Price Dynamics and Structural Breaks in Speculative Markets: A Case Study of Cryptocurrency

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Outline

Introduction

Information About Cryptocurrency Markets

- A novel idea by Nakamoto (2008): Bitcoin, the first cryptocurrency
  - Decentralized digital currency designed to work as medium of exchange
  - Peer–to–peer network secured by a system of cryptographic hashes
  - No third–party intervention
  - Significantly lower transaction costs
  - Decentralized and fully distributed public ledger, called blockchain
  - Mining process for the security and integrity of the blockchain
- Alternative digital currencies, called altcoins
- Unprecedented growth over the last few years
- As of July 2017, more than 980 cryptocurrencies exist with a total market capitalization of approximately $89 billion (CoinMarketCap, 2017).

See the Figure

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- In October 2008, a programmer under the pseudonym Satoshi Nakamoto came up with a novel idea: a decentralized digital currency that can be transferred online via a peer–to–peer network with significantly lower transaction costs (Nakamoto, 2008).
- The decentralized feature of the currency allows its users to interact with one another anonymously and without a third–party intervention.
- In essence, this feature is the Nakamoto's response to the global financial system as well as to the role of third–party institutions in mediating financial transactions.
- In January 2009, Satoshi launched the network and the first units of the digital currency, known as *Bitcoin*.
- Cryptocurrencies have become very popular with the emergence of Bitcoin and have shown an unprecedented growth over the last few years.
- By using the advantage of being first, Bitcoin is still being the most popular and valuable one.

Purpose

- Examining how the dynamic relationships between rival cryptocurrencies have changed over time and affected by shocks
- Understanding the price dynamics between these rival cryptocurrencies and how they change over time can help small investors to take trade positions in advance and reduce risks by hedging in highly speculative cryptocurrency markets.
- The price dynamics are investigated by allowing multiple structural breaks.
  - Data segments determined by the endogenously estimated two structural breaks.
  - Vector Autoregressive Model
  - Granger–Causality
  - Generalized Impulse Response Functions

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- In the cryptocurrency world, Bitcoin is often considered as a primary gateway that allows investors and speculators to enter various cryptocurrency markets and trade altcoins since the majority of the altcoins are traded only against Bitcoin. In essence, this fundamental connection creates an inherent relationship between the prices of Bitcoin and altcoins. An understanding of this relationship is of utmost importance for investors.

- During the short history of Bitcoin there have been major fluctuations in the price because of security breaches in an exchange, government restrictions, reward halving for miners and even mafia involvement.

- It seeks to understand how the dynamic relationships between rival cryptocurrencies change over time and are affected by shocks. In particular, the price dynamics of Bitcoin, Litecoin, and Ripple are investigated by allowing multiple structural breaks.

- Understanding the price dynamics between these rival markets and how they change over time can help small investors to take trade positions in advance and reduce risks by hedging in highly speculative cryptocurrency markets.

Literature Review

- The literature mainly focused on
  - Speculative behavior of the Bitcoin price.
  - Microeconomic and macroeconomic determinants of the Bitcoin price.
  - Cointegration relations among the Bitcoin prices in different exchanges.
  - Cointegration and dynamic relationships between the Bitcoin price, Dow Jones Industry Average, oil price, Federal Funds Rate, and gold price.
- Only one study
  - Examined the structural breaks in the Bitcoin prices (Malhotra and Maloo, 2014).
  - Investigated correlations and tail dependencies between various cryptocurrencies using copula (Osterrieder et al., 2017).

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- Recently, Bitcoin's prominence, extreme price volatility, and the essential features such as decentralized network and cryptographic security have grabbed the attention of researchers. In overall, most studies of Bitcoin have been carried out in four main areas: (1) the speculative behavior of the Bitcoin price; (2) the microeconomic and macroeconomic determinants of the Bitcoin price; (3) cointegration relations among the Bitcoin prices in different exchange platforms; and (4) cointegration and dynamic relationships between the Bitcoin prices and some macroeconomic variables such as Dow Jones Industry Average, oil price, Federal Funds Rate, and gold price.

- During the short history of Bitcoin there have been major fluctuations in the price because of security breaches in an exchange, government restrictions, reward halving for miners and even mafia involvement.

