and Branmermeier's (2011) definition is that in their perspective, the conditional value was defined such that virtual currency *i* was exactly in its VaR value, but in the present definition, we modify the CoVaR (Adrian and Branmermeier, 2011) and change the definition of financial distress from equating the virtual currency with the exact measure of the specified VaR to considering the virtual currency at a return value smaller than its VaR; therefore, the probability of greater distress for virtual currency *i* depends on obtaining more reliable results from backtest data in terms of CoVaR.

With this definition, the amount of change in CoVaR is equated to the value of systemic risk evaluated between real and virtual currencies. ΔCoVaR calculates the percentage change in the value of risk in the market, assuming that virtual currency *i* is in the distress state.

$$\Delta CoVaR_{q,t}^{m|i} = 100 \times \left(CoVaR_{q,t}^{m|i} - CoVaR_{q,t}^{m|b^{i}}\right)/CoVaR_{q,t}^{m|b^{i}} \tag{4}$$

Multivariate GARCH models, including the DCC model, can be used in measuring this index as well as the MES index. Equation (5) can also be used to measure the long-term MES based on one-day MES.

$$LRMES_{i,t+180|t}\left(C_{t+180|t}\right) = 1 - exp\left(-18 \times MES_{i,t+1|t}\left(C_{t+1|t}\right)\right) \tag{5}$$

The one-day MES is defined as the conditional tail expectation of virtual currency returns under the assumption that the market is in a distress state, i.e.:

$$MES_{i,t+1|t}\left(C_{t+1|t}\right) = -E_t\left(R_{i,t+1|t} | R_{m,t+1|t} < C\right) \qquad (6)$$

where R,t+1|t and Ri,t+1|t represent the daily returns of virtual and real currencies and the foreign exchange market, respectively, and C is the market collapse threshold, the value of which varies depending on the characteristics of each economy.

By calculating the systemic risk of virtual and real currencies based on the introduced indicators and reconciling their results, the possibility of error in the estimation of systemic risk is minimized. On this basis, after measuring these indicators, the simultaneous movement of these mentioned indicators over time for different currencies is studied and analyzed, and in case of the presence of simultaneous movement between them, it is tried to name controlled policies for these movements.

The statistical population includes all cryptocurrencies and real currencies. Considering the statistical population, using the method of systematic elimination sampling, five virtual codes were selected considering the following conditions.

1- The currencies must have the highest trading rate during the study period;

2- Their mining must have started before the time range of the study (2015).

Among the real currency exchange rates, the Pound to Dollar exchange rate, the Yuan to Dollar exchange rate, the Lira to Dollar exchange rate, and the Euro to Dollar exchange rate are used. The time series of this research is based on the daily price returns of cryptocurrencies and real currencies over the period of 2015-2020. To calculate the systemic risk from logarithmic returns related to the daily data of price, indices of five cryptocurrencies (Bitcoin, Ethereum, Ripple, LiteCoin and Ethereum Classic) were used.

4. Experimental Results

This section provides the obtained results from the experimental investigation of the systemic risk between real currencies and cryptocurrencies. Based on the descriptions in the previous sections, data based on the exchange rate of each of the real and virtual currencies are used to calculate the systemic risk. Considering the observations of Pena and Rodriguez (2013) and Choi (2012) to calculate the systemic risk criteria in this paper, the exchange rate and the return on the exchange rate of the currencies were used. The currency information in this study is obtained from central bank systems and the website https://coinmarketcap.com. Table 1 provides some of the information data used to calculate systemic risk.

Table 1. Statistical Information on the Return of Real and Virtual Currencies

Variables	Average	Standard deviation	Jarque-Bera Statistic	Probability
The logarithm of the exchange rate of the Pound to the Dollar	0.315	0.016	59.36	0.000
The logarithm of the exchange rate of the Yuan to the Dollar	0.385	0.008	66.14	0.000
The logarithm of the exchange rate of the Lira to the Dollar	0.415	0.019	69.48	0.000
The logarithm of the exchange rate of the Euro to the Dollar	0.369	0.013	48.57	0.000
The logarithm of the Bitcoin	0.795	0.021	54.19	0.000
The logarithm of the Ethereum	0.698	0.026	68.19	0.000
The logarithm of the Ripple	0.749	0.017	49.85	0.000
The logarithm of the Litecoin	0.854	0.016	57.13	0.000
The logarithm of the Ethereum classic	0.0624	0.021	59.33	0.000

Source: Research finding.

The results of the Jarque-Bera test showed that the returns on the currencies under study did not have a normal distribution, and the standard deviation of these variables indicated the dispersion in the observations related to these variables.

