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An Investigation on the Volatility of Cryptocurrencies by means of Heterogeneous Panel Data Analysis

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Abstract

Cryptocurrencies have emerged about ten years ago as a new form of currency and have attracted much attention since they depend on a fully decentralized system, and so their transactions are very fast and have zero transaction cost. Therefore, character of cryptocurrencies and their volatility have been discussed widely by investors, policymakers and economists in recent years. From this point of view, this study aims to explain the price volatility of cryptocurrencies with macro-financial indicators, and thereby, the effects of S&P 500 stock market index, gold price, oil price, 2-year benchmark US Bond interest rate and US Dollar index on the prices of four major cryptocurrencies, Bitcoin, Litecoin, Ethereum, and Ripple, are investigated. The study comprises a panel data analysis applied to daily data over the period of August 2016 – April 2019, and analysis results show that increases in gold price, oil price and S&P 500 index raise the prices of cryptocurrencies, while increases in 2-year benchmark US Bond interest rate and US Dollar index cause to a fall. This adverse effects of the US Dollar index and US Bond interest rate on the prices of cryptocurrencies indicates that when the value of US Dollar and US Bond yield decrease investors prefer to invest in cryptocurrencies as alternative investment instruments. On the other hand, cryptocurrencies move with a similar trend of stock market index, gold price and oil price which are overall market indicators. Thereby, findings of this study show that cryptocurrencies behave more like an investment instrument than a currency, and prices of these financial assets interact with significant macro-financial indicators.

Keywords: *Cryptocurrency; bitcoin; market volatility; financial innovation; financial indicators.*

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1. Introduction

Cryptocurrencies have become one of the most popular economic and financial issues in recent years. Such that, 2194 cryptocurrencies are traded on the market currently, and their total market value has reached about $ 245 billion [7]. A cryptocurrency can be defined as a virtual currency based on electronic communication and designed to work as a medium of exchange using cryptography to prevent counterfeiting and fraudulent transactions. Despite the rapid increase in their numbers, Bitcoin – the first ever introduced cryptocurrency which is currently being traded at around $7,800 [7] – is the most popular one. Bitcoin was invented in 2009 by an entity under the pseudonym of Satoshi Nakamoto [12] and has attracted the attention of policymakers and investors since it depends on a fully decentralized system that bypass financial controllers, and so transactions are very fast and have zero transaction cost.

Cryptocurrencies consist of three factors: *(i) the protocol*, which is a computer code specifying how participants can transact, *(ii) a ledger* that store the history of transactions, and *(iii) a decentralized network of participants* that update, store and read the ledger of transactions following the rules of the protocol [2]. With these three factors, cryptocurrencies allow for *a digital peer-to-peer exchange* by which individuals move currencies from their accounts to the account of others without the need for a central authority to execute the exchange. In other words, cryptocurrencies can be freely traded on digital exchanges and have no central bank or another financial institution standing behind them. On the one hand, this feature lets cryptocurrencies to attract lots of attention, while on the other hand, many doubts and questions about the present and future of these decentralized virtual currencies have raised in time. Actually, there are two major views. One of them argues that since there are no real assets, this bubble will inevitably end with burst, while the other opines that cryptocurrency markets will become a profitable opportunity for millions of people [15].

Although their literature is yet scant, this increasing interest in cryptocurrencies leads to an increase in the number of academic studies on this issue. In this respect, we also conduct a study that aims to explain the price volatility of cryptocurrencies with macro-financial indicators. For this purpose, after explaining characteristics of cryptocurrencies and reviewing the literature on this issue, the effects of S&P 500 stock market index, gold price, oil price, 2-year benchmark US Bond interest rate and US Dollar index on the prices of four major cryptocurrencies, Bitcoin, Litecoin, Ethereum, and Ripple, are investigated by using a panel data analysis applied to daily data over the period of August 2016 – April 2019.

