CRYPTOCURRENCY, CRYPTOCOMMODITY OR CRYPTOSTOCK?

ANALYSIS OF CRYPTOCURRENCY AND MAJOR ASSET CLASS VOLATILITY SPILLOVER

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Abstract

In this paper the authors analyse connectedness between major asset classes and cryptocurrencies. From all asset classes, 6 important financial instruments are chosen to represent it. Stock markets are represented by stock indices: S&P500, Dow Jones Industrial Average, FTSE100, DAX, Nikkei 225 and the Shanghai Composite Index. Currencies are foreign exchange crosses against U.S dollar: euro, Japanese yen, British pound, Australian-, New Zealand-, and Canadian dollar. Commodities are sugar, gold, corn, wheat, natural gas and crude oil. Connectedness is analysed using the Diebold-Yilmaz spillover framework which uses forecast error variance decompositions associated with VAR-models. The results show that cryptocurrencies constitute a separate asset class which is connected to stocks and commodities as well, and more connected to them then to currencies. This result has implications for risk management. As derivates markets for cryptocurrencies develop, they could become a considerable tool for diversification.

JEL-Classification: C58, G15, G23

Keywords: volatility, spillover, stock indices, commodities, currencies, cryptocurrencies
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1. Introduction

One of the most interesting and exciting financial phenomena of recent years was the emergence of cryptocurrencies. When this new type of asset started becoming a global sensation, most news were only focusing on Bitcoin and its skyrocketing price. Since then however, many other currencies (e.g. Ethereum, Dash) became popular and in 2017 cryptocurrencies were one of the most talked about trends in the world.

But what does the term cryptocurrency really mean? These are digital, decentralized currencies that are not backed up by any government or financial institution. Nor do they have any inherent value. They exist in a decentralized settlement system that is completely operated by a community of users, and their prices reflect how much this community is willing to pay for these assets. Although it’s true that some of these currencies can be used to buy different goods on specific websites on the internet, but this feature in itself cannot fully justify the huge increase in cryptocurrency prices in the last years. For example, the cryptocurrency Dogecoin that was launched in 2013 has absolutely no use whatsoever, still its price increased more than tenfold since its launch, only because a community of users was interested in trading it. Whether or not cryptocurrencies are actually worth anything or will they ever reform the financial world has been the subject of many debates. Many say that these new type of assets, and the underlying technology, blockchain will radically change the financial world, and many are sceptical. Deciding this question is not the goal of this paper. However today there are a number of cryptocurrencies, and they are not likely to disappear anytime soon, which motivates us to try to better understand the way these currencies work, how their prices evolve over time and how investors treat them. (Grinberg, 2011)

One unusual feature of cryptocurrencies is their abnormally large volatility. Their daily returns can have volatilities that are up to ten times larger than that of traditional financial assets (e.g. indices). If an investor is interested in holding a cryptocurrency portfolio then this large volatility will make managing the risk of the portfolio more problematic. Not only their volatility is a huge problem, but also the fact that the return of cryptocurrencies tends to correlate strongly with each other, but
not so much with other asset classes. This further limit one’s opportunities for risk management. (Glaser et al, 2014; Osterrieder-Lorenz, 2017; variance.hu, 2017)

Another question that is still yet to be answered is as which asset class can cryptocurrencies be classified? Although the number of websites that accept cryptocurrency payment is dynamically growing, still most of the users tend to buy them in the hope of realizing great profits from the price fluctuations. This suggests that they are probably not so similar to traditional currencies (as their names would suggest). But then what are they? Do they behave more like commodities? Or do they form a completely new asset class? (Barber et al, 2012; Yermack, 2013)

These are the main questions that motivated our study. To try to better understand the nature of cryptocurrencies, we are going to use econometric and network science methodology. We are going to use the volatility spillover framework developed by Diebold and Yilmaz in 2009 and further improved in 2012. This framework uses vector-autoregressive models to calculate the so called spillover measure. This measure will show us how much the volatility of one asset in the model has affected the volatilities of the other assets. This will help us better understand what dynamics do the volatilities of cryptocurrencies follow, and what connections they have with other asset classes. Therefore, our two main research questions are as follows. What are the main dynamics that drive the evolution of the unusual volatilities of cryptocurrencies? Can cryptocurrencies be classified as a completely new type of assets, or do they have some strong connection with an already existing asset class?

