NATIONAL RESEARCH UNIVERSITY
«HIGHER SCHOOL OF ECONOMICS»

COURSEWORK

«Uncertainty as a Factor of Cryptocurrency Market»

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Contents

Introduction

By now, the effect of many different kinds of uncertainty on cryptocurrencies has already been studied. It is known that the Volatility Index (VIX) and cryptocurrencies are positively dependent (Akyildirim et al., 2020). However, the other group of researchers found out that the Economic Policy Uncertainty Index (EPU) and cryptocurrencies are negatively dependent (Demir et al., 2018). Apart from the results mentioned above, we know that the EPU is positively correlated with the VIX. Hence, there is a controversy between the two groups of researchers.

Our research is aimed to check whether these researches are integrated or not. While the researchers used different datasets, we decided to check the effects on the unified dataset with the model that allows to estimate coefficients for all of the selected cryptocurrencies.

In this research, we studied the simultaneous effects of both VIX and EPU to shed light on the overall effect of uncertainty in the market of cryptocurrencies. Are the effects of EPU and VIX on the cryptocurrency market different? Yes, indeed they are.

To find the estimates, we used 17 of the oldest cryptocurrencies on the market. For estimation, the DCC GARCH model was used. During estimation, it was revealed that the elasticity of return of a cryptocurrency in relation to VIX equals 0.26 and in relation to EPU equals -0.03. These estimations reveal for us that depictions of uncertainty and returns of cryptocurrencies move independently from each other.

Literature Review

Cryptocurrency is a relatively new topic in academic discussion; however, a lot has been established in this filed in the recent years. With the constantly rising public interest towards this unique type of asset a lot of researchers try their best at explaining its properties and specific qualities. In our research we have studied several papers regarding cryptocurrencies and uncertainty. And we can clearly distinguish these as some of the most informative and noble.

The paper “The relationship between implied volatility and cryptocurrency returns” by Erdinc Akyildirim, Shaen Corbet, Brian Lucey, Ahmet Sensoy and Larisa Yarovaya tries to analyze the relationship between price volatility of several cryptocurrencies and implied volatility of US and EU financial markets. The study is concerned with 22 cryptocurrencies including BTC, ETH, ZEC, XMR and others and financial indexes VIX and VSTOXX. The study distinguishes strong interrelationships between conditional correlations of these cryptocurrencies and stress indexes. Cryptocurrencies experience periods of increased volatility during high financial market stress.

In “Risks and Returns of cryptocurrency” by Yukun Liu and Aleh Tsyvinski a broad study of cryptocurrency−specific factors and properties was established. The data consists of BTC, ETH and XPR daily returns for varying periods, Google search results for corresponding queries and twitter mentions of the stated above cryptocurrencies. The researchers were able to build strong evidence that risk−return tradeoff of crypto assets does not mimic those of traditional assets, such as fiat currencies, stocks, or commodities. Most importantly Yukun Liu and Aleh Tsyvinski form a robust argument, that returns of cryptocurrencies can be best predicted by momentum, investor interest. However, mining costs and realized volatility do not seem to have a strong effect.

In the study “Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation” Ender Demir, Giray Gozgor, Chi Keung Marco Lau, Samuel A. Vigne analyze influence of Economic Uncertainty Index (EPU) on daily Bitcoin returns. Logarithmic daily returns of BTC from July 18, 2010, up to November 15, 2017, are used in the model. With GGSVAR model and OLS and QQ estimators EPU has been indicated a predictive factor on daily BTC returns, bitcoin is negatively related to the economic uncertainty, hence BTC can be used to hedge risks during times of high economic uncertainty.

In “Cryptocurrencies: a crash course in digital monetary economics” by Jesús Fernández−Villaverdeb and “Understanding Cryptocurrencies” by Wolfgang Karl Hardle, Campbell R. Harvey and Raphael C. G. Reule authors develop a complex analysis of cryptocurrencies fundamentals, he states that cryptocurrencies are a bubble and do not have any fundamental value, however their role in future digital economy can be substantial. This paper also cites lots of informative researches regarding the blockchain and related technologies and recent development of crypto assets.

Data Review

For our research we have gathered data from CoinGecko exchange, this exchange was chosen because of their python integrated API and long-standing reputation. We have requested the top hundred cryptocurrencies by market capitalization. We chose to work with daily returns constructed form daily closing prices, due to Economic Uncertainty Index's (EPU) and VIX's non-scalability. Due to indexes' specifics, we had filled some gaps in these series with the closest previous values. For our tests we chose top 17 cryptocurrencies by introduction date. These are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (USDT), Dogecoin (DOGE), Litecoin (LTC), Stellar (XLM), Neo (NEO), Monero (XMR), Ethereum Classic (ETC), Nem (XEM), Dash (DASH), Zcash (ZEC), Decred (DCR), Siacoin (SC), Digibyte (DGB), and Waves (WAVES). Total number of observations amounted to approximately 35,700 observations

Methodology Review

Because of correlation between VIX and EPU, there might be a multicollinearity problem. To overcome this issue, we decided to use logarithmic scale for returns.

