The Effects of the Stock Market on Bitcoin Price: A Time Series Analysis

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**Introduction**

Bitcoin is a burgeoning form of investment creating a plethora of questions about how this new marketplace will respond to already existing forms of investment. The relationship between traditional markets and these new markets may provide important investment information for future investors. Furthermore, discovering this relationship may allow for the creation of new investment strategies that properly implement these new crypto markets.

The hypothesis of this project is that bitcoin price will increase with an increase in value of the S&P 500 when controlling for the econometric variable GDP and bitcoin market variables. The reasoning for this is that an upward movement in the market should represent an increase in the total amount of investment. If bitcoin is seen as a viable source of diversification, as people invest in the S&P 500, pushing its price up there should also be an increase in investment in bitcoin also pushing its price upwards. Furthermore, this project also predicts that this same phenomenon should be observable in the XLK technology select sector possibly to an even greater degree. The reasoning for this is that someone willing to bet on the growth of the technology sector may be more willing to bet on the growth of bitcoin.

Five models were employed to examine this hypothesis. Due to the presence of unit roots, all models used data where the previous observation was subtracted from each observation. Bitcoin price will be the dependent variable in all models. The first model set the log S&P 500 as the only independent variable. The second model set the log XLK as its only independent variable. The third model included both the log S&P 500 and the log XLK as the independent variables. The fourth model included the log S&P 500, the log XLK, log GDP, the log hash rate, and the log trade volume as its independent variables. Finally, the fifth model included everything from the fourth model plus dummy variables for trend and seasonality as the independent variables. All models found that the S&P 500 was statistically significant and with positive coefficients. This provided evidence for the hypothesis that the S&P 500 is positively related to Bitcoin price. This shows that the stock market could be used to predict changes in Bitcoin prices and provides evidence that these two markets move upwards together.

**Literature Review**

This paper’s goal is to discover the relationship between stock market prices and Bitcoin prices. In order to formulate proper models, discovering which control variables should be included is important. In order to achieve this, literature concerned with predicting the future price of Bitcoin was analyzed.

The first piece of literature to be reviewed is “Improving the Predictability of Stock Returns with Bitcoin Prices” written by Salisu, Isah, and Akanni. This paper examined the role Bitcoin prices had on the predictability of stock returns within countries in the G7 political trade forum. The researchers studied this question due to the possibility of utilizing Bitcoin’s uniqueness as a powerful predictor of stock returns that could help alleviate risk factors in the stock market through the model’s predictive power. The paper retrieved data from Bloomberg on the returns of the CAC 40, DAX, FTSE 100, FTSE MIB, Nikkei 225, the S&P 500, and the S&P/Tsx composite over time. These stock market indexes represented a measure of the overall stock market in their respective G7 country. This study also retrieved data on the commodity price, exchange rate, inflation, long term interest rate, oil price, stock returns, short term interest rate, and output from the International Financial Statistics group. These are considered the “traditional macroeconomic variables” throughout the paper. These variables were retrieved from the time period July 2010 to June 2017. The paper used the Feasible Quasi Generalized Least Squares estimator which is a modified OLS model to help account for heteroscedasticity. The independent variables include Bitcoin prices plus commodity price, exchange rate, inflation, long term interest rate, oil price, stock returns, short term interest rate, and output. The dependent variable was the stock market return for each G7 country. A model without Bitcoin prices and just the macroeconomic variables was also created to function as a baseline of comparison for the Bitcoin price plus macroeconomic variable model. The paper found that Bitcoin price was a significant variable in the prediction of stock returns and that this model better fit the data than just utilizing the traditional macroeconomic variables that were pulled from the International Financial Statistics group. This paper did not address the relationship of stock returns to a single country, it also lacks the most modern data as it only pulled data from July 2017 at the farthest.

