Master Thesis Financial Economics

A GARCH Model Approach and The Effect of Forks to Cryptocurrencies

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Abstract

This study examines the relation between Bitcoin and other popular coins in the Crypto-market, it shows that there is a relatively high correlation between them and that Crypto-market co-moves. Using the GARCH (1,1) model, the result shows that returns of these Cryptocurrencies in the previous period are not significant in forecasting the current period's returns of Bitcoin, indicating there is no arbitrage opportunity and that past volatility effects should be used when forecasting Bitcoin's volatility. In addition, this study observes the occurrence of forks in explaining the movement of both returns and volume of these Cryptocurrencies. This study discovered that the occurrence of forks explains the return of the Cryptocurrencies they are forked from to increase before the actual day of fork occurrence and will be followed with a decreased in returns days after these coins are forked. Whereas, trading volume for most of the Cryptocurrencies are proven to increase in the period of fork occurrences. This thesis is limited to the period of 1/3/17 until 3/12/18.

Keywords: Cryptocurrency, Bitcoin, Volatility, GARCH, Forks

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Abbreviations

ARCH	Autoregressive Conditional Heteroskedasticity
BTC	Bitcoin
CRIX	Cryptocurrency Index
DASH	Digital Cash
DOGE	Doge Coin
ETC	Ethereum Classic
ETH	Ethereum
GARCH	Generalized Auto-Regressive Conditional Heteroskedasticity
LTC	Litecoin
NEO	Neo Coin
NXT	Nxt
USD	U.S. dollar
XMR	Monero
XRP	Ripple

1. Introduction

Recently there has been a significant increase not only in the market capitalization of so-called Cryptocurrencies by more than 1,204% after starting out 2017 at $17.7 Billion, but also an increase in the public attention regarding these assets. The popularity of Cryptocurrencies is all thanks to the outstanding performance of Bitcoin in the recent years. Bitcoin, the most famous and earliest cryptocurrency, was initially introduced in a paper by Nakamoto (2008) and came into existence in 2009. Since then the market for cryptocurrencies has evolved dramatically. Even though Bitcoin has become more popular than ever, due to its rising price in the Crypto-market, investors are starting to invest their money on other coins in the market in the hope for those coins to have the same success or even more than Bitcoin.

While significant attention has focused on to the dramatic increase in the volume and price of cryptocurrencies, and many observers have highlighted their price volatility, there has not been a systematic analysis regarding price volatility of Bitcoin in in respect to the other popular coins in the market. In this thesis, I attempt to fill this gap. I have developed a GARCH-type modeling of the ten most popular Cryptocurrencies. These coins are Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Digital Cash (DASH), Monero (XMR), Nxt (NXT), Ethereum Classic (ETC), Doge (DOGE), Ripple (XRP), and Neo (NEO). The GARCH (1,1) model is used to analyze Bitcoin's volatility in respect to the other Cryptocurrencies and to see whether or not these other nine coins influence forecasting the current period's log returns of Bitcoin. Furthermore, I have also conducted a regression analysis with considering external factors that could influence the log returns and trading volumes of these coins, so-called forks.

The motivation behind this research thesis is that even though the topic Cryptocurrencies has become more popular than ever, the academic focus from an economic perspective has been rambling. Three reasons that may help explain this; First, is the relative obscurity of Cryptocurrencies to those outside of the computing and Cryptography community (Lee, 2013). Second, the amount and value of Cryptocurrencies created so far have been quite small compared to the size of the global economy (Velde, 2013). Lastly, many Cryptocurrencies active members of the community that run the mining of the coins and maintain the records of their transactions are incredibly skeptical of central banks entrusted with the management of fiat currencies. Instead, they prefer “hard” currencies that cannot be controlled and created at will by central banks, such as currencies tied to a commodity (Grinberg, 2011). Moreover, even though Cryptocurrency has frequently been criticized as a risky investment, the extremely speculative nature of this virtual money needs a more in-depth assessment to reach better paths.

The result of this thesis revealed that even though Crypto-market tend to move in tandem with the price movement of Bitcoin, none of the Cryptocurrencies being analyzed in the previous period are significant in forecasting the current period’s log returns of Bitcoin. In other words, Bitcoin’s returns are independent of the influence of all of the other Cryptocurrencies, and there is no arbitrage opportunity. Furthermore, the previous day’s return information of Bitcoin does affect today’s volatility of Bitcoin and also that the previous day’s volatility of Bitcoin does influence today’s volatility of Bitcoin, and past volatility effects are superior to past shock effects and therefore past volatility effects should be used when forecasting Bitcoin’s volatility. As the effect of fork occurrence in respect to excess price changes of Cryptocurrencies, the analysis revealed that fork occurrence is affecting the Cryptocurrencies where these forks are forked from, which are Bitcoin, Ethereum, Bitcoin Cash, and Litecoin. The occurrence of forks will drive the return of the Cryptocurrencies they are forked from to increase before the actual day of fork occurrence and will be followed with a decreased in returns days after these coins are forked. Whereas when analyzing the volume transaction, both three days before and after fork occurrence will lead to an increase in trading volume in most of the Cryptocurrencies even if they are not related to the forks.

The remainder of this paper is organized as follows. In the following section, Section 2, the theoretical framework and the hypothesis development is presented. Subsequently, in Section 3 the data is described. In Section 4 the GARCH (1,1) analysis and also the discussion of the result is presented. In Section 5 the analysis of the effect of forks followed by result discussion is presented. Finally, Section 6 concludes and discusses reflecting remarks.

2. Literature review and hypothesis development

Cryptocurrencies have only recently entered the economic and finance literature, so the field is wide open to study. There has been a growing amount of interest in the topic Cryptocurrencies over the years. Harvey (2014) draws out the origins of the blockchain technology, some of its economics, and identifies a variety of risks. Fink and Johann (2014) make use of publicly available pricing and exchange trade data to perform a variety of financial econometrics tests to characterize market microstructure. Gleizes and Zimmerman (2014) evaluate the revealed intentions of users to estimate whether they consider Bitcoin to be an alternative currency or a speculative asset and Hanley (2013) proposes that the value of Cryptocurrencies floats against other currencies as a pure market valuation with no fundamental value to support it. Furthermore, Woo et al. (2013) suggest that Cryptocurrencies may have some fair value due to its money-like characteristics as a medium of exchange and a store of value, but without any other fundamental basis. The analysis of Cryptocurrencies has recently received much attention. This can be attributed to its innovative features, simplicity, transparency and its rising popularity (Urquhart, 2016). The rise in popularity of Cryptocurrencies can be credited to the outstanding performance of Bitcoin in the recent years, while since its introduction it has posed significant challenges and opportunities for policymakers, economists, entrepreneurs, and consumers (Dyhrberg, 2016). Bitcoin is undoubtedly the most successful and perhaps most controversial Cryptocurrencies to date. In fact, as Bitcoin is mainly used as an asset rather than a currency (Glaser et al., 2014; Baek and Elbeck, 2015; Dyhrberg, 2016), the Bitcoin market is currently highly speculative, and more volatile and susceptible to speculative bubbles than other currencies (Grinberg, 2012; Cheah and Fry, 2015). Bitcoin has, therefore, a place in the financial markets and portfolio management (Dyhrberg, 2016), and examining its volatility is crucial. Moreover, the presence of long memory and persistent volatility justifies the application of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (Bariviera et al., 2017). There exists little work on the fitting of GARCH-type models to Bitcoin or Cryptocurrencies in general. Stavroyiannis and Babalos (2017) examined the dynamic properties of Bitcoin modeling through univariate and multivariate GARCH models and autoregressive vector specifications. Cermak (2017) used a GARCH (1, 1) to model Bitcoin's volatility concerning macroeconomic variables, in countries where Bitcoin is traded the most. Furthermore, Dyhrberg (2016) applied the asymmetric GARCH methodology to explore the hedging capabilities of Bitcoin and it was shown that Bitcoin could be used as a hedge against stocks in the Financial Times-Stock Exchange Index and against the American dollar in the short term.

