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Dynamic Return Relationships in the Market for Cryptocurrency: A VAR Approach

Julian Gouffray

Photo credit: "Fingers Pointing at iPad Screen with Graph" by AlphaTradeZone on Pexels

Abstract

This paper examines how the Bitcoin-altcoin return relationship has evolved in periods between 2015 and 2020. To understand this relation, we observe data on the cryptocurrency Bitcoin and prominent altcoins Ethereum, Litecoin, Ripple, Stellar, and Monero, which collectively represent over 90% of the market throughout the observed period. We employ a vector autoregressive model (VAR) to produce forecast error variance decompositions, orthogonal impulse response functions, and Granger-causality tests. We find evidence that Bitcoin return variation has increasingly explained altcoin returns and that market inefficiency increased between 2017 and 2020, as shown by increased Granger causality between Bitcoin and altcoins. These results align with the academic consensus that efficiency within the cryptocurrency market varies substantially over time and that inefficiency has increased after 2017.The findings suggest that the properties of the cryptocurrency market are highly dynamic and that researchers should be hesitant to generalize market properties observed during idiosyncratic periods.

1. Introduction

Cryptocurrencies are an emerging asset class characterized by their utilization of blockchain technology, a distributed and public ledger of financial transactions which create a certifiable and guaranteed record (Crosby, 2016). The term *cryptocurrency* comes from the cryptographic consensus-keeping process which allows any two willing parties to transact directly with each other without the need for a trusted third party. In contrast, cash and other types of transactions typically rely on contract enforcement from social, political, and financial structures. Cryptocurrency transactions are decentralized, requiring a distributed and independent consensus for market participation. While Bitcoin, the first and largest cryptocurrency, has received most institutional and academic attention, recent literature increasingly focuses on the relationship between Bitcoin and the other cryptocurrencies, commonly referred to as *altcoins*.

The cryptocurrency market has been characterized as inefficient. Corbet et al. (2020) found evidence of bidirectional Granger causality between Bitcoin and altcoin returns.[1] The presence of Granger causality indicates that lags of one variable improve capacity to predict another variable, which in turn indicates market inefficiency. For example, if Bitcoin price returns Granger cause[2] Ethereum price returns, then lags of Bitcoin return have non-zero coefficients in a reduced form vector autoregressive (VAR) equation.[3]

According to Fama's (1970) efficient market hypothesis, in an efficient market, all known information is reflected by an asset's price. Therefore, an efficient market should not exhibit signs of autocorrelation or Granger causality: past information should not be predictive of future information. Le Tran and Leirvik (2019) considered temporal changes to market efficiency and foud that "before 2017, cryptocurrency-markets are mostly inefficient .... [and] the cryptocurrency-markets become more efficient over time in the period 2017–2019" (p. 1).

Like Corbet et al. (2020), this analysis investigates the dynamic relationship between Bitcoin and altcoin returns. However, we expand upon their work by exploring how Granger causality and forecast error variance decompositions have changed over time.[4] To do so, we segment our data into pre- and post-2017 periods, selected because they align with the periods of differing efficiency that Le Tran and Leirvik (2019) noted. We then estimate a VAR model to produce orthogonal impulse response functions and to observe trends in Granger causality and forecast error variance decomposition. The orthogonal impulse response function visualizes how a shock to Bitcoin returns affects altcoin returns over time.

In both the hourly and daily data, impulse response functions reveal that a positive shock to Bitcoin returns elicits a positive, statistically significant, and immediate response from altcoin returns—indicative of strong return co-movement. We also find increased Granger causality between cryptocurrencies in more recent periods. Variance decompositions show the proportion of altcoin return variation which can be

1 This analysis uses the term "returns" to refer to an appreciation or depreciation in the crypto-dollar exchange rate. It is atypical to discuss a currency in terms of return—exchange rates aside—given the face value of a fiat currency is fixed: a dollar is a dollar regardless of fluctuations in real value.