The next piece of literature, “How Futures Trading Changed Bitcoin Prices” by Hale, Krishnamurthy, Kudlyak, and Shultz, sought to answer if the rapid decrease in Bitcoin pricing is related to the introduction of new financial instruments allowing “pessimists” to bet against the market. The authors’ wished to provide information on how the introduction of new financial inventions affect the overall financial market. The authors were particularly interested in observing the affects the introduction of financial instruments that let “pessimists” enter the market. Pessimists were defined as those who bet against the future price of something, a conventional example of this would be shorting a stock. The data utilized within this article were Bitcoin prices and the value of the S&P 500 in 2017 sourced from Bloomberg. This article created a graph that mapped the percentage changes of Bitcoin prices to the percentage changes in the S&P 500 valuation. The article also graphed the percentage changes of three different rise and falls of Bitcoin prices in order to examine the difference in the magnitude of each fall in price. This article found that after the introduction of new financial instruments allowing “pessimists” to bet against the market, the decline in Bitcoin price is much larger than when “pessimists” could not enter the market when a decline occurred. This paper did not address what actually drives the price of bitcoin or what bitcoin could drive the price of. However, the paper does give some speculation on what they believe to be the most likely variables that drive Bitcoin prices, namely the Volume of Bitcoin, additional Bitcoin available to be mined, the transactional demand of bitcoin, and its integration as a means of an exchange. To reiterate, the latest data used within this study comes from 2017 meaning an updated dataset may provide different results.

Another piece of literature is “A Comparative Study of Bitcoin Price Prediction Using Deep Learning” by Suhwan Ji, Jongmin Kim, and Hyeonseung Im which compared different deep learning models to see which would be the best at examining Bitcoin prices. They wished to see the accuracy of the models in regression, getting as close a prediction to the exact price, and classification, getting the correct prediction on whether Bitcoin prices went up or down. The authors’ interest stemmed from the desire to find out which model would be best to develop further for possible future algorithmic Bitcoin trading. They retrieved Bitcoin price data between the 29 of November 2011 to the 31 of December 2018 from the website bitstamp.net. The paper also retrieved data from blockchain.com/charts to retrieve information on the various changing features of bitcoin over time. This was used for the independent variables to feed the neural network and included avg block size, cost per transaction, hash rate, market cap, and market price. Other variables available from the blockchain charts were also used. This paper compared the Deep Neural Network, Recurrent Neural Network, Long Short-term Memory model, Convolutional Neural Networks, Deep Residual Networks, and Ensemble models. The results found that the Long Short-term Memory model was best in predicting Bitcoin price in regressions and that the Deep Neural Network was best in classification. This paper did not use conventional (non-machine learning) methods of predicting Bitcoin prices. Furthermore, it utilized factors of the Bitcoin system itself as independent variables such as the hash rate. A model that uses information found outside the Bitcoin system itself might be an extension of this research. The use of newer data could also be used to expand this research.

The paper “Using Time-Series and Sentiment Analysis to detect the Determinants of Bitcoin Prices” by Ifigeneia Georgoula, Demitrios Pournarakis, Christos Bilanakos, Dionisios Sotiropoulos, and George M. Giaglis seeks to analyze the relationships of Bitcoin prices to various economic variables and general public sentiment towards Bitcoin on social media. The authors were interested in this research question in that they wanted to see if standard economic theory of how a medium of exchange should function applies to bitcoin. In other words, this paper examined whether the quantity theory of money that MV=PT, where M is the Money supply, V is the number of times money moves from one person to another, P is the average price level, and T is the volume of transactions of goods and services, holds up when dealing with Bitcoin. The dependent variable in this paper is the Bitcoin closing price and the independent variables included the stock of Bitcoins in circulation, number of Bitcoin transactions, Bitcoin Days which is the number of Bitcoins in a particular transactions multiplied by the number of days since they were spent, the exchange rate of the dollar to the euro, S&P 500 price, and the mining difficulty represented by the hash rate, a measure of computing power currently being used within the Bitcoin network, all retrieved from quandl.com. Furthermore, they used Wikipedia bitcoin searches, googleviews from google trends, and tweets relating to bitcoin as a proxy variable for public recognition. Finally, they developed a vector space model to comb through twitter to create a variable to represent general sentiment towards bitcoin. This paper then used an Augmented Dickey Fuller test to avoid the problems of spurious regression in the model. An OLS model was then used to identify the short run relationships of Bitcoin price and the independent variables listed above. This literature found that Twitter(general) sentiment and increases in the hash rate had a positive short run effect on Bitcoin price. The US dollar to euro exchange rate also had a negative short run relationship to Bitcoin price. Overall, the stock or supply of Bitcoins had a positive effect on its price. The S&P500 price also had a negative effect on Bitcoin price showing that the Bitcoin market might be considered a form of substitute to the stock market. This paper could be updated by utilizing new Bitcoin data, the introduction of different independent variables, and the use of a different regression model.