While there is a wide range of research focusing on Bitcoin as an investment vehicle and linking Bitcoin to other assets (gold, fiat currencies, etc.), up until this point, there has been no academic research attempting to analyze the Crypto-market itself, especially how the other Cryptocurrencies is correlated to Bitcoin as the leading coin in this market. Thus, this is where this research paper fills in the gap. When compared to other Cryptocurrencies, which are also decentralized, anonymous and unregulated, Bitcoin's sole value lies in its network effect and a first mover advantage. Due to its decentralized nature, its price is strictly determined by supply and demand. One can argue that Bitcoin prices has an influence on the price changes of other coins in the Crypto-market or the other way around. Thus, the first hypothesis is:

H1: The Crypto-market co-moves with the change of Bitcoin price, therefore there is a high correlation of excess returns.

Furthermore, the Crypto-market is significantly more complicated than the public lexicon might suggest. Cryptocurrencies are entirely virtual and decentralized, meaning it is not issued by any government, bank or organization (Ron & Shamir, 2013). Every machine that mines Cryptocurrencies and processes transactions make up a part of the network and the machines work together, which means in theory, one central authority cannot interfere with monetary policy and cause a meltdown or decide to take people's bitcoins away from them. This decentralized nature characteristic of Cryptocurrencies leads to the occurrence of forks. Forks are created by agreement on the decentralized ledger where there is only one chain of blocks, observed by all and on which all agree (Biais et al., 2018). In general, when forks occurred in the blockchain, there would be competing branches, each registering a potentially different version of the ledger. Such forks could make the ledger less stable, reliable and useful, as they could create uncertainty about the distribution of property rights. In reality, which will be discussed later in the paper, there have been several forks, some of which have persisted until now. While the popularity of Cryptocurrencies in the academic field is rising, up until to this date there has been no academic research attempting to analyze on how these forks can affect the price volatility of Cryptocurrencies. Thus, this is where this research paper fills in the gap. Forks can either be planned and guided by the core development team of a project or be proposed by a group of developers dissatisfied with an element of an existing project (Goodman, 2014). In order for a fork to be successful, it is needed that developers believe in the new approach and recognize it. In this way, forks are open source and democratic. Forks are generally accepted as an element of the Cryptocurrency ecosystem that allows the community to assess and decide which ideas are most promising for their profitability. This open source governance means that no group has absolute control over the fate of a cryptocurrency project. The trading price of an asset or market entity has nothing to do with fork occurrence. While technically, a lot of the code and function will remain the same, it will have an impact on both short and long-term returns of coins. Owners of coins where to fork occurred will theoretically be holding double the number of tokens (one copy in each fork). This will drive up the demand of these coins and therefore increase the returns before the forks have occurred. Thus, the second hypothesis is:

H2: In the short run, the occurrence of forks generates a significant and positive return and volumes for coins that are associated with these forks.

3. Data

The data for this empirical analysis is obtained through building an API in Python to obtain daily Price (all in USD) data on all cryptocurrencies from a provider of data regarding this asset class, namely CoinCompare[1], which shows live prices, graphs and market analyzes of Crypto exchanges worldwide. The selection of the Cryptocurrencies for this research is selected from the rank provided by CoinMarketCap[2], which lists and ranks all major representatives of this asset class by providing a volume-per-exchange weighted market price, the market capitalization and the total

[1] https://www.cryptocompare.com/

[2] https://coinmarketcap.com/

trading volume itself. The volume-per-exchange weighted approach is determining an asset i's price by weighting an exchange j's volume VOL for this individual asset i during the last 24 hours relative to the overall volume for this asset over the last 24 hours on all major exchanges J which are charging fees, multiplied with its price. More formally,

$$Coinmarketcap\_Price_{i,t} = \sum_{j=1}^{j=J} \frac{VOL_{i,j,t-24hours}}{\sum_{j=1}^{j=J} VOL_{i,j,t-24hours}} * Price_{i,j,t} \tag{1}$$

I have selected top ten coins in the market based on CoinMarketCap's website, namely Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), DigitalCash (DASH), Monero (XMR), Ethereum Classic (ETC), Dogecoin (DOGE), Ripple (XRP), NeoCoin (NEO). Furthermore, due to the dynamic movement of the cryptocurrencies I have limit my research into the period of the last 360-days since 12th March 2018.

As a response variable, I am using the excess returns of the daily price of the coins during the period. Excess returns are investment returns from a security or portfolio that exceed the riskless rate on a security generally perceived to be risk free, such as a certificate of deposit or a government-issued bond. Additionally, the concept of excess returns may also be applied to returns that exceed a particular benchmark, or index with a similar level of risk. For this analysis, I have chosen CRIX index a market capitalization weighted index calculated by the Humboldt University Berlin (Trimborn and Haerdle, 2016) as the benchmark asset. More formally,

$$r_{Excess\ t,i} = r_{t,i} - r_{t,\ CRIX} \tag{2}$$

r_i and r_{crix} denotes the excess returns of the selected crypto assets and the returns of CRIX Index, respectively. Where, returns $r_{t,i}$ are defined as the first difference of the natural logarithm of the prices as seen in Equation (3) where $P_{t,i}$ is the price of individual asset i in USD at time t,

$$r_{t,i} = \ln\left(P_{t,i}\right) - \ln\left(P_{t,i-1}\right) \tag{3}$$

Table 3.1. Summary statistics and correlation matrix of the excess returns of the selected Cryptocurrencies for the period 1/3/17 to 3/12/18

Panel A. Descriptive statistic of excess returns of cryptocurrencies

	BTC Returns	ETH Returns	LTC Returns	DASH Returns	XMR Returns	NXT Returns	ETC Returns	DOGE Returns	XRP Returns	NEO Returns
Mean	0.0117	0.0134	0.0162	0.0104	0.0127	0.0138	0.0126	0.0137	0.0193	0.0117
Median	0.0205	0.0135	0.0145	0.0127	0.0125	0.0144	0.0084	0.0155	0.0076	0.0207
Std. Dev.	0.0994	0.1110	0.1205	0.1050	0.1182	0.1479	0.1243	0.1350	0.1503	0.0994
Min.	-0.4775	-0.4851	-0.5817	-0.5172	-0.5648	-0.6843	-0.6506	-0.6839	-0.6756	-0.4777
Max.	0.3834	0.3397	0.5564	0.3247	0.5161	0.5766	0.5815	0.5411	1.0759	0.3835
Count	360	360	360	360	360	360	360	360	360	360