- Although extensive research has been carried out on Bitcoin, there is only one study that has examined structural breaks in the Bitcoin prices. It is an astonishing gap in the literature considering the previously mentioned extreme events that may have caused structural breaks.

- Based on the Perron (1997) endogenous structural break test, Malhotra and Maloo (2014) provide evidence that the most significant breakpoint is in October 2013, which coincides with the crash in Bitcoin price after the Silk Road event.

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- In the cryptocurrency world, Bitcoin is often considered as a primary gateway that allows investors and speculators to enter various cryptocurrency markets and trade altcoins since the majority of the altcoins are traded only against Bitcoin. In essence, this fundamental connection creates an inherent relationship between the prices of Bitcoin and altcoins. An understanding of this relationship is of utmost importance for investors.

- However, in the literature, there is only one study that has investigated the price dependencies between various cryptocurrencies, especially Bitcoin and altcoins. It is a surprising gap considering the variety of altcoins and how their prices are related to the Bitcoin price.

- Using empirical and Gaussian copulas, Osterrieder et al. (2017) analyze correlations and tail dependencies among cryptocurrencies as well as their statistical properties. They provide statistical evidence that cryptocurrencies exhibit large tail dependencies, especially that share the same underlying technology.

- Instead of focusing only on Bitcoin or examining the tail dependencies of various cryptocurrencies, this study diverges from the primary focus of the previous research and aims to fill the two gaps in the literature (i.e., structural break and inherent relationship between the prices of Bitcoin and altcoins).

Data Descriptions

- A daily dataset
  - Collected by BraveNewCoin (2017) and distributed by Quandl (2017).
  - Covers from 04-01-2014 to 07-29-2017.
- Historical global price indices for rival cryptocurrencies based on volume–weighted average prices from multiple exchanges
- Rival cryptocurrencies are selected in terms of market capitalization and monthly volume as of July 30, 2017.
  - Bitcoin (BTC)
  - Litecoin (LTC)
  - Ripple (XRP)
- In total, the selected cryptocurrencies represent %59.95 and %45.93 of the market capitalization and monthly volume shares respectively as of July 30, 2017.
- The final merged data covers three variables in the rate of return form.

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- The analyses of this study are conducted with a daily dataset collected by BraveNewCoin (2017) and distributed by Quandl (2017). The data consist of historical global price indices for cryptocurrencies based on volume–weighted average prices from multiple exchanges.

- The BraveNewCoin (2017)'s data is downloaded from its starting date, 04-01-2014, until 07-29-2017. In order to analyze the price dynamics between rival cryptocurrencies, this study uses three out of the four largest coins in terms of the market capitalization as of July 30, 2017. The selected cryptocurrencies are Bitcoin, Litecoin, and Ripple.

- Among the selected coins, Bitcoin is the most valuable coin traded at \$2739.43 with a %50.43 market capitalization share. Litecoin and Ripple are traded at \$40.96 and \$0.17 with a %2.39 and %7.13 market capitalization share respectively. Moreover, these coins are in the top five cryptocurrencies regarding monthly volume. In total, the selected cryptocurrencies represent %59.95 and %45.93 of the market capitalization and monthly volume share as of July 30, 2017.

Vector Autoregressive Model (VAR)

The k-dimensional VAR(p) is employed as the main model.

$$\mathbf{y_t} = \mathbf{c} + A_1 \mathbf{y_{t-1}} + \cdots + A_p \mathbf{y_{t-p}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{1}$$

where p is the lag length; T is the sample size; t indicates a temporal observation for $t = (1, \ldots, T)$; k is the number of endogenous time series variables and the total number of equations; $\mathbf{y_t} = (y_{1t}, \ldots, y_{kt})'$ is a $k \times 1$ vector for a set of k endogenous time series variables; $\mathbf{c} = (c_1, \ldots, c_k)'$ is a $k \times 1$ vector of constants; A_i's are $k \times k$ coefficient matrices for $i = (1, \ldots, p)$; and $\boldsymbol{\varepsilon}_\mathbf{t} = (\varepsilon_{1t}, \ldots, \varepsilon_{kt})'$ is a $k \times 1$ vector of errors with $\boldsymbol{\varepsilon}_\mathbf{t} \overset{iid}{\sim} (0, \Sigma_\varepsilon)$.

