DYNAMIC ECONOMETRIC MODELS

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Dependency Analysis between Bitcoin and Selected Global Currencies

A b s t r a c t. In this research we have tried to identify the relationship between the exchange rate for bitcoin to the leading currencies such as Dollar, Euro, British Pound and Chinese Yuan and Polish zloty as well. We have applied ARMA and GARCH models to model and to analyze the conditional mean and variance. The appliance of GARCH models have identified some dependency in explanation conditional variance between bitcoin and US Dollar, Euro and Yuan, while ARMA analysis have shown no relations between bitcoin and other dependent variables.

K e y w o r d s: ARMA, Bitcoin, Dependency, GARCH, Variability.

J E L Classification: F31; C32.

Introduction

Progressive globalization and dynamic technological development has led to inequalities in sharing of resources and increase of distrust to governments, banks and other state and financial institutions. People began to look for new alternatives that would respond to the growing consumerism and surveillance. The creation of virtual currencies (VC) was such an answer. VC's are developing in a dynamic way and are gaining more and more atten-

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tion. The experts from PriceWaterhouseCoopers in their report have admitted, that *VC is a beginning of a new phase of technology-driven markets that have the potential to disrupt conventional market strategies, longstanding business practices, and established regulatory perspectives—all to the benefit of consumers and broader macroeconomic efficiency.* [VC] *Carry groundbreaking potential to allow consumers access to a global payment system—anywhere, anytime.* (PwC, 2015). Following information Available via: mapofcoins.com, currently there are ca. 600 different, active virtual currencies. Among them is bitcoin – one of the most prominent examples, with the biggest capitalization (ca. 10 bn USD). It is the most popular and most widely recognized VC. Many global companies are now accepting payments in bitcoin, e.g. WordPress.com, Amazon, Victoria's Secret, Subway, Bloomberg.com, Sears, GAP, Apple App Store, Miscrosoft, DELL, LOT Polish Airlines, T-Mobile Polska, Profident, etc. The father of bitcoin is considered Satoshi Nakamoto, who in 2008 published an article "Bitcoin: A Peer-to-Peer Electronic Cash System", in which he described the concept of virtual, decentralized and independent means of payment. He has based his solution on the information protocol (block chain), which aims to eliminate all of the transactions factors, which are based on trust[1]. Bitcoin supporters consider anonymity as its major advantage, as well as its broadest sense independence.

Therefore in this article we have used autoregressive models, such as ARMA and GARCH, to model and to analyze Bitcoin's conditional mean and variance in relation to other world currencies like US Dollar (USD), Euro (EUR), British pound sterling (GBP) and Chinese Yuan (CNY). The currencies were selected based on the transaction volume, in which the most of the transactions were performed. The results would give us an answer, whether bitcoin is impervious to external influences. Such a feature would imply that this VC is impossible to control by third party agents, hence can be seen as a fully independent means of payment.

1. Literature Overview

Current achievements of scientists related to bitcoin, can be divided into four main streams of interest. Considerations of a general and theoretical form for example: (Dwyer, 2015), (Dopierała and Borodo, 2014), (Liu et.al., 2015), (Jagwani, 2015), (Rogojanu and Badea , 2015), etc. This group include

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[1] For more information about bitcoin and it's technical details of creation, mining and functioning, please refer to (Nakamoto, 2008), (Nowakowski, 2013) and (Nielsen, 2013).

a number of studies on the classification of bitcoin as a commodity or a currency. The scientists in their work roll extensive discussion regarding the intrinsic value of bitcoin, the future and the potential it can bring. The Committee for Payments and Market Infrastructure (CPMI) acting at the Bank for International Settlements in its publication "Virtual currency" (CPMI, 2015), has stated, that bitcoin is similar in its concept to goods, such as gold, whose price is created by the power of supply and demand, with an except that it has no intrinsic value. (Haubno-Dyhrberg, 2016) raises other similarities between bitcoin and gold, e.g. limited amount and a similar way of its extraction ("mining"). Other similarities lists (Weber, 2016), who points out that both gold and bitcoin supply is not controlled by any state or institution, and both products have the same means of exchange. The second group of papers, for example: (Badev and Chen, 2014), (Taha, 2015), (Luther and Olson, 2015), (Campbell, 2014) (Tasca and De Roure, 2014), (Karama et.al., 2015) and others, is focusing mainly on issues relating to acquisition (mining), trade and broadly understood security.