Panel B. Sample correlation matrix of excess returns of cryptocurrencies

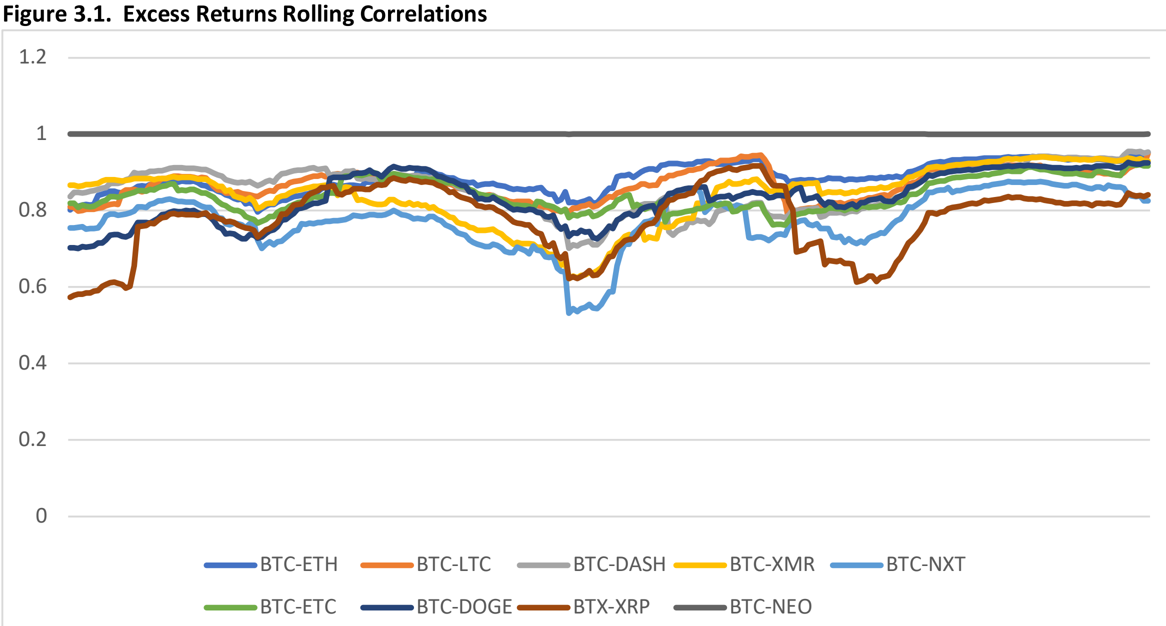
	BTC	ETH	LTC	DASH	XMR	NXT	ETC	DOGE	XRP	NEO
BTC	1									
ETH	0.82	1								
LTC	0.77	0.75	1							
DASH	0.78	0.8	0.72	1						
XMR	0.81	0.8	0.73	0.83	1					
NXT	0.73	0.67	0.64	0.67	0.69	1				
ETC	0.77	0.84	0.77	0.74	0.75	0.66	1			
DOGE	0.77	0.76	0.71	0.72	0.74	0.68	0.73	1		
XRP	0.59	0.59	0.59	0.53	0.61	0.53	0.56	0.69	1	
NEO	1	0.82	0.77	0.78	0.81	0.73	0.77	0.77	0.59	1

This table contains information on descriptive statistics (Panel A) and correlation matrix (Panel B) for excess returns of top ten most popular Cryptocurrencies.

Table 3.1. presents summary statistics for the returns over the period of 1/3/17 until 3/12/18. Panel A provides the descriptive statistics of the excess returns to Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), DigitalCash (DASH), Monero (XMR), Ethereum Classic (ETC), Dogecoin (DOGE), Ripple (XRP), and NeoCoin (NEO). Panel B shows the Pearson correlations from daily returns over 360-days. Correlation among assets is the degree to which they move in tandem. The values range between -1 and +1, where a value of -1 means that the returns move in opposite directions and a value of +1 means the returns move in the same direction. A value of zero denotes no (linear) dependence between the assets. The results from the chosen crypto assets mostly shows a strong positive relationship with Bitcoin movement, which can be interpret as; if Bitcoin increases other coins will follow this direction and the same goes if it decreases. In the last 360 days, Bitcoin are most correlated with NEC, XMR, and ETH, in that order.

Moreover, I have conducted rolling 90-day Pearson correlations of the excess return of Bitcoin (BTC) against Ethereum (ETH), Litecoin (LTC), DigitalCash (DASH), Monero (XMR), Ethereum Classic (ETC), Dogecoin (DOGE), Ripple (XRP), and NeoCoin (NEO) using excel. This is done by simply applying a correlation between Bitcoin (BTC) and the other Cryptocurrencies as a rolling window calculation. As shown in Figure 3.1, the correlations tend to move in tandem, in certain moments correlations between Bitcoin and the coins shows lower correlations than other moments. However, this is exceptional for NeoCoins, this is maybe can be caused by exponential growth of NeoCoins and Bitcoin, particularly in 2017. In 2017, bitcoin rose from having a price of around $1,000 per coin to having a price of almost $20,000 per coin in December 2017. NEO rose from having a price of just a few cents in 2017 to having a price of over $100 by the start of 2018.

Figure 3.1. Excess Returns Rolling Correlations



4. GARCH (1,1) Model Analysis

4.1. Methodology

Before estimating the GARCH (1,1) model, the statistical properties of the mean equation are investigated. The two preconditions that must be met in order to estimate the GARCH (1,1) model are clustering volatility and ARCH effect in the residual.

Figure 4.1.1 shows the results of the test of clustering volatility in the residuals. Periods of low volatility of the error term are followed by the periods of low volatility and vice versa. This indicates that large returns are followed by large returns, and small returns are followed by small returns. This phenomenon is called clustering volatility, which means that the residual is conditionally heteroskedastic. Therefore, the first precondition is met.

Moving to the second precondition, whether there is an ARCH effect in the residual. An ARCH effect determines whether there is a serial correlation of the heteroskedasticity. In order to determine whether there is an ARCH effect, I have conducted an LM ARCH test. The null hypothesis in this test is that there is no ARCH effect and the alternative hypothesis is the opposite. The results of the test can be seen in Table 4.1.1., the LM test for ARCH provides evidence that there is an ARCH effect in the mean equation because we can reject the null hypothesis (0%).