The remainder of the paper is organized as follows. In section 2 we are going to give a short overview about the history and the basic principles of cryptocurrencies, pointing out some of the economics problems they face. Section 3 is data description. In section 4 we are going to introduce the Diebold-Yilmaz (2012) spillover framework. Sections 5 and 6 are the results and robustness checks of our models and section 6 contains the concluding remarks.
2. A short introduction to cryptocurrencies

The main purpose of this section is to introduce the technological and economic background of cryptocurrencies to the reader. This way the reader will get a clearer picture of what motivated us in writing this paper. To do this we are going to look at what the advantages and disadvantages of the blockchain technology are, why different cryptos are more appealing than others and what the main problems with these assets are.

2.1. The beginning of Bitcoin

To show why the blockchain technology behind cryptocurrencies got so much attention, and why many people think it is the next big innovation since the internet, we are going to introduce how Bitcoin started out back in 2008, and what has happened with it since then.

Since the 1990’s, online communities have been interested in creating a secure, decentralized system of settlement, in which monetary transactions could be made using digital currencies without the supervision of a central authority. In 2008 a proposal for such a decentralized currency was posted by a user under the username Satoshi Nakamoto. Nakamoto also posted a program that implemented the ideas written in the proposal. That was the start of Bitcoin and since then it became a worldwide phenomenon. (Grinberg, 2011; Nakamoto, 2008)

Just like many other cryptocurrencies, Bitcoin exists in a peer-to-peer system, which is operated and maintained by the community of its users. A user can obtain Bitcoin in two ways. One way is buying it with traditional money like U.S. dollar or even Hungarian forint. The second way is the so-called mining. During mining an individual uses the processing power of his computers to solve cryptographic puzzles in this peer-to-peer system. These puzzles serve the purpose of keeping each transaction in the secret and secure. For lending his processing power to the system, a user can obtain a specific amount of Bitcoin. This way miners will be motivated in operating the whole system, and keeping it a safe place for monetary settlements. (Grinberg, 2011)

Thus, miners are competing with each other in solving these cryptographic puzzles. The system of Bitcoin was designed in a way that the more miners are trying to solve these puzzles, the harder the puzzles get. This way a creation of new coins is stable over time. Another feature of the system
is that the number of coins that can be obtained by mining is decreasing over time (halving in every four year). This means that by the 22nd century the number of Bitcoins will reach its theoretical maximum of 21 million. Paradoxically the feature that makes this system so appealing to its user base can be its greatest weakness in the long run. That is because if Bitcoin were to become a worldwide currency with an inelastic volume then the whole system would eventually face a great deflationary pressure. (Barber et al, 2012; Grinberg, 2011)

The appearance of Bitcoin and the technology behind it has motivated other online communities to come up with their own cryptocurrencies by mimicking some of Bitcoin’s features or even by coming up with solutions that Bitcoin lacked. One example for this would be the smart contracts of Ethereum that is considered in many ways superior to Bitcoin. (Smart contracts are basically programs that execute different transactions according to how they were written by a programmer.) (coindesk.com, 2018)

2.2. Currency or commodity?

It can be seen so far that cryptocurrencies are interesting new assets in the financial world. There are a growing number of websites that accept them as payment, more and more crypto exchanges are getting legalized and in 2017 Bitcoin futures contracts became available in the United States (Cheng, 2017). But then the question arises. What are the users’ true intentions with these currencies? What do they use cryptos for? To buy goods online or to speculate on its price in the hope of earning large amounts of profit? (Glaser et al, 2014; Grinberg, 2011)

Glaser et al in 2014 wrote a paper to answer this question. They wanted to reveal the users’ intentions by analyzing the reason they buy cryptocurrencies. In this case they looked at data from Bitcoin’s transaction history. They analyzed whether or not there is a connection between the number of new users and the number of payments settled in Bitcoin. Although they didn’t have any data about the number of new users, they used the number of Wikipedia searches for the word Bitcoin as a proxy. The logic behind this choice is that new users who have no prior information about cryptocurrencies will most likely search for it in Wikipedia. The authors found that there is statistically significant connection between how many Bitcoin do users buy with traditional currency and the number of Wikipedia searches. However, they found no connection between the
number of Wikipedia searches and the number of actual transactions. From these results they concluded that users who are new to cryptocurrencies tend to buy them and not spend them immediately. This could be because they obtain these currencies not in order to spend them online but rather to speculate on their value and try to achieve profits by selling them at a higher price.

In another study Dyhrberg (2016) pointed out that there are important similarities between Bitcoin, gold and the United States dollar. He also concluded that there is economically and statistically significant connection between the returns of Bitcoin and the changes in the United States interest rates. This could be explained by the macroeconomic effects of the FED raising interest rates. After an increase the demand for the dollar will also increase which leads to the appreciation of the dollar compared to other currencies. This will ultimately lead to the increase in the number of imported goods to the United States. Because Bitcoin can be considered as an easy and practical way of settling international payments, increasing the U.S. interest rate would indirectly lead to the increasing demand for Bitcoin and therefore drive up its price. By pointing this out, Dyhrberg emphasizes that cryptocurrencies have a nature similar to other currencies.