2. Characteristics of Cryptocurrency

As mentioned before, one of the key features of cryptocurrencies is the implementation of a set of rules, *the protocol*, that aims to create a reliable payment technology without a central authority. The protocol determines the supply of the cryptocurrency – for instance, in the case of Bitcoin, it states that no more than 21 million Bitcoins can exist [5] – and it is also designed to ensure that all participants follow the rules. Since the cryptocurrency is not issued by any central authority, it is theoretically insensitive to government interference or manipulation, and the value of the cryptocurrency is dependent on what investors are willing to pay for it at a point in time [15].

Cryptocurrencies use a digital peer-to-peer exchange which involves *the double-spending problem*, that any digital money is easily replicable and can thus be fraudulently spent more than once. Before the emergence of cryptocurrencies, the only solution for this problem was to have a centralized agent to record and verify all of the transactions. On the other hand, cryptocurrencies overcome the double-spending problem via decentralized record-keeping through *a distributed ledger* which is a file starts with an initial distribution of cryptocurrency and records the history of all subsequent transactions. Since an up-to-date copy of the entire ledger is stored by each user, it is said to be *distributed*. Thereby, cryptocurrency transactions are verified by the user's computers that logged into the currency's network and each user can directly verify whether a transfer took place and that there was no attempt to double-spend [2].

All cryptocurrencies are based on a distributed ledger, but they are divided into two groups according to how the ledger is updated. One of these groups uses *permissioned distributed ledger technology* in which the ledger can only be updated by trusted participants known as *trusted nodes*. These participants are chosen by a central authority, like the firm that developed the cryptocurrency, and so, an institution-based setup is valid in this technology. On the other hand, the second group of cryptocurrencies uses *permissionless distributed ledger technology* in which the ledger can only be updated by a consensus of the participants. A fully decentralized setting is generated in this technology, and while anybody can participate, nobody has a special key to change the ledger [2].

The concept of permissionless distributed ledger technology was initially designed under the name of block chain. *The block chain*, which has initially been used by Nakamoto for Bitcoin, is a specific type of distributed ledger that is updated in groups of transactions called *blocks*. In other words, each block has a list of transactions information, and these blocks are then chained chronologically by means of the use of cryptography to form the block chain [2]. This concept has been adapted to countless other cryptocurrencies which have two groups of participants: *users* who want to transact in the cryptocurrency, and *miners* who act as bookkeepers. The user of a cryptocurrency has *a digital wallet* which is a software for sending and receiving payments in the form of cryptocurrency, and store information in files in a computer or a mobile device. Users have private keys in order to access to these files. If the file system is damaged or the wallet file is deleted by mistake, then the wallet file is lost and the bitcoins in this file are lost forever. On the other hand, the miner of a cryptocurrency solves artificial mathematical problems by dedicating his/her computational power to the network and creates new cryptocurrencies, and so new blocks [17]. The creation of a new block is a *proof of work* system of mining, which in turn require costly equipment and electricity use. Miners also receive fees from users in return for their efforts, and newly minted cryptocurrencies if specified by the protocol [2].

Finally, potential cyber-attack, fraud and money laundering risks that may occur due to the use of cryptocurrencies should be mentioned briefly. Although, the shared nature of the ledgers may mitigate the risk that *a cyber-attack* directed to a single point brings down the entire network, a flaw in the system could have extensive negative consequences. Furthermore, if the technology itself was hacked, since the protocols used by different distributed ledger technology networks tend to be similar, the risk of contagion could extend beyond the single distributed ledger technology network under attack. The other type of risk that should be considered is *the risk of fraud* which means that private/public keys might be lost or stolen and used fraudulently in the absence of a powerful governance framework. Similarly, since cryptocurrencies provide very high degree of anonymity, they are not under the adequate control of law enforcement institutions. Thus, cryptocurrencies become very attractive for the *money laundering* and *terrorist financing* activities [9]. All of these risks have caused Afghanistan, Algeria, Bangladesh, Bolivia, Ecuador, Morocco, Republic of Macedonia, and Russian Federation to declare that the use of Bitcoin is illegal, while American Samoa, China, Egypt, Mexico, Nepal, Saudi Arabia, and Zambia have restricted the use of it [15].