Table 4.1.1. ALM test for ARCH

lags(p)	chi2	df	Prob>chi2
1	3.0E+07	1	0.0000

4.2. Results

Table 4.2.1. GARCH (1,1) dependent variable return on bitcoin

Variable	Mean Equation		Variance Equation	
	Coefficient	Std. Error	Coefficient	Std. Error
ETH	0.0001524	(0.00024860)	-0.0003349	(0.00063980)**
LTC	-0.0000108	(0.00019410)	-0.0003912	(0.00036960)***
DASH	-0.0001536	(0.00021360)	-0.0005723	(0.00026510)***

XMR	0.0000321	(0.00018170)	-0.000324	(0.00038810)**
NXT	-0.0000241	(0.00012170)	-0.0002627	(0.00021440)***
ETC	-0.0000314	(0.00020150)	-0.0004264	(0.00036350)***
DOGE	-0.000024	(0.00020990)	-0.0004353	(0.00038730)***
XRP	0.0000166	(0.00015870)	-0.0002944	(0.00032750)***
NEO	0.9995108	(0.00026610)	0.9989893	(1.00003200)*
L.ar	0.3906353	(0.11994600)		
L.arch α			0.1555455	(0.62572510)***
L.arch β			3.26	(0.00100000)***
Constant	-0.00000469	(0.00000961)**	-0.0000235	(0.00001420)***

This table presents the result of the GARCH (1,1) model analysis where excess return of Bitcoin is the dependent variable. Reported in parentheses standard errors that are adjusted for heteroskedasticity. *, **, and *** indicate 5%, 1%, and 0.1% significance levels, respectively.

The table 4.2.1. represent the result of the GARCH (1,1) analysis using Bitcoin's excess return in respect to the other top ten Cryptocurrencies in the period of 1/3/17 until 3/12/18. In the mean equation, most of the explanatory variables are statistically insignificant, which is an expected outcome. All of the explanatory variables are lagged by one period, which indicates that if the variables were statistically significant, it could present an opportunity for arbitrage. Therefore, we can conclude that none of the explanatory variables in the previous period are significant in forecasting the current period's log returns of Bitcoin. In other words, Bitcoin's returns are independent of the influence of all of the analyzed explanatory variables, and there is no arbitrage opportunity. In the variance equation, both ARCH (α) and GARCH (β) terms are statistically significant, which means that the previous day's return information of Bitcoin does affect today's volatility of Bitcoin (ARCH) and also that the previous day's volatility of Bitcoin does influence today's volatility of Bitcoin (GARCH). Also, it is also important to note that due to β being greater than α, past volatility effects are superior to past shock effects and that past volatility effects should be used when forecasting Bitcoin's volatility. In contrast with the mean equation, all of the explanatory variables are significant in explaining the volatility of Bitcoin. The estimated conditional variance of daily Bitcoin log-returns can be seen in Figure 4.2.1.

5. Effects of Forks

5.1 Methodology

In order to analyze the effects of forks, I have collected the forks that occurred during this research period. Most of the fork occurred from Bitcoin and some other from Ethereum, Bitcoin Cash, and Litecoin. The date, fork names and also where the forks are forked from can be seen in table 5.1.1.

Table 5.1.1.

Date	Fork Name	Forked from
8/1/17	Bitcoin Clashic	Bitcoin
8/1/17	Bytether	Bitcoin
8/1/17	Oil BTC	Bitcoin
10/10/17	Bitcoin Gold	Bitcoin
11/2/17	Bitcore	Bitcoin
11/24/17	Bitcoin Diamond	Bitcoin
12/1/17	Bitcoin Nano	Bitcoin
12/1/17	Bitcoin Silver	Bitcoin
12/12/17	Bitcoin Hot	Bitcoin
12/12/17	BitcoinX	Bitcoin
12/12/17	Super Bitcoin	Bitcoin
12/12/17	UnitedBitcoin	Bitcoin
12/14/17	EtherGold	Ethereum
12/15/17	Ethereum Modification	Ethereum
12/17/17	Bitcoin World	Bitcoin
12/19/17	Bitcoin Faith	Bitcoin
12/19/17	Bitcoin Stake	Bitcoin
12/19/17	Lightning Bitcoin	Bitcoin
12/25/17	Bitcoin New	Bitcoin
12/26/17	Bitcoin Top	Bitcoin
12/27/17	Bitcoin File	Bitcoin
12/27/17	Bitcoin God	Bitcoin
12/28/17	Bitcoin SegWit2X x11	Bitcoin
12/28/17	Quantum Bitcoin	Bitcoin
12/31/17	Bitcoin Ore	Bitcoin
12/31/17	Bitcoin Uranium	Bitcoin
12/31/17	BitcoinBoy	Bitcoin
1/1/18	Bitcoin All	Bitcoin
1/1/18	Bitcoin Pizza	Bitcoin
1/1/18	Bitcoin Private	Bitcoin
1/1/18	EthereumFog	Ethereum

1/10/18	Bitcoin Rhodium	Bitcoin
1/13/18	Bitcoin Candy	Bitcoin Cash
1/17/18	Super Litecoin	Litecoin
1/19/18	EtherZero	Ethereum
1/21/18	BitVote	Bitcoin
1/21/18	Bitcoin Smart	Bitcoin
1/22/18	Bitcoin Interest	Bitcoin
1/30/18	Bitcoin Atom	Bitcoin
1/30/18	Bitcoin Lite	Bitcoin
2/18/18	Litecoin Cash	Litecoin

This table presents the list of the forks that occurred in the period of 1/3/17 to 3/12/18.

The relation between forks and the top ten Cryptocurrencies' excess return can be written as:

$$r_{Excess\ t,i} = \beta_0 + \delta forks_{t-3} + \delta forks_{t-2} + \delta forks_{t-1} + \delta forks_t + \delta forks_{t+1} + \delta forks_{t+2} + \delta forks_{t+3} + u_{t,i} \tag{4}$$

Whereas, the relation between forks and the top 10 crypto asset's volumes can be written as:

$$Volume_{t,i} = \beta_0 + \delta_1 * forks_{t-3} + \delta_2 * forks_{t-2} + \delta_3 * forks_{t-1} + \delta_4 * forks_t + \delta_5 * forks_{t+1} + \delta_6 * forks_{t+2} + \delta_7 * forks_{t+3} + u_{t,i} \tag{5}$$

Where $\delta Forks$ are the dummy variables that represents the occurrence of forks during the research period, where fork[t]=1 if fork occurred in period t and fork[t]=0 otherwise. In addition, I also looked at 3 days before and after the fork occurred and added this as the lagged dummy variables. $u_{i,t}$ is the error term. I use multivariate regressions to estimate the model in Equation (4) and (5).

5.2. Results

Shown in Table 5.2.1. is the result when the dependent variable is the excess returns of the Cryptocurrencies, here present the regression analyses in which the days in the fork occurrence period is separated. The effect of forks on Bitcoin's excess returns is positive and statistically significant at the 5% level for three days before the fork occurred, which implies that an occurrence of forks leads to an increase in Bitcoin's excess return by 3.05%, 0.52%, and 0.70%, respectively for these three days. The effect of forks on excess returns is negative and statistically significant at the 5% level for the actual day the fork occurred and the following three days the fork occurred. This negative relation implies that the day of a fork occurrence leads to a decrease of 0.49% in Bitcoin's excess return and a decrease of 0.64%, 1.48%, and 2.17% in Bitcoin's excess returns for the following three days of a fork occurrence.