Methods Applied Before the VAR

- Seasonal unit root tests
  - Osborn–Chui–Smith–Birchenhall and Canova–Hansen
- Unit root tests
  - Augmented Dickey–Fuller
  - Phillips–Perron
  - Elliott–Rothenberg–Stock
- Stationary tests
  - Kwiatkowski–Phillips–Schmidt–Shin
- All unit root and stationary tests are performed under two models (i.e., a model with constant or trend) with various lag lengths.

Estimation of the VAR

- The 3-dimensional VAR(p) is estimated using Bayesian Information Criterion (BIC) for the lag length selection.
- The VAR(p) results are used for
  1. Univariate and multivariate diagnostic tests for model residuals
     - Autocorrelation: Ljung–Box test
     - Heteroskedasticity: Autoregressive conditional heteroskedasticity Lagrange Multiplier test
     - Normality: Jarque–Bera test and separate tests for skewness and kurtosis
  2. Granger–causality test using BIC for the lag length selection
  3. Impulse response analysis
     - Generalized impulse response functions (IRFs) by Koop et al. (1996)
     - A 90% confidence interval generated with 10000 bootstrap replications.
     - A one-unit positive shock.
- All IRFs are interpreted in percentage-points since a one-unit positive shock in the rate of return form equals to a one-percentage-point positive shock.

Procedure in Structural Break Testing

- Employing the entire data with the 3-dimensional VAR(p), two structural breaks are endogenously estimated using Qu and Perron (2007) methodology.
- The methodology is performed under following conditions.
  - Maximum number of breaks is fixed to $m = 2$ in order to target the extreme events occurred in the history of cryptocurrencies.
  - Structural breaks are allowed in both the regression and covariance parameters.
  - No restrictions on the model parameters.
- The methodology is performed using
  - $WD \max LR_T(M)$ test to check whether at least one structural break is present.
  - $SEQ_T(\ell + 1 \mid \ell)$ test to check whether two structural breaks are present.
  - $\sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon)$ test to endogenously estimate two structural breaks dates.

Results for the Structural Break Tests

- For the entire data
  - No seasonal unit root is found and all of the variables are $I(0)$.
  - A 3-dimensional VAR(1) is constructed.
- Structural break tests for the VAR using the Qu and Perron (2007) methodology.
  - $WD \max LR_T(M)$ test: At least one structural break at the 1% significance level.
  - $SEQ_T(2 \mid 1)$ test: Two structural breaks at the 1% significance level.
  - $\sup LR_T(m, p_b, n_{bd}, n_{bo}, \epsilon)$ test: Two structural break dates are 11-12-2015 and 09-28-2016 at the 1% significance level.
- The data are separated into three segments on the structural break dates.

Conclusion:

The structural break dates are 11-12-2015 and 09-28-2016.

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Conclusion:
The structural break dates are 11-12-2015 and 09-28-2016.

- As a result, 11-12-2015 (i.e., the 590$^{\text{th}}$ observation) and 09-28-2016 (i.e., the 911$^{\text{th}}$ observation) are selected as the two structural break dates for the 3–dimensional VAR(1).

- The first break date might be linked to two distinct events.
- On September 17, 2015, the U.S. Commodity Futures Trading Commission (CFTC) filed charges against a cryptocurrency exchange for allowing trade of option contracts. Thus, the CFTC for the first time declared that cryptocurrencies are properly defined as commodities.
- On October 22, 2015, the European Court of Justice ruled that the exchange of cryptocurrencies is not subject to value–added–tax in the European Union. Hence, the ruling classified cryptocurrencies as currency, instead of goods or property.

- On the other hand, it seems that the second structural break occurred just seventy–nine days after the 2$^{\text{nd}}$ halving of the Bitcoin blockchain. Considering the fact that miners gradually adjust their cost/revenue analysis to the new reward per block after the halving, the date 09-28-2016 is a close estimation for the 2$^{\text{nd}}$ halving of the Bitcoin blockchain occurred in 07-09-2016.