2 A Granger-causality test is "an econometric hypothetical test for verifying the usage of one variable in forecasting another in multivariate time series data with a particular lag" (Padav, 2021, "Granger Causality comes to Rescue" section). *Granger cause* can be used as a verb when one variable that occurs earlier in time "contains data for forecasting" a second later variable (Padav, 2021, "Granger Causality comes to Rescue" section).

3 "A reduced form VAR expresses each variable as a linear function of its own past values, the past values of all other variables being considered, and a serially uncorrelated error term…. If the different variables are correlated with each other—as they typically are in macroeconomic applications—then the error terms in the reduced form model will also be correlated across equations" (Stock & Watson, 2001, pp. 102-103).

4 Forecast error variance decompositions reveal the proportion of the variation in the return of an observed cryptocurrency that can be attributed to shocks to themselves or another cryptocurrency.

explained by Bitcoin return variation significantly increased over time in all observed cryptocurrency. Trends in both Granger causality and variance decompositions provide evidence of increased inefficiency within the cryptocurrency market, a finding that aligns with current academic consensus but at odds with the work of Le Tran and Leirvik (2019).

2. Related Literature

Bitcoin was created in 2009 by a programmer with the pseudonym Satoshi Nakamoto. Nakamoto (2008) described how blockchain technology solves the problem of maintaining network integrity and consensus across independent and potentially malicious actors.

Existing literature largely characterizes the cryptocurrency market as inefficient. Ciaian and Rajcaniova (2018) observed the short-term and long-term relationship between Bitcoin and altcoin markets and provide evidence of short-term interdependence between exchange rates. These findings precede the work of Corbet et al. (2020), who observed bi-directional Granger causality between Bitcoin and their selected basket of cryptocurrencies. Recent work has focused on efficiency trends within the cryptocurrency market. Lo proposed in 2004 that market efficiency evolves over time, known as the adaptive market hypothesis (AMH). Chu (2019) applied the AMH to the cryptocurrency market, providing evidence in support of time-varying market efficiency. Brauneis and Mestel (2018) and Wei (2018) investigated the causal forces behind this variation, showing that increased liquidity in the form of volume and market access has reduced evidence of inefficiency.

Le Tran and Leirvik (2019) expanded on these temporal trends by considering efficiency differences in the pre- and post-2017 periods and show that cryptocurrency markets largely became more efficient over time, a finding which they acknowledge contradicts other recent results. Aligning with the work of Brauneis and Mestel (2018), Le Tran and Leirvik (2019) attributed the noted efficiency increase to the heightened attention, volume, and liquidity associated with the 2017 cryptocurrency boom. They also provided evidence that fluctuations in market inefficiency can be related to idiosyncratic events, such as the hacking of the Mt. Gox cryptocurrency exchange in 2014. We expand upon this literature and estimate a VAR model to consider the return co-movement of Bitcoin, Ethereum, Litecoin, Ripple, Stellar, and Monero throughout their observable histories, for the period before 2017, and for the period after. Accordingly, we seek to identify trends in Granger causality and variance decomposition.

3. Data

Our analysis covers the cryptocurrencies Bitcoin, Ethereum, Litecoin, Ripple, Stellar, and Monero. Ethereum acts as a foundation for the creation and deployment of blockchain smart contracts and applications. Litecoin, Ripple, and Stellar emphasize transaction speed and capacity, and Monero takes a privacy-oriented approach, prioritizing transaction anonymity.

These assets are selected because they collectively represent over 90% of the market throughout the observed period. In addition, they are some of the oldest cryptocurrencies, giving the observational capacity to undertake this analysis. Furthermore, these assets vary widely in terms of market capitalization, from roughly 3 to 500 billion USD, allowing for a more representative sample. Certain cryptocurrencies with large market capitalizations, such as Cardano and Binance Coin, are omitted as they are relatively new assets and lack the extensive price history required to undertake this analysis.