The current literature on the various effects on Bitcoin pricing does not include the most up to date data on both the various possible independent variables and the Bitcoin pricing as these variables are constantly updating. The research examined in preparation for this literature review typically had data before 2020. The current literature does not include every combination of technique and variables that may affect Bitcoin pricing leaving room for further analysis.

Therefore, after reading the literature, researching the impact that the stock market has on Bitcoin pricing can be sufficiently differentiated from previous research into this topic. This paper will focus on the effects the S&P500 stock market index and the XLK technology select sector fund have on bitcoin prices. The reason for the inclusion of both the S&P 500 and the XLK is to see whether more tech related stocks or indexes are likely to move with Bitcoin prices as the price may be more related to the valuation of the tech industry itself as they both deal with emerging technologies. It is also included due to the possibility that stocks in other industries may actually be negatively correlated with Bitcoin price as Bitcoin may function as a form of substitute (Georgoula et al. 2015, 13). Utilizing a different set of independent control variables and using updated data than prior literature will further differentiate this research. Specifically, this research will focus on the United States using the econometric control variable of US GDP. Five different models will be used that utilize different combinations of the S&P 500, XLK and control variables as the independent variables.

**Methodology**

To reiterate, this project’s objective was to find whether and to what extent Bitcoin prices changed in response to changes in the S&P 500 index and the XLK Technology select sector fund. The United States GDP was used as an econometric control variable within this projects model. Furthermore, information relating directly to bitcoin was also used as controls within this projects models and includes the Bitcoin hash rate, and the Bitcoin trade volume.

The Bitcoin market capitalization was a variable that was originally planned to be included. However, this variable caused a major endogeneity problem which violated the assumption that all independent variables are not correlated with the error term. A model utilizing two stage least squares was originally implemented that attempted to solve this problem. This two stage least squares regression used networking difficulty as an instrument for market capitalization as it was believed that this variable should represent Bitcoin supply while having no correlation with the demand of Bitcoin. This was thought to be the case as networking difficulty is the measure of computations required to create a new block within the blockchain, a necessary step for the generation of new Bitcoin. This means that networking difficulty should correlate with the creation of new Bitcoin, or in other words the supply of Bitcoin. Meanwhile, networking difficulty should not have any effects on an individual’s desire to demand more or less Bitcoin. Unfortunately, this instrument was weak and failed to deal with the endogeneity problem. Due to the inability to find another instrument the Bitcoin market capitalization variable was dropped.

The data for this project was collected from three different sources. The United States GDP was collected from the US bureau of economic analysis published online by the Federal Reserve Bank of St. Louis. This data included US quarterly GDP up to the fourth quarter of 2021. The S&P 500 and XLK Technology Sector price data was retrieved from investing.com and gave daily prices for these stocks. The bitcoin hash rate, trade volume and market capitalization were retrieved from Nasdaq Data link and gave daily updates on these values. The range of time for these datasets included January-1 2011 to October-1 2021. These datasets were then joined on the quarterly dates taken from the GDP dataset. This led to a dataset of forty-four observations for each variable. All the variables were then converted into natural log using excels ln() function. An explanation and summary statistics of all variables used within the regressions and a graph of how these variables change over time is included below.