In their study, Glaser et al (2014) showed that users mainly buy Bitcoin as an alternative form of investment. And although Dyhrberg (2016) concluded that there are important similarities between traditional currencies and Bitcoin, some features of Bitcoin limit its ability of functioning as real money. From these results our hypothesis is that although cryptocurrencies are similar to traditional currencies as well as commodities, they follow special dynamics that make them a completely new type of asset class, somewhere in-between the ones mentioned earlier. In the empirical part of this paper we are going to further investigate this question.

2.3. The role of money

Yermack in his 2013 paper have summed up three main functions money has to fill and showed that cryptocurrencies (mainly Bitcoin) are not able to do so. In order for a cryptocurrency to become a worldwide, internationally accepted form of payment it has to fill three main roles. These roles are the following: medium of exchange, unit of account and store of value (Yermack, 2013 pp. 9, 11, 13).
First an international money must be a medium of exchange, meaning that it should be acknowledged by a number of countries and has to be accepted by a variety of stores worldwide. It is easy to see that as of today there is still relatively few websites and stores that accept cryptocurrencies. Most of the sites that do are mainly focusing on services related to cryptocurrencies. Of course, there are a number webpages where you can buy different goods using cryptocurrencies, but most of these sites are only present in the dark web. This means that these sites cannot be visited using traditional browsers, and one has to use different proxy servers to reach them. This is mainly because the websites themselves are often involved in illegal activities (like drug or arm dealing), and because the legal standpoint considering cryptocurrencies is still not clear in many countries. We can see that more and more countries legalize the use of cryptos but we have still a long way ahead of ourselves before they can fulfill the role of a medium of exchange. (Yermack, 2013)

As we have mentioned before cryptocurrencies tend to have return volatilities that are an order of magnitude greater than that of regular currencies. This poses a problem for the role called unit of account. This means that money must be able to serve as a benchmark for other goods’ prices. Without money one had to keep in mind the relative price of goods compared to every other good. With money introduced to the economy one can simply compare the value of each good to the value of money. But if the value of money itself is the subject of great fluctuations than tracking the prices of goods becomes rather complicated. For example, if we wake up at morning and see that the price of a T-shirt is one unit of some cryptocurrency, than it wouldn’t be surprising if this price would go up 20% by noon, another 10% by the evening and would fall 40% by next morning. This rapid change of prices would render the currency’s role as a unit of account pointless. Another problem arises from the relatively large price of cryptos. If we were to write out the aforementioned T-shirt’s price in BTC/USD, then we would have to use several decimal places which easily confuses an average customer. Yermack points out that this is because in our everyday lives we are not used to seeing prices below zero with many decimal places, so we would not be able to make fast decisions while shopping somewhere online, but rather we would have to pause for a second and think about what the small numbers actually mean. (Yermack, 2013)
Finally, Yermack (2013) looks at the role of being a store of value. This is also a very important role of money, and it means that users have to be able to store their wealth in it. Similar to the previous to roles, this is also undermined by the volatile nature of cryptocurrencies. The possibility of the money’s value halving in one month will definitely discourage risk averse individuals from investing their savings in cryptos.

Therefore, we conclude (in agreement with the author) that cryptocurrencies today do not meet three very important requirements to be able to become internationally accepted forms of money, and cannot be classified as traditional currencies. (Yermack, 2013)

These findings presented in this section further justify our research questions. We can see that the classification of this new asset class is not as evident as the name cryptocurrency would suggest. Besides that, many problems arose from the fact that the prices of cryptos’ are subjects of great fluctuations and jumps. Therefore, in the remainder of this paper we are going to introduce our empirical findings and make conclusions about the classification of this asset class, and about the nature of its volatility.

3. Data

For our research we have used two databases. From Bloomberg (2018) we have downloaded the opening, closing, high and low prices of eighteen financial assets. Our sample consisted of six indices, six commodities and six foreign exchange crosses. We choose some of the most traded assets across exchanges in order to make sure that we use liquid assets and get reliable results from our models.

The indices we used are the S&P500 and Dow Jones (DJI) indices from the United States, DAX and FTSE100 from Europe, Nikkei225 (NKY) and the Shanghai Composite Index (SHCOMP) from Asia. By choosing indices from around the world we will be able to test if there is any relation between connectedness to cryptocurrencies and geographical location.

The six FX crosses used are from the G10 currencies that are the most important foreign exchange crosses in the world. These are crosses against the U.S. dollar against the euro, British pound,
Japanese yen, Australian dollar, Canadian dollar and New Zealand dollar. The commodities we have selected are crude oil, natural gas, sugar, wheat, corn and gold.