We selected daily adjusted close data (in USD) from Yahoo Finance beginning on 8/17/2015 and ending on 11/27/2020, with a total of 1,930 observations per cryptocurrency. We also incorporated hourly data provided by CryptoDataDownload to capture shorter-term dynamics in the Bitcoin-altcoin relationship and to present more robust results. The hourly data begins on

12/12/2017 at 9:00 p.m. and ends on 11/20/2020 at 7:00 a.m., a total of 25,765 observations for each cryptocurrency. These date parameters are selected to maximize the number of available observations, given differing launch dates and thus data availability amongst the chosen basket of cryptocurrency. Both CryptoDataDownload and Yahoo Finance are selected as they are commonly cited existing literature and have an extensive availability of data.

Table 1 shows the daily percentage change summary statistics for the selected cryptocurrencies, calculated as the difference in natural logs. Ripple exhibits the widest range of return values, followed by Stellar, Monero, Litecoin, Ethereum, and Bitcoin. The return of each variable is abbreviated and referred to by its ticker symbol: BTC (Bitcoin), ETH (Ethereum), XRP (Ripple), LTC (Litecoin), XLM (Stellar), and XMR (Monero).

Table 1. *Daily Percent Change*

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
BTC	-0.465	-0.011	0.002	0.002	0.017	0.225
ETH	-0.551	-0.023	0.00003	0.003	0.027	0.304
XRP	-0.616	-0.02	-0.002	0.002	0.017	1.027
LTC	-0.449	-0.019	-0.001	0.001	0.021	0.511
XLM	-0.41	-0.029	-0.002	0.002	0.025	0.723
XMR	-0.494	-0.025	0.0005	0.003	0.031	0.585

Initially, our variables for BTC, ETH, and LTC are denominated in USD, XRP and XMR are denominated in BTC, and XLM is denominated in ETH. To gain a dollar interpretation for all variables, we multiply our XRP/BTC and XMR/BTC exchange rate vectors by the BTC/USD vector. Likewise, we multiply our XLM/ETH vector by our ETH/USD vector.

In this analysis, we also segment our data to observe structural changes over time. The first segmentation is into pre- and post-2017 periods. The pre-2017 period begins on 8/17/2015 and ends on 1/31/2017, and the post-2017 period begins on 2/01/2017 and ends on 11/27/2020. We selected the date parameters for this division to align with the work of Le Tran and Leirvik (2019), who considered market efficiency in the pre- and post-2017 periods.

To confirm the robustness of our results and reduce the chance of a data-snooping bias,[5] we considered an alternate data segmentation. In this second segmentation, we split our observations into three roughly even periods. The first period begins on 8/17/2015 and ends on 5/21/2017, the second begins on 5/22/2017 and ends on 2/23/2019, and the third begins on 2/24/2019 and ends on 11/27/2020.

4. Methodology

Our analysis employs a vector autoregressive (VAR) model to gather three relevant types of output: orthogonal impulse response functions, Granger-causality tests, and forecast error variance decompositions.

We begin by gathering data and applying the appropriate transformations outlined in the data section. We then test for stationarity of our time-series by employing augmented Dickey-Fuller tests and find that taking the difference in natural logs of our variables imposes stationarity; all variables are i(1) stationary.[6] Then, we estimate a structural form VAR model to allow for contemporaneous linkages between cryptocurrency returns. Ciaian and Rajcaniova (2018) showed that Bitcoin and altcoin markets are interdependent, with Bitcoin return having a positive and statistically significant impact on altcoin returns in the short term. Therefore, it makes sense to allow for contemporaneous correlations and estimate a reduced form VAR. Due to the identification issue present in structural form

5 Data snooping refers to "finding seemingly significant but, in fact, spurious patterns in the data" (Lo, 1994, p. 59). According to Lo (1994), "data snooping is particularly problematic for financial analysis because of the large number of empirical studies performed on the same data sets. Given enough time, enough attempts, and enough imagination, almost any pattern can be teased out of any data set" (p. 59).

6 An i(1) stationary process refers to a system of data that has been differenced a single time such that the mean, autocorrelation, and variance do not change over time, critical for estimating many time-series models.

estimation, we utilize Cholesky decomposition and estimate a recursive model. The selected ordering for our reduced form model is BTC, ETH, XRP, LTC, XLM, XMR. It should be noted that the presented results are robust to multiple orderings.