Results for the 1^{st} Segment

- No seasonal unit root is found and all of the variables are $I(0)$.
- A 3-dimensional VAR(1) is estimated.
- Serial correlation, heteroskedasticity, and non–normality in the model residuals
- Granger–causalities: $BTC \Rightarrow XRP$

Table 1: Impulse Response Results - 1^{st} Segment

$\longrightarrow$	BTC	LTC	XRP
BTC	$1 \overset{4D}{\Longrightarrow} 0$	$1.05 \overset{2D}{\Longrightarrow} 0.04$	$0.35 \overset{1D}{\Longrightarrow} 0$
LTC	$0.35 \overset{4D}{\Longrightarrow} 0$	$1 \overset{4D}{\Longrightarrow} 0$	$0.2 \overset{1D}{\Longrightarrow} 0$
XRP	$0.12 \overset{1D}{\Longrightarrow} 0.03$	$0.22 \overset{1D}{\Longrightarrow} 0.05$	$1 \overset{6D}{\Longrightarrow} 0$

See the Figure

Results for the 2nd Segment

- No seasonal unit root is found and all of the variables are $I(0)$.
- A 3-dimensional VAR(1) is estimated.
- Serial correlation, heteroskedasticity, and non–normality in the model residuals
- Granger–causalities: None

Table 2: Impulse Response Results - 2nd Segment

$\longrightarrow$	BTC	LTC	XRP
BTC	$1 \xRightarrow{4D} 0$	$0.9 \xRightarrow{2D} 0.03$	•
LTC	$0.75 \xRightarrow{4D} 0$	$1 \xRightarrow{4D} 0$	•
XRP	•	•	$1 \xRightarrow{1D} 0.03$

Notes: • indicates statistical insignificance.

See the Figure

Results for the 3rd Segment

- No seasonal unit root is found and all of the variables are $I(0)$.
- A 3-dimensional VAR(1) is estimated.
- Serial correlation, heteroskedasticity, and non–normality in the model residuals
- Granger–causalities: $BTC \Rightarrow XRP$ and $LTC \Rightarrow XRP$

Table 3: Impulse Response Results - 3rd Segment

$\longrightarrow$	BTC	LTC	XRP
BTC	$1 \xRightarrow{4D} 0$	$0.81 \xRightarrow{1D} 0.15$	$0.38 \xRightarrow{1D} 0.3$
LTC	$0.25 \xRightarrow{5D} 0$	$1 \xRightarrow{3D} 0.01$	$0.41 \xRightarrow{3D} 0.02$
XRP	$0.05 \xRightarrow{4D} 0$	$0.15 \xRightarrow{1D} 0.05$	$1 \xRightarrow{3D} 0.01$

Notes: • indicates statistical insignificance.

See the Figure

Comparison of the Segments

Granger–causalities:

- 1^{st} Segment: $BTC \Rightarrow XRP$
- 2^{nd} Segment: None
- 3^{rd} Segment: $BTC \Rightarrow XRP$ and $LTC \Rightarrow XRP$

Table 4: Impulse Response Results - All Segments

$\longrightarrow$	*BTC:*			*LTC:*			*XRP:*		
	1^{st}	2^{nd}	3^{rd}	1^{st}	2^{nd}	3^{rd}	1^{st}	2^{nd}	3^{rd}
BTC	$1 \xrightarrow{4D} 0$	$1 \xrightarrow{4D} 0$	$1 \xrightarrow{4D} 0$	$1.05 \xrightarrow{2D} 0.04$	$0.9 \xrightarrow{2D} 0.03$	$0.81 \xrightarrow{1D} 0.15$	$0.35 \xrightarrow{1D} 0$	•	$0.38 \xrightarrow{1D} 0.3$
LTC	$0.35 \xrightarrow{4D} 0$	$0.75 \xrightarrow{4D} 0$	$0.25 \xrightarrow{5D} 0$	$1 \xrightarrow{4D} 0$	$1 \xrightarrow{4D} 0$	$1 \xrightarrow{3D} 0.01$	$0.2 \xrightarrow{1D} 0$	•	$0.41 \xrightarrow{3D} 0.02$
XRP	$0.12 \xrightarrow{1D} 0.03$	•	$0.05 \xrightarrow{4D} 0$	$0.22 \xrightarrow{1D} 0.05$	•	$0.15 \xrightarrow{1D} 0.05$	$1 \xrightarrow{6D} 0$	$1 \xrightarrow{1D} 0.03$	$1 \xrightarrow{3D} 0.01$

Notes: • indicates statistical insignificance.

Conclusion:

The Granger–causalities and dynamic relationships between the prices of rival cryptocurrencies have been affected by the structural breaks.