Articles concerning regulatory and tax issues are covered by the third group, for example. (Mandjee, 2014), (Bryans, 2014), (Plassaras, 2013), etc. This group also include the various types of reports and publications of banks, financial institutions and governments on bitcoin, i.e. European Central Bank (ECB, 2012), (ECB, 2015), (Draghi, 2015); Congressional Research Service acting on the needs of the US Congress (Murphy et.al. 2015), (Congress, 2014); Canadian Central Bank (Gans and Halaburda, 2013), (BoC, 2014), (Chiu and Wong, 2015), and others. The last group focuses on the application of quantitative methods in the study of bitcoin, for example: (Brandvold et.al., 2015) using the price discovering process studied which of the bitcoin's trading platforms has the most impact on the bitcoin's price and which one is following the general trend. The authors found that Mtgox and Btce are undisputed animators of the bitcoin's prices. (Haubno-Dyhrberg, 2016a) and (Haubno-Dyhrberg, 2016b) have used GARCH to prove that bitcoin bears similarities to both the US dollar and gold, and that it can serve as an instrument to minimize the risk by people characterized by a strong risk aversion. (Cheah and Fry, 2015) showed that bitcoin like other cryptocurrency tend to generate bubbles, and they do not have fundamental value. (Gronwald, 2015) using a generalized model of autoregressive conditional heteroscedasticity said that the fluctuations in bitcoin are characterized by sudden surges and extremes pricing, which is characteristic for immature markets. (Szetela, 2016) has investigated bitcoin and dollar price variability using control charts. She has confirmed that price variability is strongly influenced by price jumps on the one hand, but on the other hand bitcoin's

price variability is tending to decrease. (Macdonell, 2014) using ARMA model and LPPL showed that the price of bitcoin depends on the CBOE Volatility Index, which indicates the great potential of this speculative currency. (Vockathaler, 2015) confirmed that fluctuations in the price of bitcoin are positively correlated with the amount of users BTC and determined by the endogenous shocks of unknown source, origin and are not generated by the impact of specific variables, such as indexes S&P 500, gold rate against the US dollar (XAU) and the Shanghai Stock exchange index (SSE). According to (Chu et.al., 2015) bitcoin's price fluctuations are best characterized by generalized hyperbolic distribution. (Bouoiyour and Selmi, 2015) is their current research investigated the variability of Bitcoin against the dollar in the period before and after the year 2015. They have found that despite the fact that the volatility of bitcoin in 2015 significantly decreased compared with the preceding period, still it cannot be said that the bitcoin can be regarded as mature currency.

3. Methodology

To analyze the relationship between given time series, we have used vector-autoregressive models formulated by Sims in 1980.The analysis of the relationship between time series is complex and complicated. Often, the dependent variables are modeled not only by a set of explanatory variables, but may also depend on their own historical observations and/or historical values of the independent variables. Vector-autoregressive models (VAR) allow for simultaneous analysis of this type of relationship. An important advantage of these models is the lack of restrictions concerning the division of variables into endogenous and exogenous. This model also allows to analyze the bidirectional relation, that is when two variables interact with each other. This property is used e.g. (Matuszewska and Witkowska, 2006) to examine the interdependence between the exchange rate EUR/USD and selected eight independent variables. VAR method is based on ARMA and GARCH models with all their generalizations and modifications. It is often use to model rates of return on various types of assets. ARMA allows the modeling of conditional mean, while the GARCH – conditional variance. In the literature, the combination of these two models to analyze the exchange rates applied, among others, (Nakatsuma and Tsurumi, 1999) (Quaicoe et.al., 2015), (Marreh et.al., 2014), (Doman and Doman, 2014), etc.

ARMA (p, q) process is a combination of two types of processes, ie. an autoregressive of order p – AR (p) and the moving average of order q – MA (q).

Following (Montgomery et.al., 2008), the autoregressive process of an order p, can be written the formula:

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t, \tag{1}$$

where: ε_t is a white noise; $\{\theta_1, \ldots, \theta_p\}$ – parameters.