In the first application, the full return history of our variables is analyzed. We select optimal lag lengths using the Schwarz information criterion, and then obtain Granger-causality test results, impulse response functions, and variance decomposition. This output is gathered for both the daily and hourly data. Relevant output is also obtained for segmentation 1 (pre- and post-2017) and segmentation 2 (three even observation sets). As each segmentation could produce a final model with a unique number of optimal lags, we run selection tests for each. Accordingly, seven different possible final models can be estimated, shown in Table 2.

Table 2. *Model Estimation*

Model	Frequency	Segmentation
1	Daily	8/17/2015 - 11/27/2020
2	Hourly	12/12/2017 - 11/20/2020
3	Daily	8/17/2015 - 1/31/2017
4	Daily	2/01/2017 - 11/27/2020
5	Daily	8/17/2015 - 5/21/2017
6	Daily	5/22/2017 - 2/23/2019
7	Daily	2/24/2019 - 11/27/2020

For the final model estimation, we find that a VAR(1) is optimal for analyzing all daily data segmentations (Models 1, 3–7 in Table 2), as specified by Equation 1. We find that a VAR(2) is optimal for hourly data (Model 2 in Table 2), as specified by Equation 2.

$$\boldsymbol{\beta} Y_t = \boldsymbol{\beta}_0 + \boldsymbol{\phi} Y_{t\text{-}1} + \boldsymbol{\varepsilon}_t \qquad \text{Equation 1}$$

$$\boldsymbol{\beta} Y_t = \boldsymbol{\beta}_0 + \boldsymbol{\phi} Y_{t\text{-}1} + \Gamma Y_{t\text{-}2} + \boldsymbol{\varepsilon}_t \qquad \text{Equation 2}$$

Y_t, Y_{t-1}, and Y_{t-2} represent return vectors of the six selected cryptocurrencies and their first and second lags. Beta represents a coefficient matrix of the return values allowing for contemporaneous correlations. Beta$_0$ represents a vector of intercept terms, phi and gamma represent matrices of the lagged return coefficients, and epsilon represents the random white noise component.

Table 3 shows the results of the lag length selection for each model. Only Model 2 (hourly data) requires estimation with a VAR(2). All other models can be estimated with a VAR(1).

Table 3. *Lag Length Selection - SC Criterion*

Model	Lag Length
1	1
2	2
3	1
4	1
5	1
6	1
7	1

5. Results

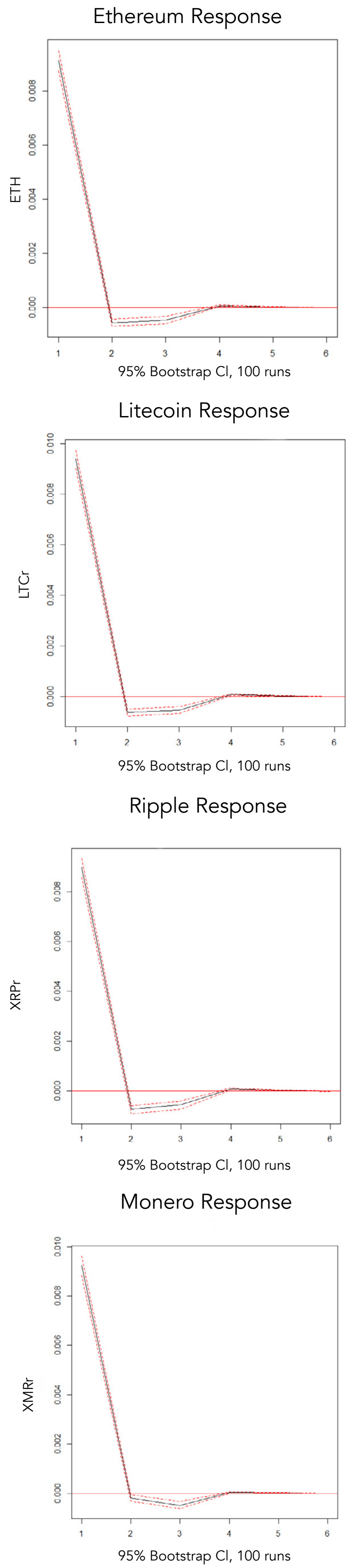
In the unsegmented hourly data beginning on 12/12/2017 and ending on 11/20/2020, we find evidence of bidirectional Granger causality in all variables. Granger-causality tests on the unsegmented daily data, beginning on 8/17/2015 and ending on 11/27/2020, show that all cryptocurrencies except Monero Granger cause at least one other cryptocurrency, a sign of market inefficiency. The results of both tests are shown in Table 4.