As for Ethereum's excess returns, the effect of fork occurrence is positive and statistically significant at the 0.1% level for three days before, the day the fork occurred and also the day after a fork has occurred. This implies the occurrence of forks leads to an increase in the excess return of Ethereum by 1.20%, 0.44%, and 0.97%, respectively for three days before a fork occurred. The actual day of a fork occurrence leads to an increase of 2.48% for Ethereum's excess return and an increase of 0.04% the day after. The effect of fork occurrence is negative and statistically significant at the 0.1% level for two days after an occurrence of forks, which implies a decrease in Ethereum's excess return by 0.65% for two days after the occurrence of forks and 1.31% for three days after the occurrence of forks.

The effect of forks on Litecoin's excess returns is positive and statistically significant at the 0.1% level for three days before an occurrence of forks and also the day of the forks occurred, which implies that an occurrence of forks leads to an increase in Litecoin's excess return by 0.41%, 0.26%, and 1.81%, respectively for three days before forks occurred and as for the actual day a fork occurred leads to an increase in Litecoin's excess return by 4.90%. The effect of forks on excess returns is negative and statistically significant at the 0.1% level for the following three days the fork occurred. This negative relation implies that the day of a fork occurrence leads to a decrease of 0.25%, 1.25%, and 3.13% in Litecoin's excess returns for the following three days of a fork occurrence.

Moreover, the effect of forks on DigitalCash's excess returns is positive and statistically significant at the 5% level for three days before, the day the fork occurred and also the day after a fork has occurred. This implies the occurrence of forks leads to an increase in the excess return of DigitalCash 2.12%, 0.45%, and 0.30%, respectively for three days before a fork occurred. The actual day of a fork occurrence leads to an increase of 1.58% for Ethereum's excess return and an increase of 0.98% the day after. The effect of fork occurrence is negative and statistically significant at the 5% level for two days after an occurrence of forks, which implies a decrease in DigitalCash's excess return by 0.24% for two days after the occurrence of forks and 0.94% for three days after the occurrence of forks. As for the other Cryptocurrencies; Monero, Ethereum Classic, Dogecoin, Ripple, and NeoCoin, I do not find a significant result when analyzing the effect of forks occurrence on excess returns of these coins. This indicates that the occurrences of forks do not explain the change in excess returns for the coins that are not related to these forks.

Table 5.2.2. presents the result when the dependent variable is the volume of the Cryptocurrencies. In contrast with the excess return, the effect of the occurrences of forks to the Volume of the analyzed Cryptocurrencies is positive and statistically significant at the 0.1% level for Bitcoin, Ethereum, Litecoin, Digital Cash, Monero, Ethereum Classic, Dogecoin, and Ripple This implies, forks occurrence leads to an increase in transaction volume for these coins both three days before and after the fork occurrence.

To conclude from the two analyses above, the occurrences of forks do not explain the change in excess returns for the coins that are not related to these forks when analyzing the daily excess return in the occurrence of forks period. The occurrences of forks only explain the changes in excess daily return for Bitcoin, Ethereum, Litecoin, and DigitalCash, which are all where the forks are forked from. Whereas, the occurrence of forks will drive up the volume transaction of the Cryptocurrencies even if they are not related to these forks.

6. Conclusion and Discussions

Bitcoin is the leading Cryptocurrencies regarding market cap, volume, and general popularity. Thus, one can state that Bitcoin is the center of the Crypto-economy and has some importance to it. When analyzing the correlation of Bitcoin to the other popular Cryptocurrencies in the market, the correlations are relatively high, and these correlations mostly move in tandem, this indicates that the Crypto-market co-moves. There is more than one sole reason behind understanding why other Cryptocurrencies follow the movement of Bitcoin, one to name a few is that the fact that every major exchange offers Bitcoin trading pairs, where one can trade Bitcoin for other coins in the Crypto-market rather than these for fiat or USD. Another potential reason is it is hard to come up with a fundamental algorithm with which to price coins, so coin prices follow Bitcoin as a sort of benchmark. The bottom line is that Bitcoin can, for a myriad of reasons, lift up the other Cryptocurrencies in the market, suppress them, or even depress these coins.

When analyzing the forecasting ability of the other Cryptocurrencies in respect to Bitcoin's return, none of the log returns of these Cryptocurrencies in the previous period are significant in forecasting the current period's log returns of Bitcoin, which implies that Bitcoin's returns are independent of the influence of other popular Cryptocurrencies. Moreover, the result shows that both previous day's return information of Bitcoin and also that the previous day's volatility of Bitcoin does affect today's volatility of Bitcoin. Additionally, past volatility effects are superior to past shock effects. Therefore, when forecasting Bitcoin's volatility, one should use the past volatility effects.

Furthermore, in order to see the effect of fork occurrence to excess returns, I had chosen the period of the occurrence of forks as three days before and after and the actual day the fork occurred. Based on this analysis, this research has pointed out that fork occurrence is affecting the Cryptocurrencies these forks are forked from, which are Bitcoin, Ethereum, Bitcoin Cash, and Litecoin. The occurrence of forks will drive the return of the Cryptocurrencies they are forked from to increase before the actual day of fork occurrence and will be followed with a decreased in returns days after these coins are forked. Whereas for the trading volume of these Cryptocurrencies, the occurrence of forks has led the volume to increase both three days before and after a fork occurrence. This could indicate the return of Cryptocurrencies that are related to forks will increase in value when news of forks is announced. This can potentially be explained by investor's investing behavior, as the value of holders of the coins where forks take place are automatically given the same number of new tokens when the fork takes place. Thus, will lead investors purchasing some of the cryptocurrency before the fork takes place in anticipation of making a speculative profit. However, in order to prove this, there needs to be more in-depth research regarding the investor's behavior regarding the effects of forks and how it influences their investment decisions.

When the results are interpreted, one has to put into account that selecting the assets based on their popularity potentially creates a selection bias, the other Cryptocurrencies which can be related to Bitcoin are probably excluded from the analysis due to the data selection process. Thus, suggesting further research to expand the range of Cryptocurrencies and also the sample period. Furthermore, while forks have shown a significant driver to Cryptocurrencies' return, I believe this is not the only explanation for the change in returns both in the short-run and in the long run. Therefore, I suggest considering other factors, such as psychological factors of an investor, which analyze how investors process decisions, whether based on the behavior of other market participants and their intuitions. Political factors are also important to notice. For instance, the pound started plummeting around May 20, 2016, by July 25 it was more than 10% below its pre-Brexit value and for the same period the price of Bitcoin increased by over 65%. Lastly, I would suggest looking at regulatory factors. For example, China's decision to shut down several Bitcoin exchanges and ban initial coin offerings sent the price of Bitcoin to plummet by 29% in 24 hours. In general, further analysis of Cryptocurrencies and their price drivers is necessary to evaluate. While assuming that Cryptocurrencies will grow in the future, the data availability and the information regarding the Crypto-market will become more professional, and I want to close by highlighting that this analysis of Cryptocurrencies provide researchers a unique opportunity to witness a new asset class growing.

