I first tested these time series to determine whether they are stationary using the Augmented Dickey-Fuller test, and as is usual with price data, I found that they are not. After detrending the data, I investigate whether there are any Granger causality relationships between the different price series, and comment on whether this suggests anything about the state of the Efficient Market Hypothesis in this quite young financial market.

The data I use for this paper comes from a public available source, www.investing.com, which lists daily price data for several crypto coins.

For purposes of comparison, I have chosen to examine price data on three price series: Bitcoin (Btc), Ethereum (Eth), and Monero (Xmr). I have chosen these because Bitcoin was the original crypto currency and therefore often seems to lead the market, and certainly is the most well- known. Ethereum, on the other hand, is another dominant force in the current market and seems to be another very stable presence, though explaining its specifics is beyond the scope of this paper. Finally, I also consider the price of Monero, an “alt” coin, which is newer than the other two. I am interested in whether the prices of the more dominant, established currencies offer patterns that may predict changes in this newer, alternative currency. The study was carried out using a VAR analysis, to understand the causal link between the previously mentioned variables. Basically, the following study was carried out through three different steps, and will be subsequently presented in this sequence:

* check the presence of the unit root.
* check the cointegration between the variables (if necessary).
* carry out the VAR analysis.

Figure 1 illustrates the three-price series over the two years Feb. 14, 2016, through Feb. 14, 2018. Since the price of Bitcoin dominates the other two, I also include Figure 2 to show only the prices of Ethereum and Monero over the same period. From the graphs the prices are closely correlated with one another over time, but before analyzing any possible causal relationships, as previously mentioned it is important to consider whether the series are stationary

In order to investigate the stationarity of time series data, the Augmented Dickey Fuller Test (ADF) was conducted, a unit root test to investigate the stationarity of time series data since, the presence of unit roots, can cause unpredictable results in time series data. ADF tests are used for this study due to their popularity and wide application in the literature.

we reject the null hypothesis that the data are stationary at all significance levels for each series. To make the data stationary, we therefore use first differences, so each data point, rather than being simply the price at time t.

With the data stationary, in this case there is no need to run a cointegration test and it is possible to put all three-time series into a vector auto regression model (VAR) to test whether the prices and lagged prices of each variable impact one another, thereby implying a form of causality.

Now, the data appear to be stationary after applying first differences to our variables. These results are presented in Figure 6, Figure 7 and Figure 8. With the data stationary, in this case there is no need to run a cointegration test and it is possible to put all three-time series into a vector auto regression model (VAR) to test whether the prices and lagged prices of each variable impact one another, thereby implying a form of causality.

B. Appropriate var length  
To estimate a VAR model, the first thing to do is to choose an appropriate var length.

As you can see from the table below containing the results of our variables, for each lag length we have different model selection criteria, which are:

* Log Likelihood → must be maximized
* Likelihood Ratio → must be minimized
* Final Prediction Error → must be minimized
* Akaike IC → must be minimized
* Hannan-Quinn IC → must be minimized
* Schwartz Bayesian IC → must be minimized

C. VAR stability

Once the best model has been chosen, it’s necessary to check if it could return credible results by running diagnostic tests; the first diagnostic test is on VAR stability which returns a table with all the eigenvalues and also a graph which represents a unite circle and the roots of the companion matrix. In this case all the eigenvalues lie inside unite circle, so this VAR satisfy the stability condition.

D. Residual autocorrelation  
The second diagnostic test is the Lagrange-Multiplier test for residual autocorrelation this case we are testing if the residuals, of the considered lag, in our VAR are a white noise process (no affected by autocorrelation). we reject the null hypothesis of no auto correlation because all the p values are less than 5% , we have auto correlation up to lag 4.

E. Normality of the residuals

A normality test was then performed on the residual series of the estimated VAR. The test used is the Jarque-Bera test, a statistical test for the verification of the hypothesis of normality widely used in the econometric field to determine if the residues are normally distributed. The null hypothesis is a joint hypothesis that both excess asymmetry and excess kurtosis are null, and this hypothesis is rejected for too large test statistic values. As we can see from the results of Jarque-Bera test, all the values are less than 5% (0 or very close to 0) so we reject the null hypothesis of normality of the residuals.

F. Confirm the lag length

the Wald lag-exclusion statistics it tests the null hypothesis that the endogenous variables at the given lag are jointly zero for each equation and for all equations together Looking at last output of this test and starting from the higher lag order, we can see how the diagnostic test confirms that the right choice is still to include 4 lags since they are jointly significant.

G. Granger Causality test

In order to check causality for each equation in a VAR model, a useful tool is the Granger causality test. The idea, behind this test, is that the significance of all the lags of a variable (excluded) are used to hypothesize the causality on the current values of the another variable ( equation).

H. Impulse Response Function:

the (IRF) of a dynamic system is its output when presented with a brief input signal, called an impulse. More generally, an impulse response is the reaction of any dynamic system in response to some external change.

A shock of DBTCP in the short term has a positive effect on DBTCP itself but this is only valid for the short term , as we can see the effect of the shock tends to disappear after 1 lag and going on to the long term we can see that this effect completely disappears, while for all of the other variables we can see that in the short term there is a small effect, almost nonexistence, that in medium and long run tends to fade.

CONCLUSION

As a conclusion from what we obtained from our analysis we can say that the results showed that there is a short-term relationship between bitcoin and its altcoins but at the same time for the medium and long period the effect faze after the first lag, the relationship is stronger with Ethereum with respect to Monero as we saw from the granger causality test.