Comparison of the Segments

Granger–causalities:

- 1st Segment: *BTC*⇒*XRP*
- 2nd Segment: None
- 3rd Segment: *BTC*⇒*XRP* and *LTC*⇒*XRP*

Table 4: Impulse Response Results - All Segments

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Notes: • indicates statistical insignificance.

Conclusion:
The Granger–causalities and dynamic relationships between the prices of rival cryptocurrencies have been affected by the structural breaks.

- The comparison shows that there is a unidirectional Granger–causality between *BTC-XRP* in the 1st and 3rd segments; however, it disappears in the 2nd segment.
- Moreover, a unidirectional Granger–causality between *LTC-XRP* appears only in the 3rd segment.
- In essence, considering the following factor might explain why *BTC* and *LTC* Granger–causes *XRP* in the 3rd segment. Bitcoin and Litecoin are often considered as the gold and silver of the cryptocurrency world due to their reliable and long history. Therefore, a price movement in these coins is interpreted as a general price change in the whole cryptocurrency market by investors.
- As a result, the Granger–causality test results imply that the structure of the price dynamics between the rival cryptocurrencies has changed after the structural breaks.

Comparison of the Segments

Granger–causalities:

- 1^{st} Segment: $BTC \Rightarrow XRP$
- 2^{nd} Segment: None
- 3^{rd} Segment: $BTC \Rightarrow XRP$ and $LTC \Rightarrow XRP$

Table 4: Impulse Response Results - All Segments

$\longrightarrow$	*BTC:* 1st	2nd	3rd	*LTC:* 1st	2nd	3rd	*XRP:* 1st	2nd	3rd
BTC	$1 \xRightarrow{4D} 0$	$1 \xRightarrow{4D} 0$	$1 \xRightarrow{4D} 0$	$1.05 \xRightarrow{2D} 0.04$	$0.9 \xRightarrow{2D} 0.03$	$0.81 \xRightarrow{1D} 0.15$	$0.35 \xRightarrow{1D} 0$	•	$0.38 \xRightarrow{1D} 0.3$
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Notes: • indicates statistical insignificance.

Conclusion:
The Granger–causalities and dynamic relationships between the prices of rival cryptocurrencies have been affected by the structural breaks.

- Shock in *BTC*: the response of *XRP* to a shock in *BTC* is not statistically significant only in the 2^{nd} segment.
- An interesting result is that the responses of *BTC* and *LTC* to a shock in *BTC* are overall the same across segments. These results, in essence, confirm the Granger–causality tests. As a result, it is concluded that in response to a shock in Bitcoin price, the change in each coin is overall the same across segments.

- Shock in *LTC*: a one-percentage-point positive shock in *LTC* yields a 0.75 percentage-point increase in *BTC* in the 2^{nd} segment, which is three times higher than the 3^{rd} segment.
- Moreover, the same shock increases *XRP* by 0.2 and 0.41 percentage-point in the 1^{st} and 3^{rd} segments respectively. However, the response is not statistically significant in the 2^{nd} segment. In overall, these results suggest that in response to a shock in Litecoin price, the impact on Bitcoin price is decreasing over time; however, the impact on Ripple price is increasing.

- Shock in *XRP*: It can be seen that the response of each variable to a shock in *XRP* are statistically insignificant in the 2^{nd} segment.
- Moreover, the response of *BTC* and *LTC* to the same shock are decreasing from the 1^{st} segment to the 2^{nd} segment. As a result, it can be said that, in overall, in response to a shock in Ripple price, the impact on the prices of Bitcoin and Litecoin are decreasing over time.

Conclusion

1. Two robust structural breaks that appear to have affected the price dynamics between the rival cryptocurrencies.
   - The first break date might be linked to two distinct events that declared cryptocurrencies not only as a commodity but also as a currency.
   - The second break might be linked to the 2nd halving of the Bitcoin blockchain.
2. After the second structural break, the Granger–causality from the prices of other coins to Ripple price have gained strength.
3. The response of each coin to a shock in Bitcoin price is same across segments.
4. In response to a shock in Litecoin price, the impact on Bitcoin price is decreasing over time; however, the impact on Ripple price is increasing.
5. In response to a shock in Ripple price, the impact on the prices of Bitcoin and Litecoin are decreasing over time.

Thank You!

Questions?