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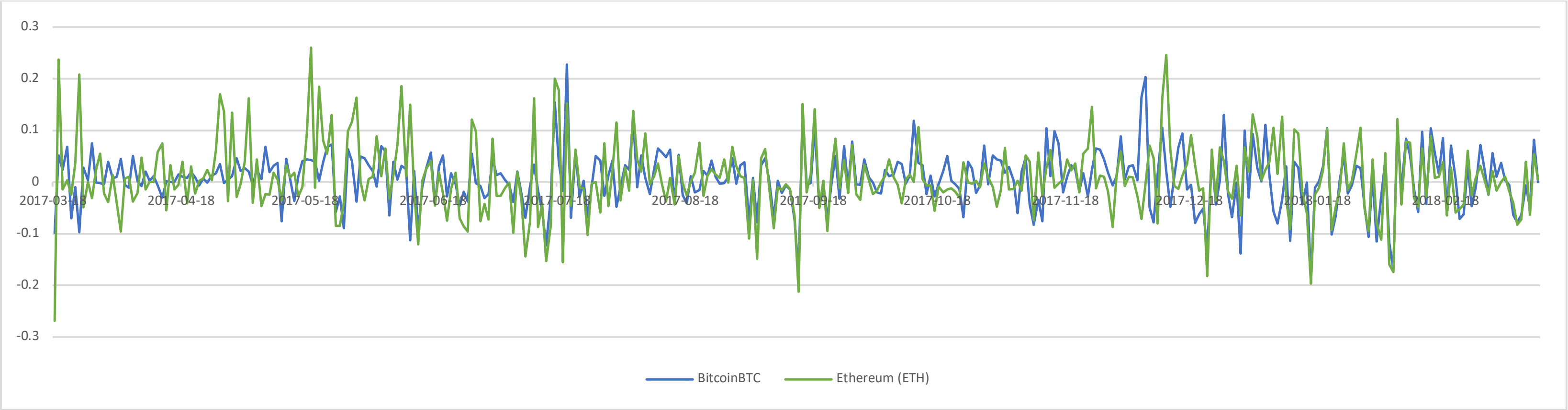
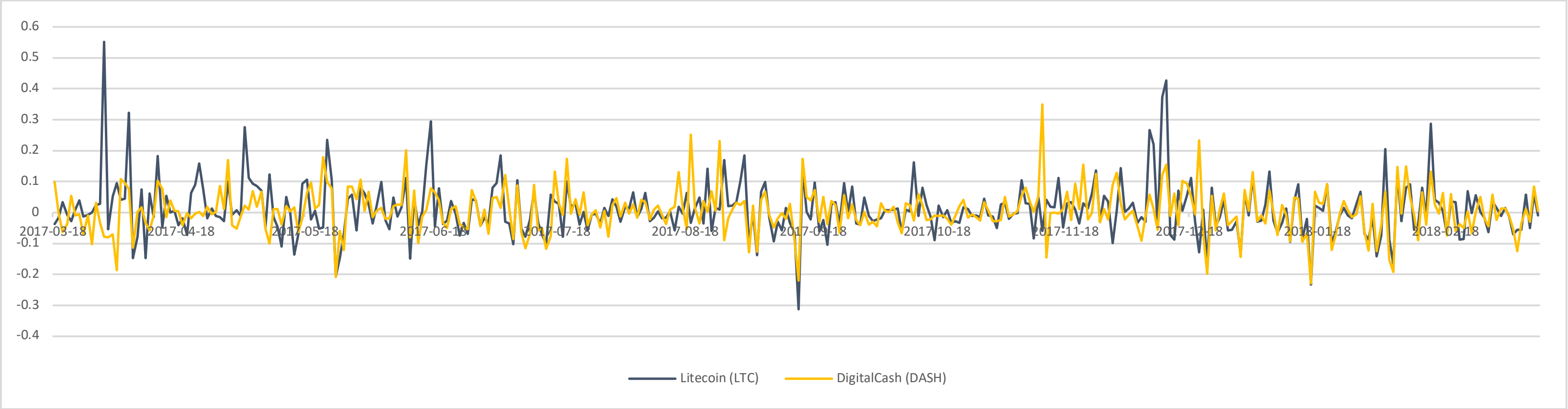
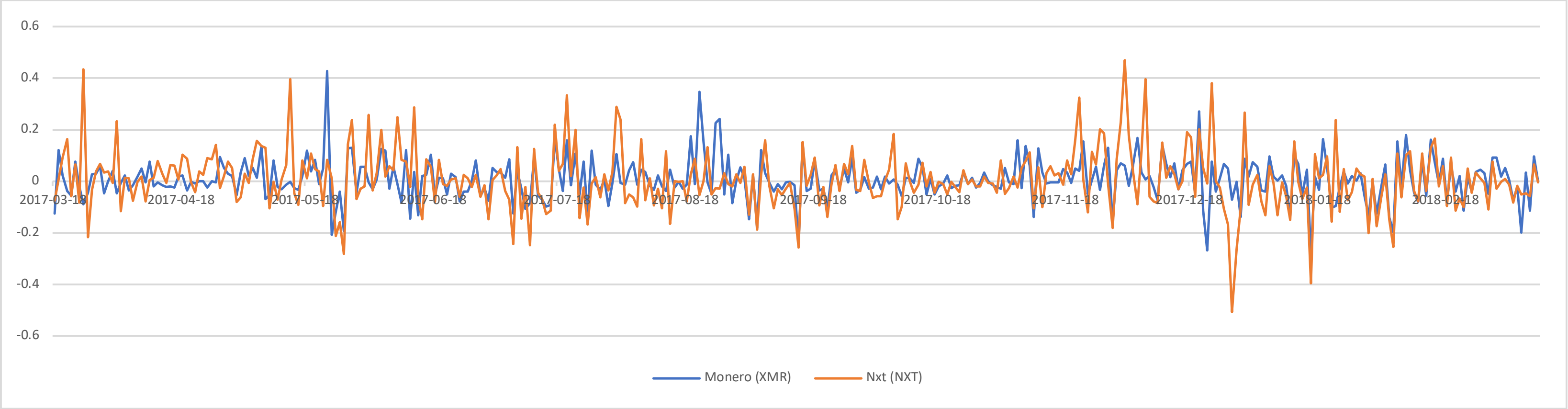
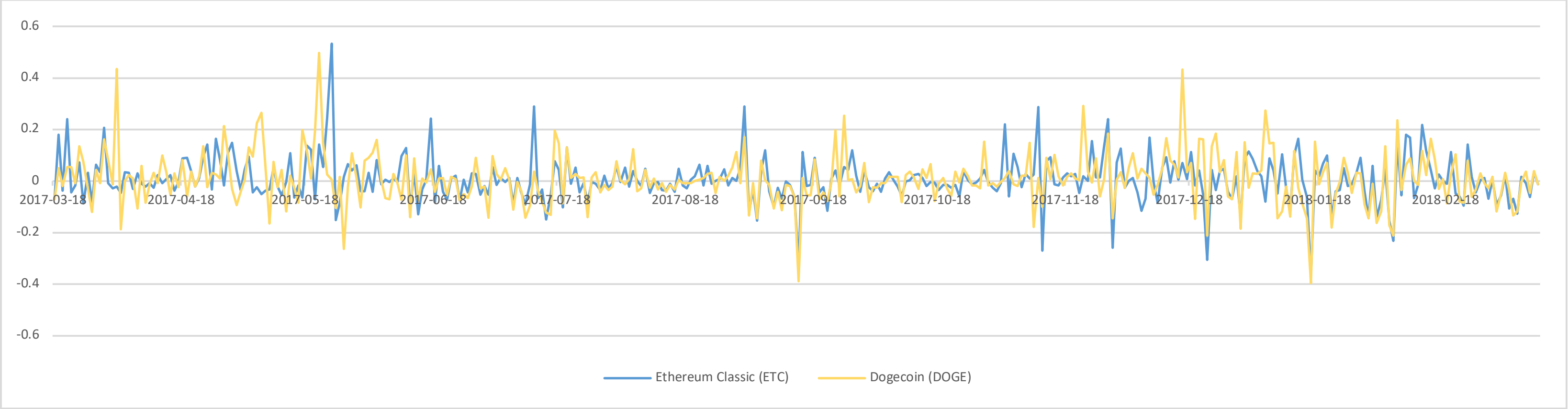
Appendix