3. Literature Review

Since cryptocurrencies have attracted much attention in recent years, the number of academic studies in this field is increasing. Most of these studies are examining the future of Bitcoin – whether it is only a speculative investment instrument or it can be a medium of exchange in the near future – and its volatility, while there have been few studies that examining the entire cryptocurrencies market. In one of these studies, Yermack (2013) discusses whether Bitcoin should be considered as a currency or a speculative investment instrument, and concludes that Bitcoin appears to behave more like a speculative investment than a currency because of its excessive volatility, the hacking and theft risks, the scarcity of merchants who accept it, the relatively high level of computer knowledge required for using it, the risky transactions due to the absence of basic consumer protection, and finally, the long-term structural economic problem related to the limit of 21 million units that can ever be issued, with no expansion possible of the bitcoin supply after the year 2140.

Vejačka (2014) investigates volatility of two major cryptocurrencies - Bitcoin and Litecoin, and compares them with volatilities of main stock indices, commodities and money pair of euro to US dollar. Furthermore, other basic aspects of cryptocurrencies including anonymity, awareness and legislation effects are briefly investigated and discussed in the study. Research findings imply that *(i)* volatility of cryptocurrencies is extremely high in comparison to basic investment instruments, and *(ii)* recent negative awareness of cryptocurrencies might lead to a change in the role of cryptocurrencies' and they might become mediums of exchange in black economy or speculation tools since the great growths of their exchange rates attracted many speculators.

Dyhrberg (2016) examines if Bitcoin behaves like a financial asset or as something in between a commodity and a currency by analyzing several aspects of its price volatility over the period from July 19, 2010 to May 22, 2015. Results of the analysis show that Bitcoin is somewhere between a currency and a commodity due to its decentralized nature and limited market size. Although Bitcoin reacts significantly to the federal funds rate like a currency, since it is both decentralized and largely unregulated it will never behave exactly like a medium of exchange. On the other hand, most aspects of Bitcoin are similar to gold as they react to similar variables in the GARCH model. Finally, Bitcoin can be used as a tool by risk averse investors in anticipation of negative shocks to the market.

Bouoiyour and Selmi (2016) use daily Bitcoin prices over two main periods, the first from December 01, 2010 to December 31, 2014, and the second from January 01, 2015 to July 20, 2016, and an optimal-GARCH model in order to address whether there is a beginning of a mature crypto-market. To address this question, they compare how behaves Bitcoin price over these two main periods, and find that while for the first period Bitcoin price appears to be too volatile, for the second one it becomes much less persistent. They explain this decrease in volatility by the fact that proper security measures are becoming more practical for the public by ensuring that Bitcoin is as safe as possible, and conclude that despite reaching a low volatility rate, Bitcoin market remains far from being mature. Findings of this study also indicate that Bitcoin price dynamics seem more driven by negative shocks (bad news) than positive ones (good news).

Letra (2016) focuses on the interaction between digital currencies, particularly Bitcoin, and web content, through the proxies Google, Wikipedia and Twitter, and uses a GARCH model on daily data. Starting point of this study is the fact that if investors are doubtful about their investment, they seek to decrease this uncertainty by increasing their knowledge/awareness through web search. Empirical results of this study indicate that Bitcoin returns are driven primarily by its popularity, and also exhibit some predictable power. In other words, both web content data and previous Bitcoin price variables have a significant impact on Bitcoin volatility.

Chu, et al. (2017), aim to provide the first GARCH modelling of seven most popular cryptocurrencies – Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple – by using daily global price indices over the period from June 22, 2014 to May 17, 2017. They assume cryptocurrencies as financial assets since most of the users are trading them either as a long-term investment in new technology or as a short-term profit instrument. Therefore, they investigate the volatility of cryptocurrencies which is an important factor in terms of financial investment, and results of their study show that cryptocurrencies exhibit extreme volatility especially for inter-daily prices. This finding is suited for risk-seeking investors who are looking for a way to invest into technology markets. Additionally, they believe in implementing more regulations and policies for cryptocurrencies as people are starting to see them as investment possibilities.