**Variable Explanations:**

* US GDP: A measure of all goods and services produced within the United States reported quarterly retrieved in billions of dollars.
* S&P 500 Historical Data Price: Daily trading price in US Dollars of the S&P 500 as reported from investing.com
* XLK Technology Select Sector Historical Price: Daily trading price in US dollars of the XLK Technology Select Sector
* Bitcoin Price: The price in US Dollars to purchase a single Bitcoin
* Bitcoin Hash Rate: a measure of the amount of computer power being utilized to run and verify the integrity of the bitcoin network in TeraHashes per second(TH/s).
* Bitcoin Trade Volume: the total value in US Dollars of bitcoin trades on any particular day on all major bitcoin exchanges.
* Bitcoin Market Capitalization: The total value of all Bitcoin in circulation measured in US dollars.
* Bitcoin Network Difficulty: Networking difficulty is a relative measure of the difficulty in creating a new block within the blockchain which is necessary for the generation of new bitcoin.

**Table One: Summary Statistics**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Median** | **Mean** | **Std.** |
| **Deviation** |
| **S&P 500** | $ 2,090.00 | $ 2,305.00 | $ 824.90 |
| **XLK** | $ 44.09 | $ 58.46 | $ 34.61 |
| **GDP(billions)** | $ 18,694.00 | $ 18,947.00 | $ 2,280.95 |
| **HashRate(TH/s)** | 1385495 | 31397036 | 48631704 |
| **TradeVolume** | $ 14,710,000.00 | $ 131,000,000.00 | $ 236,261,774.00 |
| **BitcoinPrice** | $ 661.00 | $ 6,259.40 | $ 12,360.54 |

This table displays the Median Mean and Std. Deviation summary statistics of all variables that will be used in regressions

**Table Two: Summary Statistics Continued**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable** | **Minimum** | **1st** | **3rd** | **Maximum** |
| **Quartile** | **Quartile** |
| **S&P 500** | $ 1,131.00 | $ 1,675.00 | $ 2,756.00 | $ 4,357.00 |
| **XLK** | $ 23.60 | $ 31.93 | $ 75.18 | $ 151.57 |
| **GDP(billions)** | $ 15,351.00 | $ 17,078.00 | $ 20,860.00 | $ 24,008.00 |
| **HashRate(TH/s)** | 0 | 1001 | 46390324 | 157606704 |
| **TradeVolume** | $ - | $ 2,847,000.00 | $ 172,000,000.00 | $ 1,000,000,000.00 |
| **BitcoinPrice** | $ 0.30 | $ 107.70 | $ 6,692.70 | $ 58,735.20 |

This table displays the minimum, 1st quartile, 3rd quartile, and maximum summary statistics.

**Graph One: Changes in Variables over Time**

Chart

Description automatically generated

This graph shows the change in logged values of all variables over the forty-four points in time.

Due to the time-series nature of the dataset, the first step was to determine if there were unit roots indicating the possibility of spurious correlation. An augmented Dickey-Fuller test was conducted on the bitcoin price which resulted in a test statistic of -2.1012 and a critical value of -2.60. Due to the test statistic being greater than the critical value, the null hypothesis that there is a unit root could not be rejected. Therefore, the same Augmented Dickey-Fuller test was then conducted on the t-1 differences of the bitcoin price data leading to a test statistic of -6.7467 and a critical value of -2.60. Because the test stat was smaller than the critical value, we can reject the null hypothesis of there being a unit root thus indicating the need to take the difference of the previous observation in time from each observation in time. This will need to be done for each variable as this unit root test was done on the dependent variable indicating the need to perform this for all independent and dependent variables. This will be true for all models.

After performing the unit root tests and creating a dataset of the difference of each observation minus the previous observation, a linear model was used for all models utilizing R’s lm function except for model 5. Model 5 implements a time series linear model using R’s tslm function. Due to taking the differences of the previous time period, the first time period had to be dropped leaving forty-three time periods in total for each variable. A graph of this new dataset is found on Graph 2.