4.1 Diagnostic Test of Research Variables

In traditional econometric methods, to assess the stability of a variable, it is assumed that the variables in the model are stable. In most cases, the stability hypothesis is tested by instability and the series unit root. One of the unit root tests is the ADF test. As can be seen in Table 2, according to the results of the ADF test, all research variables have a unit root and are stable through unique differentiation. Since the logarithm of the variables was used, their difference was considered equal to the return, and in the following statistics and modeling, the tests were applied to the returns of different currencies.

Table 2. Root Tests of Research Variables

Variable	ADF test	
	Test statistics	**5% of Critical Value**
The logarithm of the exchange rate of the Pound to the Dollar	-1.26	-3.42
The logarithm of the exchange rate of the Yuan to the Dollar	-2.38	-3.42
The logarithm of the exchange rate of the Lira to the Dollar	-1.88	-3.42
The logarithm of the exchange rate of the Euro to the Dollar	-2.31	-3.42
The logarithm of the Bitcoin	-1.58	-3.42
The logarithm of the Ethereum	-1.39	-3.42
The logarithm of the Ripple	-2.66	-3.42
The logarithm of the Litecoin	-1.47	-3.42
The logarithm of the Ethereum classic	-1.98	-3.42

Source: Research finding.

4.2 Systemic Risk Estimation

The systematic risk assessment for currencies is explained below. The criterion MES, which is derived from the expected shortfall (ES), defines systemic risk as the expected return on a stock of a single financial institution while the financial market is in a critical state. ES actually shows the average shortfall in a critical situation. That is, unlike VaR, which indicates the maximum shortfall under normal circumstances, ES calculates the average shortfall in the critical period, assuming that the financial market is in a critical state. From now on, the MES criterion calculates the average expected return on shares of a single financial asset by making the condition on the critical state of the financial market. The critical state of the financial market also differs based on the characteristics of each economy. In countries where the stock market may have higher volatility on a daily basis, a decline of more than 2% in the financial market is considered as a critical state. Also in this paper, according to Engel and Brownles (2012), a decline of more than 2% in the financial market is considered as a critical condition for the financial market.

The CoVaR criterion, unlike MES, takes into account the critical state for the financial market and measures the value exposed to the financial market under these circumstances. Based on the definition mentioned in the previous section, the CoVaR criterion refers to the value-at-risk of the market return (e.g., the value-at-risk of the market return with a probability of 95%), provided that the individual financial assets are in a critical state (e.g., when the stock return of that individual financial asset equals its one-day value-at-risk with a probability of 95%). Adrian and Branmermeier (2011) proposed CoVaR as the market's value-at-risk for calculating systemic risk, assuming the financial institution is in a critical condition.

Nonetheless, Gerardi and Ergon (2013) introduced a new technique for measuring systemic risk by changing the definition of critical state from a financial institution exposed to an exact VaR value to a financial institution exposed to a return value smaller than its VaR. These changes allow the consideration of a more severe critical state for the institution to improve the consistency (uniformity) of the dependent parameters, and more reliable results can be obtained by testing the historical data in terms of CoVaR. Two criteria, MES and CoVaR, were measured for the studied period and the correlation between these indicators was shown.

Table 3. Average Level of Systemic Risk of Real and Virtual Currencies

		Statistics
Average MES	Real Currencies	0.0184
	Virtual Currencies	0.0127
Average CoVaR	Real Currencies	0.0084
	Virtual Currencies	0.0065

Source: Research finding.

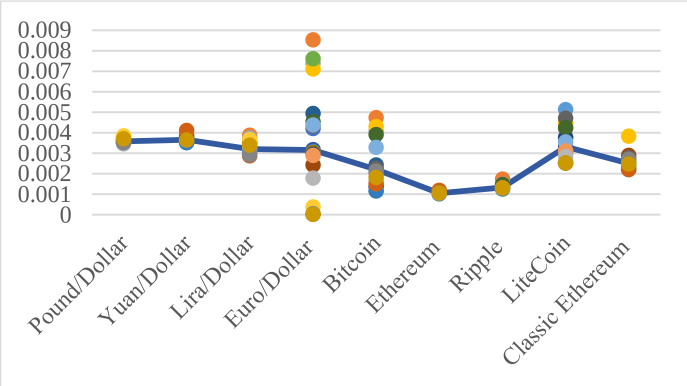

Figure 1. Systemic Risk According To MES Criteria for the Studied Currencies
Source: Research finding.