From our second database we downloaded the data of cryptocurrencies: the database of investing.com (2018). Similarly, we have downloaded the opening, closing, high and low prices of six cryptocurrencies. We chose the currencies based on their market capitalization and the length of their time series. This way the following cryptos made it to our dataset: Bitcoin, Ethereum, Ethereum Classic, Litecoin, Dash and Ripple.

After we had downloaded all the data needed, we calculated the daily log-returns of each asset and their daily volatility. But because the volatility of a time series is a latent variable (meaning it cannot be observed directly) a further question arises regarding the data. On which of the existing volatility measures should we run our models? In the existing literature one of the most popular choices for the volatility proxy is the realized volatility measure. (Patton-Sheppard, 2015 pp. 684)

\[ RV_t = \sum_{k=1}^{n} r_k^2 \]  

In this measure we approximate the underlying variance of a time series at time period \( t \) by summing up the squared intraday returns during that period. It could be shown that if in Equation 1 \( n \) approaches infinity (meaning that the time interval between each return approaches zero) the \( RV_t \) will converge in probability to the underlying, in other words to the integrated variance of a time series. But because we had limited access to high quality, intraday data, especially in the case of cryptocurrencies, we had to use another measure that has proven to be an adequate approximator of the integrated volatility. (Patton-Sheppard, 2015)

Nevertheless, to estimate volatility one has other options than using high frequency intraday data. Molnár (2012) provides a detailed discussion on properties of range based volatility estimators. In this approach, volatility is the diffusion parameter of log-price, which follows a geometric Brownian motion. It is assumed to be constant on a day, but can change from day to day. (Molnár 2012)
Apart from the fact range-based estimators are convenient, because one doesn’t need to collect intraday day, they are also exempt from market microstructure noise. Garman-Klass (1980) develop a volatility estimator that uses all public information that is available for most of financial assets daily. These are daily open, close, high and low prices.

The estimation method is as follows: daily log-returns for close, high and low are calculated. This practically means subtracting the log open price from the log close, high, and low prices. These values are named \(c, h\) and \(l\) respectively (Molnár 2012, p. 21). Garman-Klass (1980) finds that the minimum variance analytical estimator can be simplified to Equation 2. Throughout this paper, for estimating volatility this estimator is used.

\[
\sigma^2 = 0.5(h - l)^2 - (2 \ln(2) - 1)c^2 \quad \text{(Molnár, 2012, p. 22)}
\]

After our dataset was complete ran our models. Later on, in this paper the reader will see that we used two methods to get results from our models. Firstly, we had ran the models in each year from 2013 to 2017. Then from the output tables of the models we constructed networks in order to visualize the strength of the connections between the financial assets in each year. If one of the assets didn’t have enough observations in one specific year (mainly because that specific cryptocurrency did not exist in that year yet) then it was excluded from the model.

The second method we used was to run the models with a rolling window technique. We ran our model two times this way. One time with the 18 regular assets and with Bitcoin. The second time we included two more cryptocurrencies: Dash and Ripple. The reason why we didn’t include all of the cryptos in this model was that most of the cryptocurrencies did not have long enough time series for us to be able to draw relevant conclusions from them. This way we got a time series of the spillover measure that we introduced earlier. This time series formed the basis of our research in the second part of the empirical tests. In the next section we are going to introduce our findings.

4. The Diebold-Yilmaz Spillover Framework

The Diebold-Yilmaz (2009) Spillover Framework is a useful and intuitive tool for measuring connectedness of time series. It is based on variance decomposition associated with VAR-models. The idea is simple as follows: find what portion of forecast error variance of an asset come from
shocks in other assets. This formulation of the methodology therefore gave the answer on the following question: how connected is a time series to all the other time series in directional terms? So, how much volatility it transmits, and how much it receives from other time series.

To be precise, consider an N-variable first order VAR-model forecast as presented in Equation 3. The $X_{t+1}$ vector is the N-variable vector of one period after the current, $\theta * X_t$ is the Wiener-Kolmogorov linear least-squares forecast (Diebold-Yilmaz, 2009, p. 159.), and $\epsilon_{t+1,t}$ is the forecast error of which we are particularly interested in. This error vector’s covariance matrix is decomposed into own variance shares, and cross-variance shares. The cross-variance shares are spillover from one variable to the other. These values are normalized with the total forecast error variance.

$$X_{t+1} = \theta X_t + \epsilon_{t+1,t} ; X_{t+1,t} = \theta X_t$$ (3)

As it can be seen, the methodology had its limitations, which are addressed by Diebold & Yilmaz (2012). The version wrote down in 2009 relied on Cholesky factor identification of VAR’s (Diebold-Yilmaz, 2012, p. 57), which resulted in the spillover being dependent on the ordering of the variables. The use of a generalized vector autoregressive framework of Koop et al. (1996) and Pesaran-Shin (1998) makes the framework invariant to variable ordering, and creates the possibility to measure pairwise spillover. Consequently, one can answer the question how connected is a time series to another time series in directional terms, too.