The realization of a process at time *t* depends on p prior observations and the white noise at point *t*. If however the realization of a process at time *t* depends on q previous random terms, then such a process is a moving average of order q (Pesaran, 2015). Such dependency has the form:

$$y_t = \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \cdots + \alpha_q \varepsilon_{t-q} = \sum_{i=1}^{q} \alpha_i \varepsilon_{t-q}, \tag{2}$$

where: ε_t is a white noise; $\{\alpha_1, \ldots, \alpha_q\}$ – parameters.

The ARMA model is a combination of the autoregressive process of order p and a moving average process of order and can be written in the following form:

$$y_t = \delta + \sum_{i=1}^{p} \theta_i y_{t-i} + u_t + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}, \tag{3}$$

The ARCH models (Auto Regressive Conditional Heteroskedasticity) were introduced to the literature by Eagle in 1982. They are based on the assumption that variance of the process residuals is not constant over time. (Mandelbrot, 1963) has proven, that in particular the financial data are affected by the presence of outliers and volatility clustering, which impacts the distortion of the distribution of the exanimated variables.

ARCH models assume that the conditional variance of the error term at point t is dependent on the p previous error terms:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2, \tag{4}$$

where h_t – variance, ε_t – error term, $\{\alpha_1, \ldots, \alpha_q\}$ – parameters, α_0 – constant.

The generalization of the ARCH model, a GARCH models[2], was introduced in 1986 by Boleslev, and has a form:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2, \tag{5}$$

where: ε_t is a white noise; σ_t^2 – variance at time *t*; $\{\alpha_1, \ldots, \alpha_q\}$, $\{\beta_1, \ldots, \beta_q\}$ – parameters.

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[2] For further details considered applied models please refer to Hamilton (1994), Montgomery et.al. (2008) and Alberg et.al. (2008).

Vector autoregressive models can be applied to stationary time series. A time series is assumed to be strict stationarity, if the probability distribution function remains unchanged at each point of time, (Markellos & Mills, 2008):

$$f(x_{t1}, x_{t2}, \dots, x_{tn}) = f(x_{t1+h}, x_{t2+h}, \dots, x_{tn+h}) \tag{6}$$

The process can be described as stationary in a broader sense, if it has a constant mean and variance, and covariance of the observation depends solely on the distance between them. Formally this conditions are described as follows:

$$E(x_1) = E(x_2) = \cdots = E(x_T) = E(x_t) = \mu \tag{7}$$

$$V(x_1) = V(x_2) = \cdots = V(x_T) = V(x_t) = \sigma_x^2 \tag{8}$$

$$Cov(x_t, x_{t+h}) = \gamma_h \tag{9}$$

In order to investigate, whether a considered time series follows a stationary process, a Dickey Fuller test is applied, which verifies a presence of a unit root under the Null hypothesis ($H_0: \delta = 0$) versus an alternative hypothesis, which assumes process stationarity ($H_1: \delta < 0$).

4. Empirical Results

In our research we have taken into the consideration daily logarithmic rate of return for bitcoin to Polish zloty (rBTC/PLN) and compared it with the logarithmic rate of return for euro to zloty (rEUR/PLN), US Dollar to zloty (rUSD/PLN), British pound to zloty (rGBP/PLN) and Chinese Yuan to zloty (rCNY/PLN). The mentioned currencies were chosen based on the volume of transactions performed on bitcoin[3]. We analyzed the period from January 2014 to June 2016. The Data were collected from www.quandl.com and contained in total 641 full observations.

The assumption of stationarity was verified by the Dickey Fuller Unit Root test (DF). The test results presented in table 1, show that in all cases the DF test was able to reject the null hypothesis of appearance of a unit root, proving stationarity for all of included variables.

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[3] Following information Available via: bitcoinity.org, the majority of transactions in terms of volume was performed in yuan, which accounted for approx. 84% of all transactions. The US dollar covered approximately 13% of all transactions performed on bitcoin, euro ca. 1%, British pound ca. 0.3% and Polish zloty ca. 0.2%.