References

BraveNewCoin (2017). *Historical Global Price Indices for Cryptocurrencies*. URL: `https://goo.gl/9JOOrU` (visited on July 30, 2017).

CoinMarketCap (2017). *CryptoCurrency Historical Weekly Snapshots*. URL: `https://goo.gl/v1dFCi` (visited on July 30, 2017).

Koop, G., M.H. Pesaran, and S.M. Potter (1996). “Impulse Response Analysis in Nonlinear Multivariate Models”. *Journal of Econometrics* 74.1, pp. 119–147.

Malhotra, A. and M. Maloo (2014). “Bitcoin is it a Bubble? Evidence from Unit Root Tests”. *SSRN Electronic Journal*.

Nakamoto, S. (2008). “Bitcoin: A Peer-to-Peer Electronic Cash System”. *Consulted* 1.2012, p. 28.

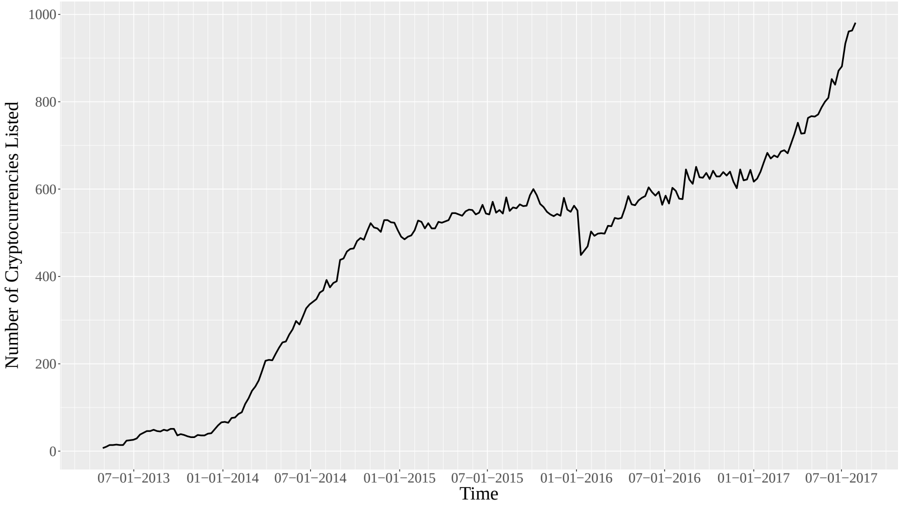
Osterrieder, J., M. Strika, and J. Lorenz (2017). “Bitcoin and Cryptocurrencies—not for the Faint-Hearted”. *International Finance and Banking* 4.1, p. 56.

Perron, P. (1997). “Further Evidence on Breaking Trend Functions in Macroeconomic Variables”. *Journal of Econometrics* 80.2, pp. 355–385.

Qu, Z. and P. Perron (2007). “Estimating and Testing Structural Changes in Multivariate Regressions”. *Econometrica* 75.2, pp. 459–502.

Quandl (2017). *BNC Digital Currency Indexed EOD*. URL: `https://goo.gl/BVpCJe` (visited on July 30, 2017).

Additional Figure



Note: Based on weekly snapshots from April 28, 2013 to July 30, 2017 (CoinMarketCap, 2017).

Figure 1: Number of Cryptocurrencies Listed

Additional Figure

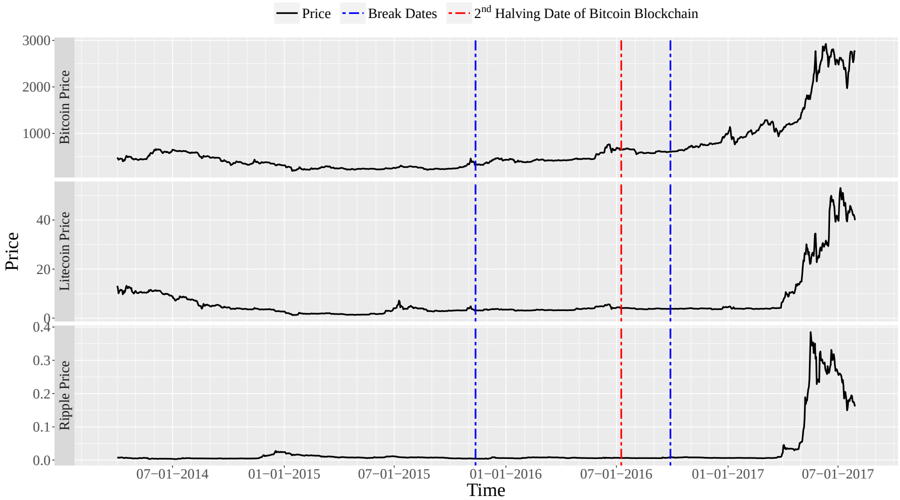
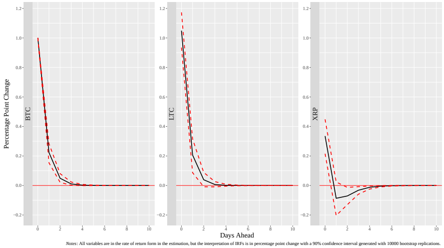