Table 4. *Granger-causality Test Results*

Variable	P-Value (hourly)	P-Value (daily)
BTC	.001	.001
ETH	.001	.001
XRP	.001	.001
LTC	.001	.015
XLM	.001	.001
XMR	.001	.408

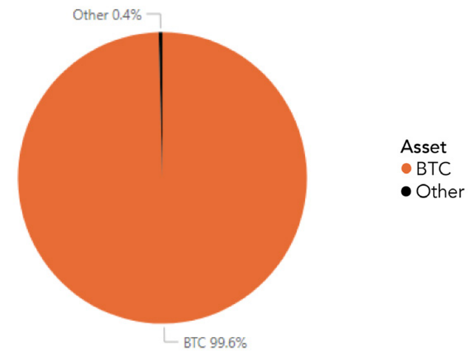
Impulse responses from the unsegmented hourly and daily data show that a positive shock to Bitcoin return elicits a positive response from altcoins in the first period. In the hourly data, this effect becomes negative and statistically significant until period 4. The hourly impulse response results for Ethereum, Ripple, Litecoin, and Monero are shown in Figure 1.

Figure 1. *Altcoin Hourly Impulse Response Results*



The results of the variance decompositions show altcoins play little role in explaining Bitcoin variation. Bitcoin explains roughly 99.6% of its own variation. These findings are shown in Figure 2.

Figure 2. *BTC Variance Decomposition*



Figures 3 and 4 reveal a significant portion of altcoin variation can be attributed to Bitcoin. Specifically, 28.4% of Ethereum variation and 32% of Monero variation are explained by Bitcoin variation in the full unsegmented time series.

Figure 3. *ETH Variance Decomposition*

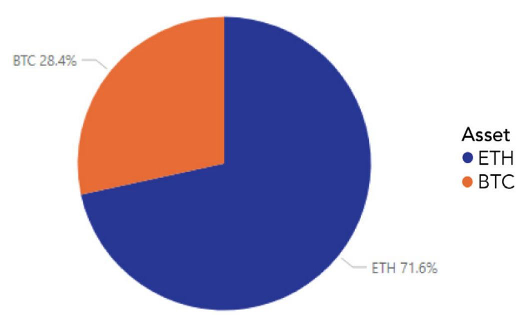
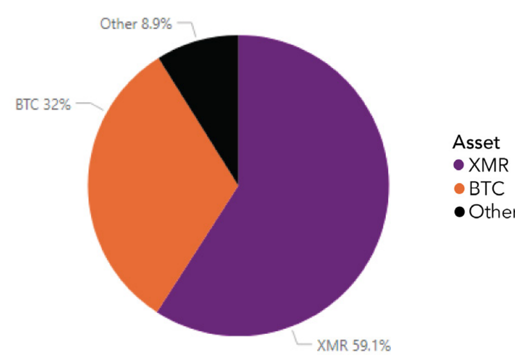


Figure 4. *XMR Variance Decomposition*



We then turn to the results of our two data segmentations: the pre- and post-2017 cut and the segmentation into three even periods. In Granger-causality tests for pre-2017 data, we find no evidence of any Granger causality. However, in the post-2017 period, we find evidence that all cryptocurrencies, except for Monero, Granger cause each other—an indication of increasing inefficiency between the two periods. The results of the pre- and post-2017 Granger-causality tests are shown in Table 5.