Figure 4.1.1. Volatility clustering in daily log return of selected coins in the last 360-days.






0.6
0.4
0.2
0
-0.2
-0.4
-0.6
2017-03-18
2017-04-18
2017-05-18
2017-06-18
2017-07-18
2017-08-18
2017-09-18
2017-10-18
2017-11-18
2017-12-18
2018-01-18
2018-02-18
Monero (XMR)
Nxt (NXT)


0.6
0.4
0.2
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-0.2
-0.4
-0.6
2017-03-18
2017-04-18
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2017-07-18
2017-08-18
2017-09-18
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2017-11-18
2017-12-18
2018-01-18
2018-02-18
Ethereum Classic (ETC)
Dogecoin (DOGE)

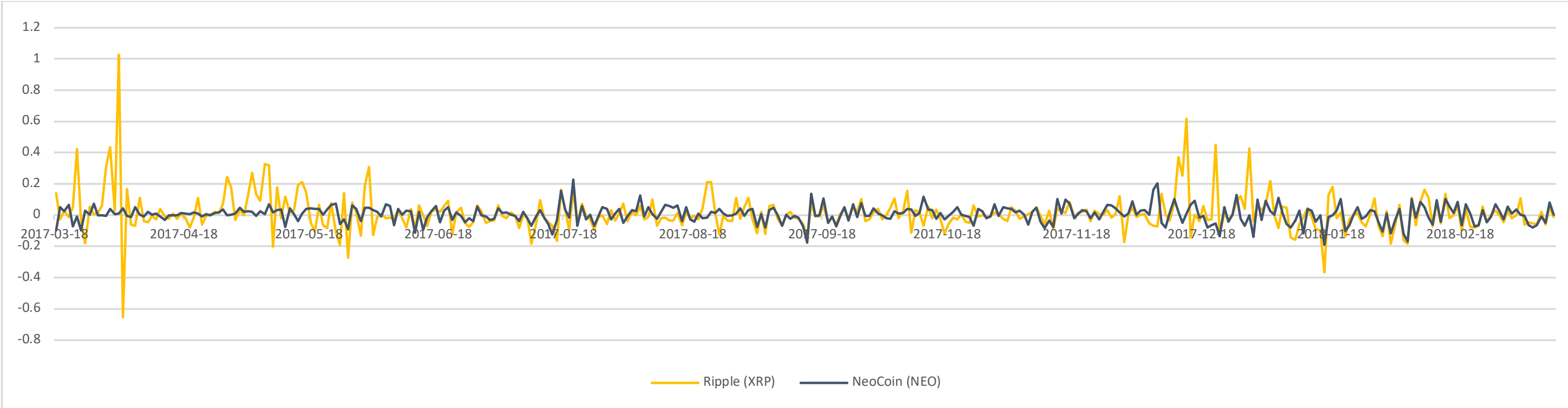

Figure 4.2.1. Conditional variance of daily Bitcoin log-returns

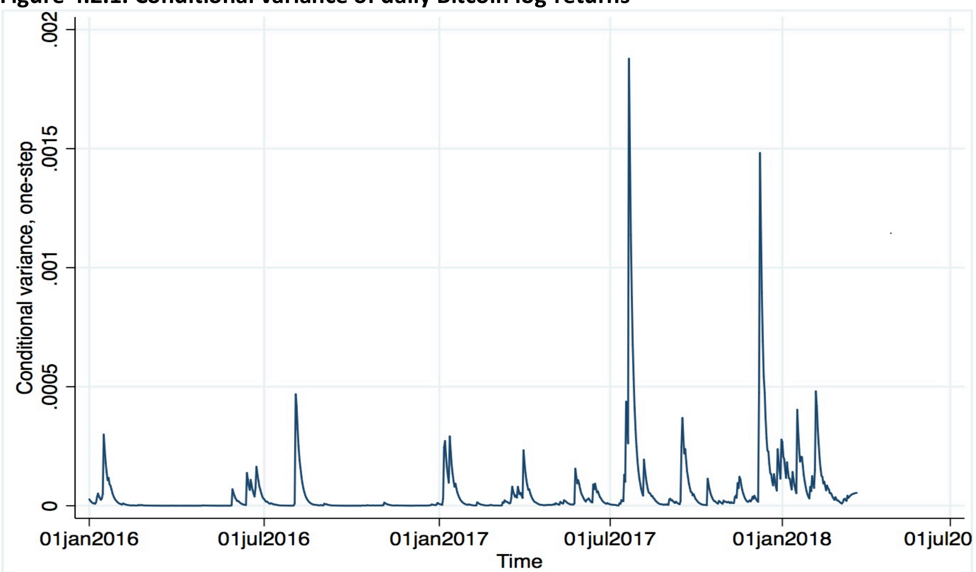

Table 5.2.1. regression of fork effects on excess returns.

Variable	N	Parameters	R^2	R^2 Adjusted
BTC Excess Returns	360	8	0.8%	10.0%
ETH Excess Returns	360	8	0.5%	11.2%
LTC Excess Returns	360	8	1.4%	12.1%
DASH Excess Returns	360	8	0.4%	10.6%
XMR Excess Returns	360	8	0.3%	11.9%
NXT Excess Returns	360	8	0.8%	14.9%
ETC Excess Returns	360	8	0.9%	12.5%
DOGE Excess Returns	360	8	0.4%	13.6%
XRP Excess Returns	360	8	1.1%	15.1%
NEO Excess Returns	360	8	0.8%	10.0%

	t-1	*t-2*	*t-3*	*t*	*t+1*	*t+2*	*t+3*	*Constant*
BTC Excess Returns	0.0305*	0.0052*	0.0070*	-0.0049*	-0.0064*	-0.0148*	-0.0217*	0.0126*
	(0.0225)	(0.0226)	(0.0228)	(0.0219)	(0.0231)	(0.0230)	(0.0227)	(0.0058)
ETH Excess Returns	0.0120***	0.0044***	0.0097***	0.0248***	0.0004***	-0.0065***	-0.0131***	0.0118***
	(0.0252)	(0.0252)	(0.0255)	(0.0245)	(0.0259)	(0.0257)	(0.0253)	(0.0065)
LTC Excess Returns	0.0041***	0.0026***	0.0181***	0.0490***	-0.0025***	-0.0125***	-0.0313***	0.0168***
	(0.0273)	(0.0273)	(0.0276)	(0.0265)	(0.0280)	(0.0278)	(0.0274)	(0.0071)