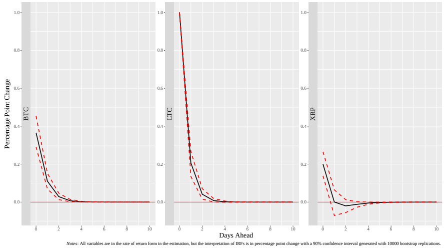
Figure 2: Plot of All Variables Together

Go Back to Presentation

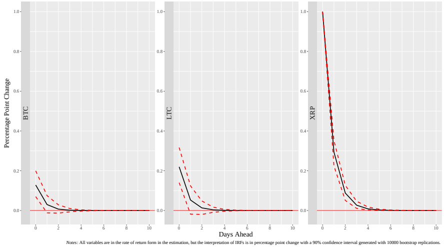
Additional Figure



(a) BTC



(b) LTC

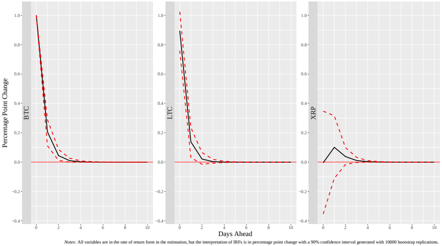


(c) XRP

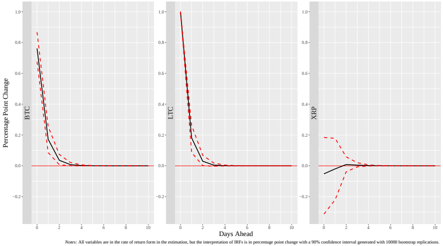
Figure 3: Impulse Responses Analysis - 1st Segment

Go Back to Presentation

Additional Figure



(a) BTC



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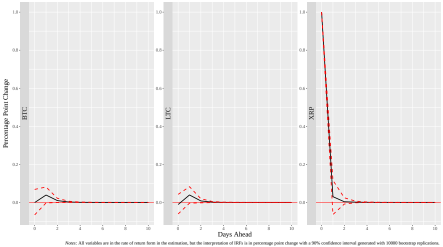
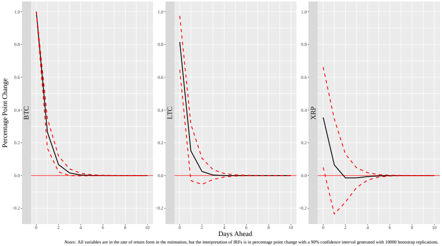


(c) XRP

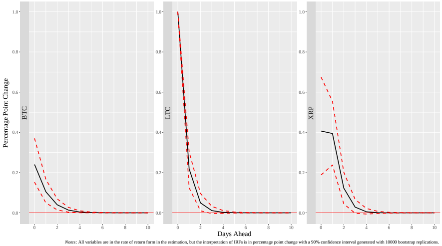
Figure 4: Impulse Responses Analysis - 2^{nd} Segment

Go Back to Presentation

Additional Figure



(a) BTC



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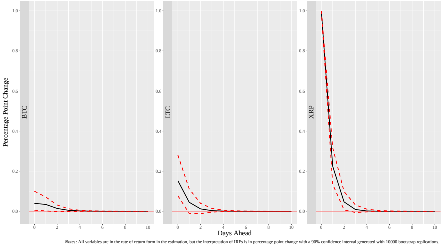

(c) XRP

Figure 5: Impulse Responses Analysis - 3rd Segment

Go Back to Presentation