Poyser (2017) investigates internal and external factors that affect the prices of cryptocurrencies, and focuses on Bitcoin as the first ever introduced and also the most popular cryptocurrency. Findings implies that *supply and demand* of a cryptocurrency are main internal factors that have direct impact on its market price. Since the supply of Bitcoin is exogenously determined only the demand side can affect Bitcoin's price. On the other hand, few *crypto-market*, *macro-financial*, and *political factors* can be regarded as external drivers. All of the studied factors listed in Table 1 [15], and it is concluded that Bitcoin might be entering in a new phase. In this regard, the increasing effect of *attractiveness*, for which search trends and Wikipedia articles' views are used as proxies in most of the papers, may be indicative prospect of such argument, and also the consequences of signals from government's policies to find a *legal framework*.

Table 1. Factors that influence cryptocurrency prices.

Internal Factors	External Factors		
Supply & Demand	*Crypto-market*	*Macro-financial*	*Political*
• Transaction Cost • Reward System • Mining Difficulty • Coins Circulation • Forks (Rule Changes)	• Attractiveness (Popularity) • Market Trend • Speculations	• Stock Markets • Exchange Rate • Gold Price • Interest Rate • Others	• Legalization (Adaptation) • Restrictions (Ban) • Others

Likewise, Sovbetov (2018) examines factors that influence prices of most common five cryptocurrencies such Bitcoin, Ethereum, Dash, Litecoin, and Monero both in short-run and long-run over the period 2010-2018 using ARDL technique on weekly basis. Specifically, the interaction between these five cryptocurrencies and the stock market

(SP500 index), gold prices, and macroeconomic indicators (interest rate) is investigated in this study. Findings indicate a statistically significant impact running from crypto-market factors such as total market prices, trading volume, and volatility on to the selected five cryptocurrencies in long-run and short-run respectively. By analyzing this impact in detail, it is concluded that *(i)* responses of Bitcoin and Ethereum are more sensitive to the market in short-run, *(ii)* responses of these five cryptocurrencies to the fluctuations in market trading volume are higher in long-run, *(iii)* volatility of the cryptocurrency market appears to be a statistically significant determinant both in long-run and short-run for all cryptocurrencies, and *(iv)* attractiveness of cryptocurrencies also matters for all except Dash, but only in long-run.

4. Panel Data Analysis of Cryptocurrencies

In this section, in order to explain the price volatility of cryptocurrencies with macro-financial indicators, the effects of S&P 500 stock market index, gold price, oil price, 2-year benchmark US Bond interest rate and US Dollar index on the prices of four major cryptocurrencies, Bitcoin, Litecoin, Ethereum, and Ripple, are investigated by using a panel data analysis applied to daily data over the period of August 2016 – April 2019. In this analysis, tests of the unit effects and parameter constancy are applied as a first step. After confirming heterogeneity of the panel, cross-sectional dependence is investigated, and then, the model is estimated by Seemingly Unrelated Regressions (SUR). The SUR Model make possible the units to be interpreted separately. In this way, the regression models for Bitcoin, Litecoin, Ethereum, and Ripple are generated, and effects of independent variables on their prices are obtained on the basis of units.

4.1. Data and model

In order to explain the price volatility of cryptocurrencies with macro-financial indicators, Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC) are selected as proxies of cryptocurrencies, and market prices of these cryptocurrencies denominated in US Dollar are determined as dependent variable. On the other hand, independent variables are the S&P 500 stock index, gold price, oil price, 2-year benchmark US Bond interest rate and US Dollar index, and descriptions of these variables are given in Table 2. The panel dataset, obtained from Bloomberg [3] and Investing.com [10], includes 655 working days in over the period August 2016 – April 2019, and is analyzed through the Stata 14 program.

Table 2. Descriptions of the variables.