$r_t = ln(P_t) - ln(P_{t-1})$, where

P_t - price of a cryptocurrency in period t,

P_{t-1} - price of a cryptocurrency in period t-1

For estimation, the DCC GARCCH model was used. This model is more flexible than other classes of multivariate GARCH model. Moreover, it allows us to check the value of dynamic correlation of EPU, VIX and selected cryptocurrencies

$R_t = VIX_t + EPU_t + \epsilon_t$

$\epsilon_t|\Omega_t \sim i.i.d.N(0,h_t)$

$h_t = \alpha + \beta_1 h_{t-1} + \beta_2 \sigma^2_{t-1} + u_t$

The DCC GARCH model allows us to estimate coefficients of all cryptocurrencies simultaneously. Hence R_t denotes the matrix of returns of 17 cryptocurrencies.

Empirical Results

First of all, we decided to look at dynamic correlation between VIX, EPU and cryptocurrencies. The values are as follows in the Table 1:

Table 1: Dynamic correlation between VIX, EPU, and cryptocurrencies

	BTC	ETH	XRP	USDT	DOGE	LTC
VIX	0.9989839	0.9958411	0.9986794	0.9992959	0.9989158	0.999068
EPU	0.9649915	0.9526574	0.9627994	0.9634393	0.9628677	0.96419

	XLM	NEO	XMR	ETC	XEM	DASH
VIX	0.9979247	0.9935241	0.9983225	0.9950507	0.99581	0.9987694
EPU	0.9589157	0.9534235	0.9593711	0.9581514	0.9521517	0.9615774

	ZEC	DCR	SC	DGB	WAVES
VIX	0.9947132	0.9947132	0.9936792	0.9951309	0.9939378
EPU	0.9514809	0.9514809	0.9439028	0.9755173	0.9527094

All figures are statistically significant at the 0.1% level. Such values allow us to conclude that depictions of uncertainty are approximately strictly positively correlated with returns of cryptocurrencies. Without regressions, we can be confident that returns and uncertainty move in the same way.

The results of the regression analysis are as follows in the Table 2 and 3. As we can see, coefficients in each model are statistically significant at 0.1% and positive for each of cryptocurrencies. It means that VIX and EPU have different effect on cryptocurrencies.

According to the model, 1% change in VIX leads to 3.5% change in return, while 1%change in EPU leads to 0.07% opposite change in return.

The impact of VIX is stronger than EPU. This is because VIX denotes only uncertainty related to financial markets, while EPU denotes economic uncertainty. The increasing level of uncertainty on financial markets signals to investor that it would be better to escape from capital markets to crypto market. Economic policy uncertainty is not fully connected with financial market. Hence, not all of the economic agents have the access to financial markets. Such value of EPU can be used for hedging risks on capital markets.

Conclusion

In this paper, we examined the simulataneous effect of VIX and EPU on cryptocurrency returns. Unfortunately, we cannot prove that effects have the same sign. However, we sure that estimated model can help future researchers and finance workers to get better results.

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Table 2: Estimation results

	BTC	ETH	XRP	USDT	DOGE
VIX	0.034733	0.0348956	0.0347989	0.0347506	0.0349184
z	65.15	65.97	65.88	65.84	66.06
EPU	-0.0006951	-0.0007161	-0.0007063	-0.0006986	-0.0007153
z	-13.65	-14.12	-13.94	-13.79	-14.07
L1.arch	0.0840574	0.0826136	0.0832549	0.0850228	0.0833378
z	21.27	21.94	22	21.61	22.01
L1.garch	0.9296819	0.0826136	0.9299147	0.9289294	0.9297438
z	294.59	303.69	304.17	295.64	303.47
_cons	0.0029184	0.0029553	0.0029471	0.0029287	0.002963
z	14.17	14.98	14.93	14.69	14.77
	LTC	XLM	NEO	XMR	ETC
VIX	0.0348505	0.0349454	0.0349891	0.0348355	0.0349289
z	65.88	65.83	65.99	65.65	65.88
EPU	-0.0007088	-0.0007187	-0.0007234	-0.0007095	-0.0007134
z	-13.98	-14.01	-14.23	-13.95	-13.99
L1.arch	0.0827881	0.0829219	0.0824722	0.082418	0.0828085
z	22.16	21.81	22.01	22.04	22.04
L1.garch	0.9302658	0.9296251	0.9302968	0.9306947	0.9301573
z	308.66	299.64	306.83	308.36	306.55
_cons	0.0029268	0.0030148	0.0029544	0.002929	0.0029482
z	14.99	14.82	14.92	14.86	14.85
	XEM	DASH	ZEC	DCR	SC
VIX	0.0348627	0.0348752	0.0349842	0.0348124	0.0350015
z	65.62	65.56	65.68	65.52	65.67
EPU	-0.0007134	-0.0007092	-0.0007213	-0.0007063	-0.0007254
z	-14.08	-13.94	-14.12	-13.84	-14.15
L1.arch	0.0837496	0.0826171	0.0828035	0.0815749	0.0827735
z	21.89	21.83	21.6	21.79	21.36
L1.garch	0.9298973	0.9309314	0.9299934	0.9316686	0.9306542
z	300.63	303.95	296.23	308.63	297.77
_cons	0.0029064	0.0028944	0.0029717	0.002874	0.0029093
z	14.44	14.7	14.61	14.43	14.34

Table 3: Estimation results

	DGB	WAVES
VIX	0.0349789	0.0348585
z	65.88	65.66
EPU	-0.0007213	-0.000711
z	-14	-14
L1.arch	0.0821322	0.0834388
z	21.07	21.41
L1.garch	0.9306415	0.9300545
z	296.72	293.55
_cons	0.0029403	0.0029359
z	14.31	14.16