The framework can be extended many ways. For instance, Barunik et al. (2014, 2016) develop the Spillover Asymmetry Measure (SAM), a useful tool to measure the spread of good and bad volatility, meaning volatility from positive and negative returns respectively. For that, a good and
a bad volatility is constructed from intraday data, summarizing the square of positive and negative returns, respectively. They study petroleum prices (2014) and U.S. stocks (2016) as well.

5. Results

In this section we are going to sum up our main result from the models introduced earlier. Firstly, we are going to look at the correlation structure between the returns and volatilities of all the time series. This way we will have a very simple benchmark model, the results of which could be later compared to the results of the spillover framework. By looking at the results of multiple models we can draw stronger conclusions about our hypotheses, and also, we can examine whether or not the spillover framework has any added value to our research.

5.1. Correlation structure of returns and volatilities

As we have mentioned before we looked at the correlation structure between returns and volatilities in each year from 2013 to 2017, and when a cryptocurrency did not have enough observations in a given year, then it was excluded from our sample. From 2013 to 2015 only Bitcoin had enough data to be included in the analysis, and the resulting networks gave us very similar results. That’s why we are only going to present the networks from 2015 to 2017 (the rest of the networks are available upon request).
Before we jump into the analysis of our graphs, let’s take a look at how these networks build up, in order for the reader to get a clear understanding of what these figures really mean. Throughout the rest of this paper our networks will be presented this way. On Figure 1 we can see the three networks constructed using the correlation structure of the assets from the year 2015, 2016 and 2017. Each node in the network represent a financial asset. Colors represent the four asset classes. Cryptocurrencies are in purple, indices in orange, commodities in blue and FX crosses in green. The edges represent the connection between the assets. Basically, a network should be a complete network, meaning that every node should be connected with every other node, because we calculated the correlation between each of the asset pairs. However, we decided to delete edges where the correlation strength between two assets was less than 0.1, in order for our results not to
be biased by weak links in any way. (Nodes that didn’t have links stronger than 0.1 with any other node have been left out of the graph altogether.) One further remark is that in these cases we didn’t mark stronger links with thicker edges, because in our opinion it would have made it harder for the reader to interpret the graphs.

To construct these networks, we used the Gephi program, where we ran the Force Atlas algorithm to create this layout of nodes. This algorithm places nodes according to the strength of the links between each node. This way the distance between nodes and groups of nodes on these figures represent how strongly they are connected.

After the brief introduction to the basic structure of the graphs, now we are going to interpret our figures. Firstly, we are going to note that there are several structural similarities between the three graphs. Assets that are in some way similar to each other are always located close to one another. This signals that there is to some degree a strong correlation between their returns. Great examples for this are the S&P500 (SPX) and Dow Jones (DJI) indices, Corn and Wheat commodities and the six FX crosses marked in green. Secondly, another thing that is worth noting is that in every graph the node representing gold is always somewhere in the neighborhood of the regular currencies, which is not surprising considering the nature of gold. It’s a known fact that gold functions in certain aspects as a currency. It’s highly liquid, easily convertible to other currencies, and as we can see from the graph, its price changes correlate with other currencies’ returns. (Dyhrberg, 2016)

As for cryptocurrencies we can’t see any clear pattern in 2015 or in 2016. On the 2015 graph, Bitcoin is located at the bottom left corner, far from and with few connections to the other assets. In 2016 we still can’t see any clear pattern in the way cryptocurrencies are located. They have connections to different assets, and they are relatively far from each other. One thing that is interesting is that the Shanghai Composite Index (SHCOMP) is located relatively close to cryptocurrencies. As we will see in the later sections of this paper the Shanghai Index will remain close to cryptocurrencies in other aspects as well. This would mean that there is definitely some connection between the index and the asset class. Our hypothesis is that this is because a great percentage of trades in cryptocurrencies is generated by investors from Asia, who are more possible to get involved in the SHCOMP index.
Looking at the graph of 2017 in Figure 1 we can see that there has been a structural change in the network and cryptocurrencies got very close to each other in one cluster, seemingly forming a whole new class of assets. 2017 was the year when Bitcoin’s and many other cryptocurrencies prices started skyrocketing. By the second half of the year the media was filled with news about cryptocurrencies and lot of people were guessing if blockchain would be the next thing to revolutionize our world. Considering this it’s no wonder that the graph looks like the way it does in Figure 1.