**Graph 2: Differenced Changes in Variables over Time**

Chart, histogram

Description automatically generated

All five models will have the superscript ′ to represent how each observation in time (t) had its valued subtracted by the previous observation or t-1.

The first model uses the lm function and has log S&P500 as the only independent variable and can be represented with the following equation

The second model used the lm function and used the log XLK as the only independent variable and can be represented with the following equation.

The third model also used the lm function and had the log S&P 500 and the log XLK as the independent variables. The equation for this model can be seen below.

The fourth model utilized the lm function and had the log S&P 500, the log XLK, the log GDP, the log hash rate, and the log trade volume as its independent variables. The equation for this model can be seen below.

The fifth and final model used R’s time series linear model or tslm function to be able to account for the trend and seasonality. This model all of the same independent variables as the fourth model plus the aforementioned trend and seasonality. The frequency of the seasons was inputted into R as 4 as these represent the four quarters of the year. The equation for the fifth model can be seen below.

Once more, the primary question is whether and to what degree that Bitcoin prices change in response to changes in the S&P 500 index. Again, the primary hypothesis is that Bitcoin prices should increase in response to an increase in the value of the S&P 500 when controlling for GDP, the bitcoin hash rate, the trade volume. The formula for this hypothesis and the null hypothesis is shown below.

𝐻0 : 𝑐𝑜𝑟(S&P500 Price , Bitcoin Price) <= 0

𝐻A : 𝑐𝑜𝑟(S&P500 Price , Bitcoin Price) > 0

The null hypothesis is that the correlation between the S&P500 and Bitcoin price is either zero or negative. The alternative hypothesis is that the correlation between the S&P500 and Bitcoin price is positive. This suggests that an increase in the S&P 500 price will result in an increase in Bitcoin price. Whether the null hypothesis can be rejected will be examined for all relevant models.

The secondary question of this project is to find to what degree that Bitcoin prices change in response to changes in the XLK technology select sector fund. The hypothesis for this is that as the XLK fund increases there should be an increase to Bitcoin prices. The formula for the null and alternative hypothesis for the secondary question can be seen below.

𝐻0 : 𝑐𝑜𝑟(XLK Price , Bitcoin Price) <= 0

𝐻A : 𝑐𝑜𝑟(XLK Price , Bitcoin Price) > 0

The null hypothesis is that the correlation between the XLK technology select sector is either zero or negative. The alternative hypothesis is that the correlation between the XLK technology select sector and Bitcoin price is positive. Rejecting the null hypothesis would suggest that there is evidence that an increase in XLK price should result in an increase in Bitcoin prices. Whether the null hypothesis can be rejected will also be examined for all relevant models.

**Results**

**Table Three: Bitcoin Price Regressions**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| DlogS&P500 | 3.093\*  (1.390) |  | 9.244\*  (3.421) | 8.908\*\*  (3.165) | 8.863\*  (3.730) |
| DlogXLK |  | 1.700  (1.357) | -6.283.  (3.212) | -4.871.  (2.674) | -5.139  (3.132) |
| DlogGdp |  |  |  | -10.05.  (5.567) | -10.800.  (6.040) |
| DlogHashRate |  |  |  | 0.587\*\*\*  (0.136) | 0.689\*\*\*  (0.157) |
| DlogTradeVolume |  |  |  | -9.004e-4  (2.465e-2) | 0.019  (0.028) |
| Trend |  |  |  |  | 0.011  (0.009) |
| Season 2 |  |  |  |  | -0.108  (0.272) |
| Season 3 |  |  |  |  | 0.180  (0.277) |
| Season 4 |  |  |  |  | -0.163  (0.296) |
| Significance Codes | 0 ‘\*\*\*’ | 0.001’\*\*’ | 0.01’\*’ | 0.05’.’ |  |
| Adjusted R2 | 0.08596 | 0.0134 | 0.1449 | 0.4495 | 0.4399 |