Variables		Descriptions
crpt	(dependent variable)	The market price of the cryptocurrencies which have the highest market values (Bitcoin, Ethereum, Ripple, Litecoin in turn)
sp500	(independent variable)	S&P 500 stock market index which is formed by Standard & Poor's and represents the shares of 500 large American companies
gld	(independent variable)	1 ounce gold price (in US Dollar)
oil	(independent variable)	oil price (in US Dollar)
int	(independent variable)	2-year benchmark US Bond interest rate
usd	(independent variable)	US Dollar index

While examining the effects of these independent variables on the market prices of four major cryptocurrencies, we look whether there is a difference among the cryptocurrency units. The econometric model used for this purpose is as below.

$$crpt_{it} = \beta_0 + \beta_1 sp500_{it} + \beta_2 gld_{it} + \beta_3 oil_{it} + \beta_4 int_{it} + \beta_5 usd_{it} + u_{it} \tag{1}$$

4.2. Tests of unit effects and homogeneity

By using panel data analysis, it is possible to evaluate the data of different units as a whole in only one model. However, each unit may have its own characteristic, and these different characteristics cause differentiation of the parameters. Therefore, detection of these unobservable unit effects in the model is important in terms of estimating the parameters. The existence of these effects is tested through the Maximum Likelihood Method and the results of the LR Test are presented in Table 3.

Table 3. Test of unit effects.

Random-effects parameters	Estimate	Std. Err.	[95% Conf. Interval]	
_all: Identity	25994.67	9204.8	12985.87	52035.25
sd(R.id)				
sd(Residual)	27170.05	323.3614	26543.61	27811.27
LR test vs. linear model: chibar2(01) = 1850.39			Prob >= chibar2 = 0.0000	

According to these results, it is seen that the constant parameter $\left(\beta_0\right)$ varies by the units. In this case, a new parameter (μ_i) must be included in the model to represent the unit effects. The sum of the constant parameter and unit effects $\left(\beta_0+\mu_i\right)$ is expressed as (β_{0i}) in equation 2. Afterwards, Swamy's S Test is applied to examine the status of slope parameters in the model where constant parameter varies by units [13], and Chi2(18) = 9374.72 and prob > chi2 = 0.0000 statistics are obtained. Thus, as a result of the parameter constancy test, it is seen that the slope parameters also vary by the units. In other words, this is a heterogeneous panel, and following the homogeneity test, the model is updated as follows.

$$crpt_{it}=\beta_{0i}+\beta_{1i}sp500_{it}+\beta_{2i}gld_{it}+\beta_{3i}oil_{it}+\beta_{4i}int_{it}+\beta_{5i}usd_{it}+u_{it} \tag{2}$$

4.3. Test of cross-sectional dependence

While the first generation panel unit root and cointegration tests, which were developed in the 1990's, assumed cross-sectional independence, the second generation ones take into account the cross-sectional dependence in the data [1]. Cross-sectional dependence can stem from spatial effects, spillover effects or unobserved factors, and leads the residuals obtained from units to be related to each other. Before determining the estimator for heterogeneous panels, the cross-sectional dependence in the model should be tested. The results of this test are presented in Table 4. According to the LM test statistics, the H_0 hypothesis which suggests that there is no cross-sectional dependence is rejected. Furthermore, the Breusch Pagan Test of independence is also applied to the dataset and Chi2(6)=1467.689 and Pr=0.0000 statistics are obtained. These results support the LM test statistics and state that there is a cross-sectional dependence.

On the other hand, Table 5 presents the correlation matrix of the residuals, and as it is seen, there is an 85 % correlation between Bitcoin (crp1) and Litecoin (crp4).

Table 4. Test of cross-sectional dependence.

Test (H_0: Cov(uit,ujt) = 0 for all t and i!=j	Statistic	p-value
LM	1285	0.0000
LM adjusted (two-sided test)	5391	0.0000
LM CD (two-sided test)	33.4	0.0000

Table 5. Correlation matrix.

	Crp1 (Bitcoin)	Crp2 (Ethereum)	Crp3 (Ripple)	Crp4 (Litecoin)
Crp1	1.0000			
Crp2	0.5489	1.0000		
Crp3	0.5773	0.2605	1.0000	
Crp4	0.8538	0.6090	0.6622	1.0000

4.4. The model estimation with Seemingly Unrelated Regressions (SUR)

The appropriate estimation method is chosen according to the results of the cross-sectional dependence test. Zellner (1962) has developed the Seemingly Unrelated Regressions (SUR) Model for heterogeneous panels with cross-sectional dependence. For the SUR Model, the time dimension should be large and the number of units should be less than 10 [13]. Since the dataset used in this study is suitable for these criteria, the model is estimated with SUR.