On Figure 2 we have illustrated the graphs that we got from calculating the correlation structure of the volatilities of each asset. By examining these graphs, we arrive to similar conclusions as we did in the case of Figure 1. Until 2017 there had been no clear patterns in the way cryptocurrencies were located. But in 2017 when the crypto craze spread around the world suddenly the correlation between cryptocurrencies volatilities became stronger and the purple nodes formed a cluster that is relatively far from the rest of the nodes. Our one additional remark about Figure 2 is that it is noteworthy how the SHCOMP index and commodities such as Crude Oil, corn, sugar and wheat are closer to cryptocurrencies than the rest of the nodes. These finding and the fact that ordinary currencies are nowhere near the nodes of cryptocurrencies support our conjecture that cryptocurrencies cannot be classified as the other, traditional currencies, and that they form a new kind of asset class that has some similarities to other financial assets like commodities or some indices.

Concerning SHCOMP index, it is interesting enough to take note of its position. It is very weakly connected to stock indices, but significantly connected to commodities, and cryptocurrencies as well. Concerning cryptocurrencies, some geographical reasons were drawn, but its closeness to commodities stems from a different reason: its components are to a very large extent industrial companies or airports and airlines, which are very closely connected to commodities. Next, we are
going to look at the networks we got from the volatility spillover framework, and at the end of this section we are going to draw somewhat more detailed conclusions about our hypotheses.

Figure 2. - The correlation structure of the volatilities of financial assets from 2015 to 2017
Own figure, based on Bloomberg (2018) and investing.com (2018)

5.2. Volatility spillover networks

In this section we are going to present the results from the volatility spillover framework. This methodology is providing additional information as it can separate the effects of different time series and shows pairwise directional relations. Looking at the output of these networks we will be able to tell more about the way volatility is spreading throughout the network. In this section we do not report the result from the return spillover model because the results from return spillover
were quite similar to that of volatility spillover. On the other hand, as Diebold - Yilmaz (2009) puts it, volatility spillover is much more interesting, as it formulates “fear connectedness”, and tend to change drastically over time, while return spillover shows a somewhat emerging trend as financial market integration develops.

On Figure 3 we have plotted the three graphs representing the outputs of the volatility spillover framework. The underlying volatility spillover framework used a predictive horizon of 12 days, and a first order VAR-model. As before, we didn’t visualize the graphs from 2013 and 2014 because they were very similar to the graph of 2015.

If we look at how the graphs evolved through time we see very similar dynamics as we have seen earlier in the previous section. Before 2017 the nodes of cryptocurrencies do not form a definite
cluster. This is probably because the fact that the spillover measure between them is relatively low (at least compared to the spillovers we see in 2017). The graphs of 2015 and 2016 however have two interesting features that are worth mentioning. First is the close connection between the cryptocurrencies Dash and Ripple. This connection can also be discovered on Figure 2 where we constructed the networks using the correlation between volatilities. This connection between the two cryptos could mean that there is an overlap between their user bases, or that they have similar properties that make them both targets for the same kind of investors. Another interesting thing about the graph of 2016 is that in this year Bitcoin suddenly became a central component of the subgraph consisting mainly of FX nodes, gold and some indices. Behind this is the fact that this year Bitcoin was a net transmitter of volatility, meaning that if the volatility of Bitcoin increased, shortly after that the volatility of the other assets followed. In the next section we are going to talk about this phenomenon in more detail.

Next if we look at the graph of 2017, we again arrive to similar conclusions as we did in the case of Figure 2. As the popularity of cryptos rose, the cryptocurrencies in our sample became strongly connected and formed a definite cluster, separate from the rest of the assets. We can also see that out of the other nodes the closest to cryptocurrencies are commodities and the SHCOMP index, which further strengthens our findings from the previous section. Furthermore, a prior expectation of ours was that the node of Nikkei225 (NKY) index would be closer to the cluster of cryptocurrencies, given that cryptocurrencies are becoming more and more popular in Japan, and the legal environment is also changing in a way that it promotes the spreading of cryptos. However we expect that if we would construct these graphs at the end of 2018, we would see the connection further strengthening between Nikkei225 index and cryptocurrencies. (japantimes.co.jp, 2018)

In this section we have examined the correlation and the spillover structure of the assets in our sample. Considering our research questions and the results from this section we have arrived to two important conclusions. The first is that after the popularity of cryptocurrencies rapidly increased in 2017, the cryptos in our sample formed a definite group, separate from the other asset classes. This supports our hypothesis that cryptocurrencies form their own asset class that is in many ways similar to commodities and indices. Our other conclusion is about the way one can manage risks while holding a crypto portfolio. We have seen in this section that there is a high
amount of correlation between not only the returns but also the volatilities of cryptocurrencies, and also that there is usually very weak connections with the rest of the assets. This fact makes it hard for the investors to manage their risks. Because of the great correlation, holding a portfolio of mixed cryptos is not beneficial, and we have found no other assets that could be used to hedge the risk of cryptocurrencies away. Hopefully in the future smart contracts and crypto derivatives will provide solutions for these problems.