DASH Excess Returns	0.0212*	0.0045*	0.0030*	0.0158*	0.0096*	-0.0024*	-0.0097*	0.0102*
	(0.0239)	(0.0239)	(0.0242)	(0.0232)	(0.0245)	(0.0243)	(0.0240)	(0.0062)
XMR Excess Returns	0.019	0.0032	0.0009	0.0162	-0.0022	-0.0091	0.0003	0.0126
	(0.0269)	(0.0269)	(0.0272)	(0.0261)	(0.0276)	(0.0274)	(0.0270)	(0.0070)
NXT Excess Returns	0.0172	0.0187	0.0032	0.0232	-0.0041	-0.0406	-0.0111	0.0178
	(0.0336)	(0.0336)	(0.0340)	(0.0326)	(0.0344)	(0.0342)	(0.0337)	(0.0087)
ETC Excess Returns	0.0258	0.0207	0.0053	-0.0322	-0.027	-0.0043	-0.0094	0.0128
	(0.0282)	(0.0282)	(0.0285)	(0.0274)	(0.0289)	(0.0287)	(0.0283)	(0.0073)
DOGE Excess Returns	0.0147	0.0203	0.0039	-0.0094	0.0146	0.0085	-0.0197	0.0122
	(0.0307)	(0.0307)	(0.0311)	(0.0298)	(0.0315)	(0.0313)	(0.0309)	(0.0080)
XRP Excess Returns	0.0172	0.0102	0.0009	-0.0222	0.0271	0.0299	-0.0332	0.0143
	(0.0341)	(0.0341)	(0.0345)	(0.0330)	(0.0349)	(0.0347)	(0.0342)	(0.0088)
NEO Excess Returns	0.0305	0.0052	0.007	-0.0049	-0.0064	0.0149	-0.0217	0.0126
	(0.0226)	(0.0226)	(0.0228)	(0.0219)	(0.0231)	(0.0230)	(0.0227)	(0.0058)

This table presents the result of the regression analysis on excess returns of top ten most popular Cryptocurrencies are all calculated from 1/3/17 to 3/12/18 and regressed against three days before and after fork occurrence. Fork occurrence is a dummy variable equal to one if fork occurred on that period, and zero otherwise. Reported in parentheses standard errors that are adjusted for heteroskedasticity. *, **, and *** indicate 5%, 1%, and 0.1% significance levels, respectively.

Table 5.2.2. regression of fork effects on volumes.

Variable	N	Parameters	R^2	R^2 Adjusted				
BTC Volume	360	8	31.90%	41.10%				
ETH Volume	360	8	31.90%	41.60%				
LTC Volume	360	8	29.99%	40.69%				
DASH Volume	360	8	25.34%	15.54%				
XMR Volume	360	8	24.32%	15.92%				
NXT Volume	360	8	37.84%	21.94%				
ETC Volume	360	8	21.71%	33.31%				
DOGE Volume	360	8	31.74%	24.94%				
XRP Volume	360	8	36.90%	29.90%				
NEC Volume	360	8	0.06%	1.26%				
	t-1	***t-2***	***t-3***	***t***	***t+1***	***t+2***	***t+3***	***Constant***
BTC Volume	698,000,000***	530,000,000***	404,000,000***	541,000,000***	285,000,000***	272,000,000***	686,000,000***	568,000,000***
	(161,000,000)	(161,000,000)	(163,000,000)	(156,000,000)	(165,000,000)	(164,000,000)	(162,000,000)	(41,600,000)
ETH Volume	698,000,000***	530,000,000***	404,000,000***	541,000,000***	285,000,000***	272,000,000***	686,000,000***	568,000,000***
	(161,000,000)	(161,000,000)	(163,000,000)	(156,000,000)	(165,000,000)	(164,000,000)	(162,000,000)	(41,600,000)
LTC Volume	194,000,000***	135,000,000***	49,100,000***	143,000,000***	36,900,000***	5,160,976***	77,500,000***	77,000,000***
	(34,200,000)	(34,200,000)	(34,600,000)	(33,200,000)	(35,100,000)	(34,800,000)	(34,400,000)	(8,869,465)

DASH Volume	13,200,000***	12,600,000***	6,843,620***	4,226,561***	603,144***	3,379,782***	13,100,000***	9,785,196***
	(3,070,802)	(3,071,313)	(3,107,744)	(2,979,899)	(3,148,514)	(3,127,025)	(3,086,758)	(795,854)
XMR Volume	12,300,000***	10,800,000***	7,626,899***	6,958,794***	1,836,054***	5,573,527***	10,300,000***	9,952,659***
	(3,171,438)	(3,171,966)	(3,209,591)	(3,077,556)	(3,251,698)	(3,229,504)	(3,187,917)	(821,935)
NXT Volume	3,949,776***	1,966,627***	1,815,717***	2,544,594***	3,148,113***	2,577,812***	4,396,749***	1,261,580***
	(831,214)	(831,353)	(841,214)	(806,608)	(852,250)	(846,433)	(835,533)	(215,424)
ETC Volume	25,400,000***	4,716,113***	7,508,305***	8,534,071***	17,300,000***	6,696,295***	16,700,000***	16,700,000***
	(5,415,941)	(5,416,842)	(5,481,095)	(5,255,616)	(5,553,002)	(5,515,101)	(5,444,082)	(1,403,639)
DOGE Volume	568,024***	493,312***	333,468***	246,025***	316,229***	363,124***	462,339***	334,930***
	(129,288)	(129,309)	(130,843)	(125,461)	(132,560)	(131,655)	(129,960)	(33,507)
XRP Volume	145,000,000***	137,000,000***	118,000,000***	1,302,238***	77,100,000***	161,000,000***	253,000,000***	35,000,000***
	(37,600,000)	(37,700,000)	(38,100,000)	(36,500,000)	(38,600,000)	(38,300,000)	(37,800,000)	(9,756,209)
NEC Volume	-0.0079	-0.0069	-0.0061	-0.0063	-0.0063	-0.0067	-0.0083	0.0172
	(0.0604)	(0.0604)	(0.0611)	(0.0586)	(0.0619)	(0.0615)	(0.0607)	(0.0156)

This table presents the result of the regression analysis on volume of top ten most popular Cryptocurrencies are all calculated from 1/3/17 to 3/12/18 and regressed against three days before and after fork occurrence. Fork occurrence is a dummy variable equal to one if fork occurred on that period, and zero otherwise. Reported in parentheses standard errors that are adjusted for heteroskedasticity. *, **, and *** indicate 5%, 1%, and 0.1% significance levels, respectively.