Table 5. *Granger-causality Tests*

Variable	P-Value (pre-2017)	P-Value (post-2017)
BTC	.485	.001
ETH	.188	.001
XRP	.738	.001
LTC	.219	.033
XLM	.099	.003
XMR	.059	.101

Trends in variance decompositions reveal that Bitcoin initially plays a very small role in pre-2017 altcoin return variation. However, in the post-2017 period, Bitcoin variation explains a significant portion of altcoin return variation. Roughly 4.4% of Stellar's return variation can be attributed to Bitcoin variation in the pre-2017 period, and 21.8% can be explained in the post-2017 period. Similarly, 9% of Monero's return variation can be attributed to Bitcoin variation in the pre-2017 period, and 45.5% can be explained in the post-2017. Figures 5 and 6 show pre- and post-2017 variance decompositions for Stellar and Monero.

The results from the second segmentation (three even periods) support the first. As in the pre- and post-2017 periods, the proportion of altcoin return variation attributed to Bitcoin increases substantially over time. In period 1, 24.5% of Litecoin variation is attributed to Bitcoin, 44.7% in period 2, and 65.1% in period 3. Figure 7 shows the variance decomposition for Litecoin in each of the three periods.

Figure 5. *XLM Pre- and Post-2017 Variance Decomposition*

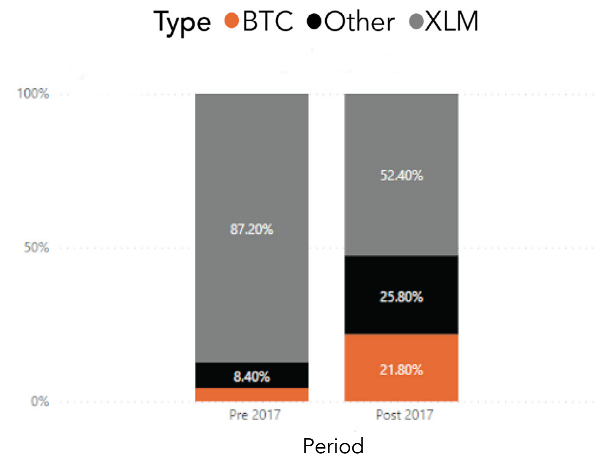


Figure 6. *XMR Pre- and Post-2017 Variance Decomposition*

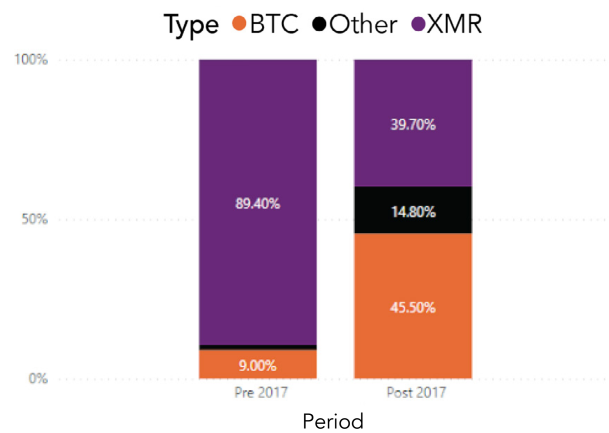


Figure 7. *LTC Variance Decomposition in Periods 1, 2, and 3*

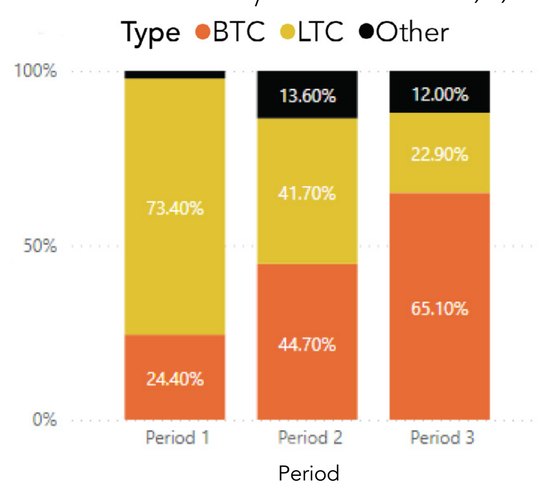


Figure 8 shows the variance decomposition for Ripple in the three periods. For Ripple, Bitcoin explains .8% of the variation in period 1, 22.7% in period 2, and 49.5% in period 3.