In the next section we are going to analyze the results of our rolling window models, focusing on the question, to which of the other asset classes are cryptocurrencies most similar. We expect that the results from the rolling window models will support our findings so far.

5.3. Rolling window analysis

In order to study the evolution of cryptocurrencies’ connectedness with major asset classes in time, a rolling window analysis was carried out. The predictive horizon is 10 days, and the underlying VAR model is of order 1, just as before in this paper. The length of the window is 200 days, which is an approximation of one year for which the explanation is twofold.

Firstly, even though cryptos have data for all days, regular financial instruments (stock indices for example) are only traded on working days, therefore 250 should be a better approximation. But secondly, using several much time series results in more days missing from at least one time series. In that case, that day needs to be dropped from our analysis, hence the 200-day rolling window.

It is important to note, that choosing window-size is an important parameter, to which results can be very sensitive. For example, Diebold-Yilmaz (2014) use a 100-day length, Diebold & Yilmaz (2009) a 75 and a 200-day length and Diebold-Yilmaz (2015) a 200-, and a 150-day length rolling window. In this paper, we opted for the longer window because the prices of cryptocurrencies are very volatile and change rapidly, therefore a longer window seemed to be a better choice to smooth sudden changes. In the end of this paper robustness to window size is further discussed.

In the rolling window analysis, the question of interest is still the connection between cryptocurrencies and major asset classes. Therefore, the net overall volatility spillover, and the
volatility spillover concerning the representatives of asset classes are considered. Net spillover for an asset class can be calculated by summing the spillover for each asset that is included in the class.

The conducted analysis can be separated into two parts. First, only Bitcoin was involved because it has a much longer history of existence. Figure 4 shows the net overall volatility spillover, and for specific asset classes. It can be seen, that most of the time net spillover is very close to zero, with some shorter periods where net volatility spillover skyrockets in one direction. It is important to note, that the axis goes from 0 to 6. That is because the highest possible value for an asset class’s net spillover against Bitcoin or any other cryptocurrency is 6, because 6 assets are summed in every class, and for one the net spillover’s maximum is 1, the net spillover value being normalized.

The most significant spike is at throughout the end of 2016 and the beginning of 2017. A high positive value in this chart means that Bitcoin was transmitting volatility at that time to other asset classes. Note that this is the same phenomenon that we have previously talked about in section 5.2. In this period, there were much talk about CME, the world’s largest futures exchange launching Bitcoin futures (Cheng, 2017). It is interesting though that this effect is only present for a short period of time. The ranking for asset classes in this spike is FX, indices and then commodities. So most importantly currencies received volatility from Bitcoin, then indices and commodities. Another explanation is that early 2017 was the time when Bitcoin’s price started skyrocketing from around a thousand dollars, first doubling by May, and then peaking at around 19.000 dollars on the 17th December. However, the disappearance of spillover remains a puzzle concerning that explanation, too.

There are some smaller downward spikes as well, which signal net volatility receiving from the asset classes. In these cases, most of the time indices lead the way, with FX as the second biggest net volatility transmitters to Bitcoin. In early 2018, this can be due to the market correction in stock exchanges that has been erased by a powerful comeback later on, causing excess volatility (Egan, 2018). Note that the negative spillover we examined throughout the end of 2017 and at the beginning of 2018 was after future contracts became available in the U.S. by the CME Group. It
was also around this time that Bitcoin’s started falling and eventually it plummeted under 7000 dollars on February 5th. Our hypothesis is that it was because of the future contracts becoming available that the market conditions changed and that now we can see this pattern in the volatility spillover measure of Bitcoin and the others.

It also can be said, that in net terms, the least important transmitters of volatility were commodities for Bitcoin.