Table 1. Testing for the unit roots and stationarity results for the logarithmic rate of return for bitcoin to zloty (rBTC/PLN), euro to zloty (rEUR/PLN), dollar to zloty (rUSD/PLN), pound to zloty (rGBP/PLN), daily observations from the period Jan. 2014–June, 2016

Dickey-Fuller Unit Root Tests						
Variable	Zero Mean	p-Value	Single Mean	p-Value	Trend	p-Value
rBTC/PLN	−17.54	<.0001	−17.53	<.0001	−17.74	<.0001
rEUR/PLN	−16.68	<.0001	−16.68	<.0001	−16.68	<.0001
rUSD/PLN	−16.25	<.0001	−16.32	<.0001	−16.32	<.0001
rGBP/PLN	−15.73	<.0001	−15.75	<.0001	−15.75	<.0001
rCNY/PLN	−16.42	<.0001	−16.44	<.0001	−16.44	<.0001

Note: ADF computes a test statistic for the time series with a Zero Mean, a Single Mean, which includes a constant term and a Trend, which includes constant and a deterministic trend.

For the adopted order of the model p and q, selected by the smallest value of Corrected Akaike Inrofmation Criterion, ARMA model parameters were estimated and the results are presented in table 2. None of the lagged dependent variables were statistically significant in explaining dependency between bitcoin and other currencies. The p-Values are clearly above the 5% significance level. The results indicate, that no dependency exists between logarithmic rate of return of bitcoin to zloty and all other exchange rates in modeling conditional mean.

Table 2. Results for the significance test for the estimated ARMA(1,0) model for the BTC/PLN as an dependent variable

ARMA				
	rUSD/PLN	rEUR/PLN	rGBP/PLN	rCNY/PLN
Const	0.01410	0.02764	0.01374	0.02496
BTC/PLN (t−1)	0.04343	0.04758	0.04593	0.04629
rx/PLN (t−1)	0.19033	−0.50527	0.42876	−0.09269
P	rUSD/PLN	rEUR/PLN	rGBP/PLN	rCNY/PLN
Const	0.9321	0.8671	0.9337	0.8800
BTC/PLN (t−1)	0.04015	0.2360	0.2516	0.2502
rx/PLN (t−1)	0.26859	0.2721	0.1531	0.7314
std.err.	rUSD/PLN	rEUR/PLN	rGBP/PLN	rCNY/PLN
Const	0.16549	0.16506	0.16499	0.16532
BTC/PLN (t−1)	0.2798	0.04011	0.04003	0.04022
rx/PLN (t−1)	0.4788	0.45963	0.29974	0.26988

Note: BTC/PLN(t−1) is a lagged by one period BTC/PLN, rx/PLN(t−1) – lagged by one period independent variable, i.e. rUSD/PLN, rEUR/PLN, rGBP/PLN, rCNY/PLN.

We have applied the Lagrange multiplier test to detect the ARCH effects in residuals. The highly significant p-value (<.0001) points at rejection of the null hypothesis, what indicates the existence of autocorrelation in residuals. To model the conditional variance, we have estimated forty different

GARCH models. Based on the smallest value of the information criterion, we have chosen an exponential GARCH(1,1), as a model best fitted to the data. The results of a significance test, presented in table 3 show, that all EGARCH parameters are statistically significant. Moreover BTC/PLN logarithmic exchange rate is influenced by logarithmic exchange rate of USD/PLN, EUR/PLN and CNY/PLN.

Table 3. Results for the significance test for the estimated EGARCH(1,1) model for the BTC/PLN as an dependent variable

EGARCH				
	rUSD/PLN	rEUR/PLN	rGBP/PLN	rCNY/PLN
rx/PLN	0.4053	0.9990	–0.1348	0.3742
EARCH0	0.2423	0.2472	0.2528	0.2477
EARCH1	0.2958	0.2994	0.3057	0.2952
EGARCH1	0.9245	0.9225	0.9208	0.9224
THETA	–0.0668	–0.0609	–0.0563	–0.0633
Restrict	–10.1788		1.2521	–9.7345
P	rUSD/PLN	rEUR/PLN	rGBP/PLN	rCNY/PLN
rx/PLN	0.0406	0.0026	0.5392	0.0746
EARCH0	<.0001	<.0001	<.0001	<.0001
EARCH1	<.0001	<.0001	<.0001	<.0001
EGARCH1	<.0001	<.0001	<.0001	<.0001
THETA	0.2145	0.2570	0.3068	<.0001
Restrict	0.0210		0.7469	0.0301

Note: rx/PLN–independent variable, i.e. rUSD/PLN, rEUR/PLN, rGBP/PLN, rCNY/PLN.