Figure 8. *XRP Variance Decomposition in Periods 1, 2, and 3*

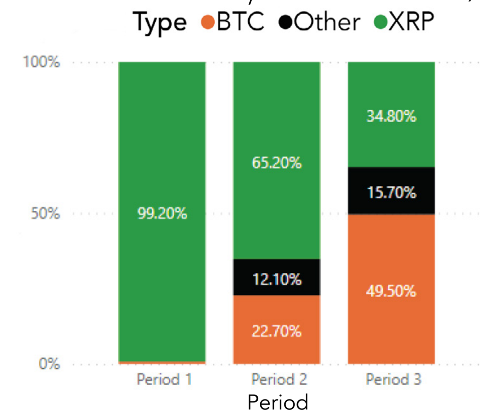


Figure 9 shows the variance decomposition for Ethereum in the three periods. For Ethereum, Bitcoin explains 2% of the variation in period 1, 43.8% in period 2, and 72.8% in period 3.

Figure 9. *ETH Variance Decomposition in Periods 1, 2, and 3*

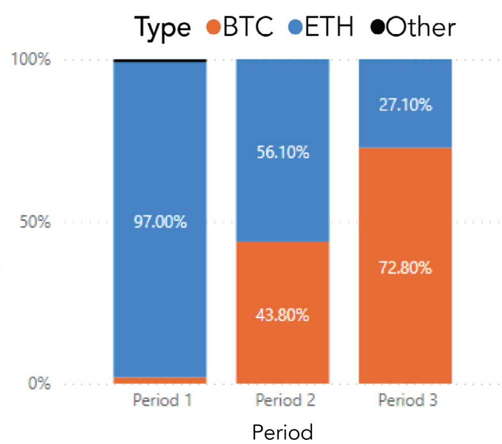


Figure 10 shows variance decomposition for Stellar in the three periods. For Stellar, Bitcoin explains 2.1% of the variation in period 1, 22.5% in period 2, and 42.3% in period 3.

Figure 11 shows the variance decomposition for Monero in the three periods. For Monero, Bitcoin explains 8.5% of the variation in period 1, 42.9% in period 2, and 63.2% in period 3.

Granger-causality results in the second segmentation align with those of the first (see Table 4) and reveal the presence of increased Granger causality in more recent periods. Table 6 Granger-causality test results shows how in period 1 (8/17/2015 to 5/21/2017), we do not find evidence that Bitcoin, Ethereum, or Litecoin Granger cause at least one other variable, but in period 3 (2/24/2019 to 11/27/2020) we do.