Although different currencies seem independent from each other, they are under the influence of similar factors in the same time period. Therefore, the error terms of the regression models may be related to each other. In the SUR Model, regression models are estimated for each unit separately. Then the general variance covariance matrix is formed. There are residual variances obtained from the regression model of each unit in the diagonal of this matrix, while there is the covariance between the residuals in the places other than diagonal. The SUR Model is estimated by using Generalized Least Squares Method [16], and estimation results are presented in Table 6 and Table 7.

Table 6. The results of Seemingly Unrelated Regressions Model.

Models	R^2	Chi2	Probability Values
Bitcoin	0.6970	1491.68	0.0000
Ethereum	0.4367	505.88	0.0000
Ripple	0.5165	690.31	0.0000
Litecoin	0.5973	955.89	0.0000

Table 7. The results of Seemingly Unrelated Regressions coefficients.

Dependent Variable	Gold	Oil	S&P500	2YearInt	USD	Constant
Bitcoin	17.0523	183.398	14.2659	-2956.05	-336.641	-25791.3
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ethereum	1.5938	11.6792	0.3905	-83.7535	-3.3385	-2943.333
	(0.000)	(0.000)	(0.000)	(0.000)	(0.177)	(0.000)
Ripple	0.0027023	0.0147252	0.000790	-0.104723	-0.014964	-4.291147
	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)
Litecoin	489.9683	3372.773	212.9757	-57100.25	-4575.131	-745812.4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

After an overall assessment of the models, it can be said that increases in gold price, oil price and S&P 500 index raise the prices of cryptocurrencies, while increases in the 2-year benchmark US Bond interest rate and US Dollar index cause to a fall. Furthermore, the most sensitive currency to financial market indicators is Litecoin, while the least sensitive one is Ripple.

On the other hand, although the value of the coefficient varies by cryptocurrencies, the independent variables have effect on the dependent variable in the same direction for all units. Additionally, variables are significant at 5 % significance level. The only exception is the US Dollar index which is not a statistically significant variable in the regression model of Ripple. Finally, 69 % of the price movements in Bitcoin, 43 % of the price movements in Ethereum, 51 % of the price movements in Ripple and 59 % of the price movements in Litecoin can be explained by the model.

5. Conclusion

This study examines macro-financial indicators that influence the prices of the four major cryptocurrencies such Bitcoin, Ethereum, Ripple and Litecoin. For this purpose, the panel data analysis was applied to daily data over the period of August 2016 – April 2019. First of all, the parameter constancy test was performed and it was seen that the dataset is suitable for heterogeneous panel data. Then, before determining the estimator for heterogeneous panels, the cross-sectional dependence in the model was tested, and the H_0 hypothesis which suggests that there is no cross-sectional dependence was rejected. Thereby, the SUR Model which is appropriate for heterogeneous panels with cross-sectional dependence has been used to estimate the model.

According to the results of the estimation model, increases in gold price, oil price and S&P 500 index raise the prices of cryptocurrencies, while increases in 2-year benchmark US Bond interest rate and US Dollar index cause to a fall. This adverse effect of the US Dollar index and US Bond interest rate on the prices of cryptocurrencies indicates that when the value of US Dollar and US Bond yield decrease investors prefer to invest in cryptocurrencies. On the other hand, cryptocurrencies, like investment instruments, move with a similar trend of stock market index, gold price and oil price which are overall market indicators. Findings of this study show that cryptocurrencies behave more like an investment instrument than a currency, and prices of these financial assets interact with significant macro-financial indicators. On the other hand, the correlation matrix of the residuals indicates that there is a high correlation between Litecoin and Bitcoin. Similarly, the most sensitive cryptocurrencies to macro-financial indicators are respectively Litecoin and Bitcoin. Approximately 70 % of the movements in the price of Bitcoin can be explained by the economic and financial variables in the model. Thereby, increasing predictability of cryptocurrencies will reduce the uncertainties faced by investors.

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