This table displays the results of all of the tslm models. DlogS&P500 is the S&P 500 price logged and the subtracted by the last observation. The standard errors are found within the parentheses below the coefficient. The DlogXLK is the XLK price logged and then subtracted by the last observation. DlogGdp is the quarterly GDP as reported by the US Bureau of Economic Analysis logged and with the last observation subtracted out. DlogHashRate is the bitcoin hash rate logged and then subtracted out by the last observation. DlogTradeVolume is bitcoin’s total value in US Dollars of bitcoin trades on any particular day on all major bitcoin exchanges logged and then subtracted from the last observation. DlogMarketCap is the market capitalization of all bitcoins logged and then subtracted from the previous observation. There are four quarters in the data and each season represents how being in each changes the price quarter relative to being in the first quarter. The trend shows how the dependent variable changes due to increasing the period of time. There are forty-three observations in total and the data begins on the second quarter of 2011 or 4/1/2011.

From the first model regression on table three, the S&P 500 was statistically significant at the 0.01 level. The coefficient can be interpreted as a 3.093% increase in Bitcoin price for every 1% increase in the S&P 500. This supports the rejection of the null hypothesis that the correlation of the S&P 500 and Bitcoin price is either zero or negative and provides evidence for the alternative hypothesis that the S&P 500 is positively correlated with Bitcoin price.

The second model on table three shows that the XLK technology select sector fund is not statistically significant when it is the only independent variable used. This would mean that the null hypothesis that the correlation Bitcoin price and the XLK technology select sector fund is either zero or negative can not be rejected.

The third model on table three has the S&P 500 being statistically significant at the .01 level and the XLK being statistically significant at the at the .05 level. The coefficient for the S&P 500 can be interpreted as an 9.244% increase in Bitcoin price for every 1% increase in the S&P 500. This also supports the rejection of the null hypothesis that the correlation of the S&P 500 to Bitcoin price is either zero or negative and provides evidence for the alternative hypothesis that the S&P 500 is positively correlated with Bitcoin price. The coefficient for the XLK variable can be interpreted as a 6.283% decrease in Bitcoin price for every 1% increase in the XLK. While the XLK coefficient is statistically significant, the coefficient is negative meaning that the null hypothesis that the correlation to Bitcoin price and the XLK technology select sector fund is either zero or negative cannot be rejected.

The fourth model resulted in the S&P 500 statistically significant at the .001 level. The coefficient shows that there is an 8.907% increase in Bitcoin price for every 1% increase in the S&P 500. The XLK was significant at the .05 level and its coefficient shows that there was a 4.871% decrease in Bitcoin price for every 1% increase in the XLK. The GDP was also significant as the .05 level and its coefficient can be interpreted as an 10.05% decrease in Bitcoin price for every 1% increase in GDP. The hash rate was significant at a near zero level and its coefficient can be interpreted as a 0.587% increase in Bitcoin price for every 1% increase in the hash rate. Finally, the trade volume was not significant.

In the fourth model the GDP was statistically significant at the .01 level. The coefficient shows that there is an 8.863% increase in Bitcoin price for every 1% increase in the S&P 500. The GDP was statistically significant at the .05 level and its coefficient resulted in a 10.80% decrease in Bitcoin price for every 1% increase in GDP. The hash rate was significant at a near zero level and its coefficient can be interpreted as a 0.689% increase in Bitcoin price for every 1% increase in the hash rate. The XLK, trade volume, trend, and season variables were not statistically significant.