Figure 10. *XLM Variance Decomposition in Periods 1, 2, and 3*

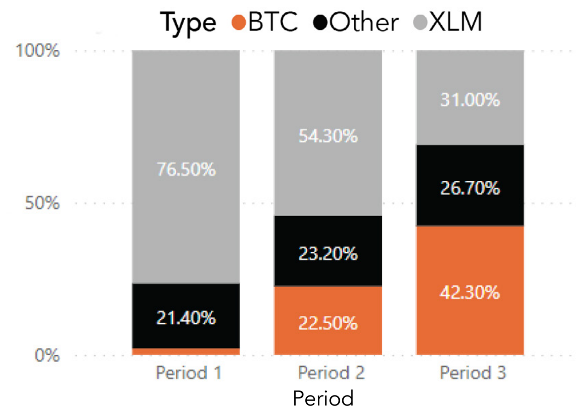


Figure 11. *XMR Variance Decomposition in Periods 1, 2, and 3*

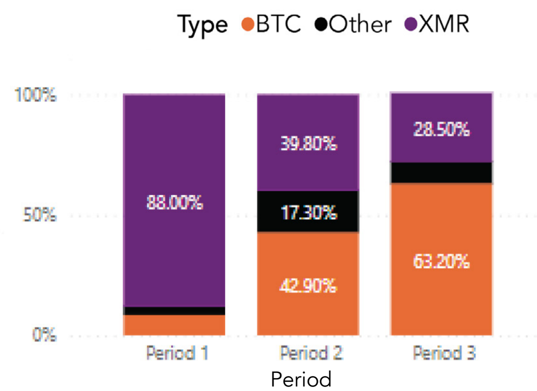


Table 6. *Granger-causality Test Results*

Variable	P-Value (8/17/2015-5/21/2017)	P-Value (2/24/2019-11/27/2020)
BTC	.105	.007
ETH	.149	.062
XRP	.001	.001
LTC	.270	.015
XLM	.001	.075
XMR	.250	.122

6. Discussion

In both hourly and daily data, we find evidence that a positive shock to Bitcoin returns initially elicits a positive, statistically significant, and immediate response from altcoins—a sign of return co-movement. In the hourly data, this effect becomes negative and statistically significant until period 4. The variance decompositions show that Bitcoin explains a significant portion of altcoin return variation but that altcoins do not explain Bitcoin return variation. A surprising trend present in both data segmentations is the substantial increase in the portion of altcoin return variation that can be attributed to Bitcoin return variation. Over time, Bitcoin return variation has increasingly explained variation in altcoin returns. The results of the Granger causality show that in the pre-2017 period, no cryptocurrency Granger causes another. However, in the post-2017 period, we find evidence of Granger causality in all cryptocurrencies except Monero, a trend that is also present in the second data segmentation.

These results align with the academic consensus that efficiency within the cryptocurrency market varies substantially over time and that inefficiency has increased in more recent periods. However, these findings are at odds with the work of Le Tran and Leirvik (2019), who observe increased efficiency over time. One explanation could be methodological differences; Le Tran and Leirvik acknowledge their work may be at odds with existing research due to their use of the Adjusted Market Inefficiency Magnitude estimator to measure fluctuations in efficiency. Furthermore, the employed approach of creating several discrete sub-periods within the data can be subject to a data-snooping bias. As a result, the pattern of increased inefficiency within the selected data segmentations may not be representative. Future research can improve upon the employed methodology by utilizing a rolling window approach to avoid a data-snooping bias and gathering higher-frequency data for a wider variety of cryptocurrencies. Furthermore, future work, especially with a long-term time horizon, should utilize models allowing for a non-constant error term variance, like ARCH variants.

To expand upon this work, future research can incorporate higher-frequency data from multiple exchanges and include a wider basket of cryptocurrencies. In addition, "meme" coins, which are coins that were started as jokes but now have serious market value, such as Dogecoin (DOGE) or Shiba Inu (SHIB), may exhibit unique properties and should be considered as well. Future research should also pay more consideration to the influence outside shocks, like the Covid-19 pandemic, have on the cryptocurrency market. Le Tran and Leirvik (2019) show that efficiency is significantly influenced by idiosyncratic events. The presented analysis observes data that occurred during the Covid-19 pandemic, which may have contributed to the stark difference in results. Researchers should understand that the properties of the cryptocurrency market are highly dynamic and should be hesitant to generalize market properties observed during idiosyncratic periods.

Author's Note

Julian Gouffray

Julian Gouffray ('20), born in Alexandria, Virginia, graduated from Gonzaga College High School before graduating from James Madison University with a double major in Economics and International Affairs and a minor in Business Spanish. During his time as an undergraduate, Julian served as an econometrics tutor, political science research assistant, and chair of the Civic Engagement Committee for the Public Affairs Student Organization.

In his current role as a data analyst, he leverages statistical methods and algorithms to extract insight from large volumes of noisy information. This year, Julian has been preparing graduate school applications in pursuit of a master's in data science or applied economics. Julian would like to thank Dr. Bhatt and Dr. Wylie for their constant support and guidance through his academic journey.

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