To confirm the quality of the model fit we performed the BDS test (table 4) and stability of the parameters were verified by the Chow test (table 5).

Table 4. Results for the BDS test for the estimated EGARCH(1,1) model for the BTC/PLN as an dependent variable

BDS Test								
	EUR/PLN		USD/PLN		GBP/PLN		CNY/PLN	
Dimen-sion	BDS	Pr > |BDS|	BDS	Pr > |BDS|	BDS	Pr > |BDS|	BDS	Pr > |BDS|
2	0.7035	0.4817	0.7654	0.4440	0.6031	0.5465	0.8044	0.4211
3	0.3521	0.7247	0.4092	0.6824	0.2908	0.7712	0.4463	0.6554
4	0.4129	0.6797	0.5354	0.5924	0.3920	0.6951	0.5691	0.5693
5	0.5807	0.5614	0.7242	0.4690	0.5796	0.5622	0.7769	0.4372
6	0.7871	0.4312	0.9528	0.3407	0.7898	0.4297	1.0111	0.3120
7	0.9275	0.3537	1.0873	0.2769	0.9216	0.3568	1.1630	0.2448
8	0.9925	0.3210	1.1470	0.2514	0.9824	0.3259	1.2311	0.2183
9	0.9798	0.3272	1.1308	0.2582	0.9781	0.3280	1.2127	0.2252
10	0.8498	0.3954	0.9882	0.3231	0.8494	0.3956	1.0701	0.2846

Note: Test prints the results for the correlation between residuals up to 10 lags.

The results of BDS test indicate, that there exists no serial non-linear relationship between residual values, therefore it is assumed that all linear relationships have previously been removed from the model, what points at good model fit (Brabazon and O'Neill, 2008).

The results of the Chow test show that at the 5% significance level the test has failed to reject the null hypothesis, which assumes that the structural parameters of the estimated model are stable over time which provides a good fit to the data model.

Table 5. Results of the Chow testing the structural stability of the parameters

Chow Test		
Variable	F Value	Pr > F
rEUR/PLN	1.20	0.2733
rUSD/PLN	0.37	0.5415
rGBP/PLN	0.51	0.4765
rCNY/PLN	0.18	0.6714

The above generated results lead to the conclusion that in terms of conditional mean bitcoin to polish zloty may be consider as independent from the impact of dollar, euro, pound and yuan. In term of conditional variance bitcoin seems to be dependent from USD, EUR and CNY, therefore it cannot be said, that bitcoin is fully independent currencies.

Conclusions

One of the most important question which appear regarding bitcoin is its independency. This is one of its the main advantages, which is underlined strongly by its supporters. Our research has focused on the analysis of certain relationships between Bitcoin expressed in Polish Zloty and selected global currencies.

In terms of conditional mean, modelled by ARMA process, we can say that bitcoin is independent from the influence of all of analyzed currencies. However bitcoin's conditional variance, modelled by GARCH process, is influenced by the logarithmic rate of return of EUR, USD and CNY to PLN and is independent from GBP/PLN.

Additionally we have indicated exponential GARCH, as the most suitable to model bitcoin's conditional variance.

The results show that BTC/PLN is not fully independent from the external influences VC, thus it can be control by third party agents. Such feature can be used, for example, by speculators to achieve abnormal gains.

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Analiza zależności pomiędzy bitcoinem a wybranymi walutami

Z a r y s t r e ś c i. W badaniach staraliśmy się przeanalizować i określić zależność pomiędzy kursem bitcoina do polskiego złotego, a innymi czołowymi walutami, takimi jak dolar, euro, funt brytyjski i chiński Yuan. Waluty zostały wybrane w oparciu o wielkość wolumenu transakcji do bitcoina. Zastosowaliśmy modele ARMA do modelowania warunkowej średniej oraz modele GARCH do analizy warunkowej wariancji. Wyniki nie wykazały związku pomiędzy logarytmiczną stopą zwrotu z bitcoina do złotówki, a pozostałymi kursami walut w zakresie warunkowej średniej. Natomiast zastosowanie modeli GACH wykazało pewną zależność pomiędzy bitcoinem a innymi walutami, w kontekście modelowania warunkowej wariancji.

S ł o w a k l u c z o w e: ARMA, Bitcoin, GARCH, VAR, Zależność.