Figure 1 depicts the homogeneity of the systemic risk of the MES criterion among currencies, where for simplicity only the monthly average of each criterion is shown with colored dots in the graphs and at the end the overall average of each currency is marked as a colored line. As can be seen from the average MES, the systemic risk of different currencies is specifically different from each other, and among them, the three currencies Bitcoin, Ethereum and Classic Ethereum have a systemic risk of less than 0.5%. Based on the definition of MES, some currencies had a shortfall of up to 3.3% because the financial market is in a critical state (decline of more than 0.5%). As of now, the currencies that experienced higher losses during the critical period of the market, such as the Yuan-to-Dollar, Pound-to- Dollar, and LiteCoin, had the highest systemic risk among the currencies under study. Consequently, these currencies are potentially vulnerable to systemic losses in the critical period.

Table 4. Correlation of MES and CoVaR Criteria

	CoVaR Criterion	**MES Criterion**
CoVaR Criterion	1	0.84
MES Criterion	0.84	1

Source: Research finding.

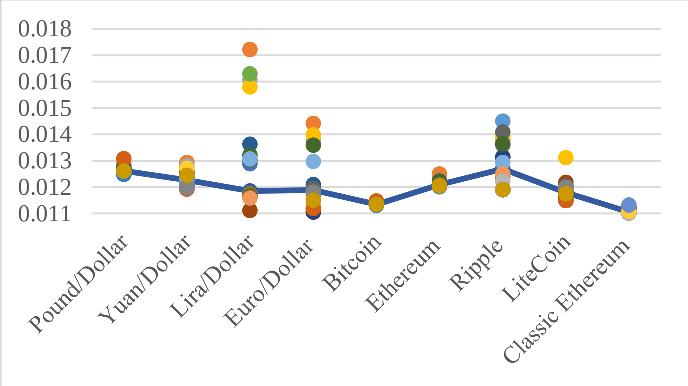

Figure 2. Systemic Risk Calculated According To Covar Criteria for the Studied Currencies
Source: Research finding.

Figure 2 shows the homogeneity of the systemic risk of the CoVaR criterion among currencies. Again, for simplicity, only the quarterly average of each criterion is shown with colored dots on the graphs, and the overall average of each currency is shown as a colored line at the end. As can be seen, the systemic risk of different currencies based on the CoVaR criterion also differs significantly from each other, and between them, the same currencies such as Bitcoin, Ethereum, and Ethereum Classic, which had the lowest risk based on MES, also have the lowest risk based on CoVaR. So, again, since the currencies with the lowest risk are classified as medium risk currencies, the relationship between systemic risk and the volume of currency transactions is intuitively negated. Based on the definition of CoVaR, if currency *i* is equal to or more critical than its VaR, the value-at-risk of the financial system increases by up to 0.4% compared to the normal state of that currency in the financial market.

5. Conclusion

The aim of this research was to investigate and calculate the systemic risk between cryptocurrencies and real currencies using the conditional risk value approach and marginal expected shortfall. In this research, the statistical data of the currencies of the exchange rate of the Pound to the Dollar, the exchange rate of the Yuan to the Dollar, the exchange rate of the Lira to the Dollar, the exchange rate of the Euro to the Dollar, Bitcoin, Ethereum, Ripple, LiteCoin and Ethereum Classic based on daily price returns of cryptocurrencies and real currencies in the period from 2015 to 2020 were used. In this research, systemic risk was calculated by using MES and ΔCoVaR criteria. The obtained results showed that there was a correlation between the systemic risk indices for the studied currencies and virtual currencies had a lower systemic risk index compared to real currencies. Based on these results, one of the most popular methods for risk management can be called diversification of currency portfolio, use of financial derivatives, balance sheet hedging, etc. The main strategies used by other successful countries to manage the risk of exchange rate fluctuations can be mentioned as chosen type of currency, financial and operational hedging and pricing policy. The financial hedging of these countries in the financial markets is done through foreign exchange derivatives or foreign currency debt, while the operational hedging is done by establishing subsidiaries abroad. It is also possible to use the results of this research to oblige the different financial sectors to consider sufficient capital for systemic risk in order to prevent the bankruptcy of crucial sectors in the country's financial system. Based on the findings of this research, the surveillance institutions should be able to identify the impact of different financial sectors that pose different risks in the economy. Therefore, there is a need for legal supervision to minimize the risk to the whole economy resulting from the crisis in the financial industry. A major limitation of this research was access to the statistics and data needed. Moreover, there are several criteria in calculating systemic risk indicators, so researchers should be cautious in extending the results of this research to all sectors of the economy.

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