To analyze all models at once, we can see that the R squared for the first three models is exceptionally low. This implies that the inclusion of the control variables is necessary and most likely forms a better model. GDP remained significant and with a positive coefficient throughout every single model it was included in. This allows for the rejection of the null hypothesis that the correlation of the S&P 500 is either zero or negative and provides major evidence for the alternative hypothesis that the S&P 500 is positively correlated with Bitcoin price. On the other hand, the XLK was not significant in the 2nd and 5th model. The XLK was significant at the .05 level within model 3 and 4. Due to these results, there is little evidence that changes in the XLK lead to changes in Bitcoin price. Furthermore, when XLK was significant, it was negatively correlated with Bitcoin price. The XLK having a negative coefficient may be due to Bitcoin acting as a substitute for investment in the technology sector rather than a compliment. Looking at all the models in aggregate, the null hypothesis relating to the XLK cannot be rejected. The GDP was also statistically significant at the .05 level and had a negative coefficient in both of the models it was included within. GDP being negatively correlated may be due to how the investment component of calculating GDP does not include Bitcoin as an investment. Trade volume not being significant in all models it was present is surprising given that it indicates the velocity of the currency and should be related to price as in the equation MV=PT, where M is the Money supply, V is the number of times money moves from one person to another, P is the average price level, and T is the volume of transactions of goods and services.

**Conclusion**

The S&P 500 and bitcoin function as a form of investment for individuals. Our main question of interest was whether there was a positive correlation between the S&P 500 and Bitcoin price allowing the stock market to be a predictor of Bitcoin price. The variables used within the models were the US GDP functioning as a measure of the general economy of the United States, the S&P 500 price as an indication of a stock that moves very closely with the entire stock market as a whole, the XLK Technology Select Sector which was a more pinpoint section of the stock market as it only included technology related companies, the bitcoin hash rate acting as a predictor of participation in the Bitcoin currency, the trade volume of bitcoin which measured the velocity of the bitcoin currency, and finally the Bitcoin price our dependent variable which is the price of obtaining one Bitcoin in US dollars. Within all models, we see that the S&P 500 was statistically significant with a positive coefficient providing evidence that there is a positive correlation between the S&P 500 and Bitcoin price. Therefore, the null hypothesis that there was either no correlation or a negative correlation between the S&P 500 and Bitcoin price was rejected. This falls in line with the findings of the first paper in the literature review “Improving the Predictability of Stock Returns with Bitcoin Prices” written by Salisu, Isah, and Akanni. This paper had stock returns as the dependent variable and Bitcoin price as an independent variable which is set up the opposite way of this research. They concluded that an increase in Bitcoin price was a useful predictor of an increase in stock returns which is a similar relationship in what was found within this paper. However, on the other hand the paper “Using Time-Series and Sentiment Analysis to detect the Determinants of Bitcoin Prices” by Ifigeneia Georgoula, Demitrios Pournarakis, Christos Bilanakos, Dionisios Sotiropoulos, and George M. Giaglis found that an increase in the S&P 500 price would lead to a decrease in Bitcoin price. Different control variables, updated data, and different econometric techniques being used could explain the differences in conclusions of the S&P 500’s effect on Bitcoin prices.

While the control variables used are reasonable, further investigation into which control variables that should be utilized in trying to model how Bitcoin prices change in response to the change in price of the S&P 500 would benefit the model. For example, finding a valid instrument that can solve Bitcoin’s market capitalization endogeneity problem so that it can be implemented as an independent variable within the model. Furthermore, a model that includes daily changes of Bitcoin prices and daily changes of the S&P 500 as opposed to quarterly changes in these variables due to the inclusion of the quarterly US GDP control variable would be another angle to examine this question. The insignificance of the trade volume control variable could be explored as well. Why the XLK technology select sector had a negative coefficient, which seems to line up more to findings in the “Using Time-Series and Sentiment Analysis to detect the Determinants of Bitcoin Prices,” could also be explored further.

Further questions that arise from the results of the regressions include what control variables could be included to provide more accurate results? Are there other stock indexes or specific stocks that could be added to the model that have a unique outcome? And given new data over time will the results of this model change? Finding the resolution to these questions may help explain ways to predict how the new burgeoning investment of Bitcoin relates to more traditional forms of investment.

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