![Image of Figure 4](image)

*Figure 4 - Net volatility spillover of Bitcoin standalone overall, and for asset classes, 2014-2018
Own figure, based on Bloomberg (2018) and investing.com (2018)*

The following three Figures (5, 6 and 7) are coming from a different rolling window analysis, where not only Bitcoin, but also Dash and Ripple were included in the spillover framework. Consequently, the time-span is shorter (starting from then end of 2016), because the time series of Ripple and Dash prices start later than Bitcoin’s. Concerning Bitcoin, Figure (5) shows very similar dynamics to what we saw in Figure 4.
As for Ripple, the positive spike in the beginning of the time span is almost invisible, while the negative peak at the end of 2017 - previously seen in the case of Bitcoin - is present to almost exactly the same extent, on both of the figures of Dash and Ripple. This reinforces our earlier finding that by that time cryptocurrencies are very tightly connected to each other, and the previously seen volatility spillover to Bitcoin affected Dash and Ripple as well. Concerning the ranking of classes, indices seem to be the most important in the negative peak, followed by currencies, and commodities are virtually having no spillover in net terms with any cryptocurrencies. Finally we would like to remark that the similarities between Dash and Ripple – pointed out in the previous sections – can also be observed in the time series of their spillover measures. This is consistent with our hypothesis that Dash and Ripple have similarities because of which they might attract a similar user base, and because of which their volatilities follow similar dynamics. It is also worth to mention that the biggest transmitters of volatility to Dash and Ripple before the end of 2017 were commodities and indices, unlike in the case of Bitcoin where we have pointed out that FX crosses also played an important role.
In conclusion we have seen in this section that how the spillover measures of different cryptocurrencies have changed throughout the years. We have pointed out that there are several differences in the way cryptocurrencies received volatility from other asset classes. While the volatility of FX crosses had a relatively big impact on Bitcoin’s volatility, in the case of Dash and Ripple commodities and indices were the main transmitters. From this we conclude that although cryptocurrencies seem to form their own asset class, there are still relevant differences between cryptos themselves. Therefore, we cannot make universal statements about the asset class of cryptocurrencies being similar to any other asset class. We also pointed out that the events of the end of 2017 have affected the way cryptocurrencies’ volatilities behave. It will definitely be interesting in the future to track how the changes in market conditions, legal environment and investors’ behaviour will affect the way cryptocurrencies volatilities evolve.
Figure 6 - Net volatility spillover of Ripple overall, and for asset classes, 2016-2018
Own figure, based on Bloomberg (2018) and investing.com (2018)

Figure 7 - Net volatility spillover of Dash overall, and for asset classes, 2016-2018
Own figure, based on Bloomberg (2018) and investing.com (2018)
6. Robustness check

To ascertain the robustness of our results several checks were done. For the predictive horizon, and the order of the underlying VAR-model, the results are not presented here. The results show very little variability, the only setup which produced significantly different results was using a 1-day predicting horizon. A more interesting analysis is the effect of window size on rolling window estimation. What we can see on Figure 8 is that the results are quite robust to window size. Figure 8 shows Bitcoin, but very similar results are obtained for Ripple and Dash as well. In conclusion one can state that our results are robust in terms of predictive horizon, underlying VAR-lag, and window size. This further strengthens our results.

![Figure 8 - Bitcoin's net spillover with 100, 150 and 200-day rolling window](Own figure, based on Bloomberg (2018) and investing.com (2018))
7. Conclusion

In our paper we looked at a phenomenon that has been the subject of many debates: cryptocurrencies. Throughout our research we were interested in mainly two questions. What are the main reasons behind the unusually large volatility of cryptos? Can they be classified as an existing and well known class of assets, or do they form a new and separate class? To answer these questions we have used econometric and network science methodology combined.

The main framework used in this paper was the spillover framework developed and further improved by Diebold-Yilmaz in 2009 and in 2012. The main benefit of this framework is that it can show us the strength of connection between the time series of any two assets volatility, and it can separate the effects of different time series. In this sense this framework is in many aspects more appealing than looking at plain correlations.

During our analysis we have examined the time series of 24 assets. Six indices, six commodities, six FX crosses and six cryptocurrencies. First we have constructed networks using the outputs of the Diebold-Yilmaz (2012) framework called the spillover tables. Then we have analysed these networks and compared them with our other networks that were plainly constructed using the correlation structure of returns and volatilities. Comparing the different graphs we drew similar conclusions. The most notable of which is that after 2017, when the popularity of cryptocurrencies suddenly rose, cryptos started to form their own asset class that is definitely distinguishable from the other asset classes. This result partially gave answers to both of our research questions. Namely that cryptocurrencies cannot be considered regular currencies such as the euro or the dollar. They should be considered as a completely new type of asset class, the properties of which should be further analysed and understood. The other answer we got was that managing the risk of a crypto-portfolio remains to be problematic for the strong correlations between cryptocurrencies limit the investors ability to hedge away risks. And the fact that cryptocurrencies have only weak links with other asset classes makes this problem even harder to solve. Hopefully with the appearance of derivative contracts and more and more advanced smart contracts this problem will be solved in the future.
Finally we took a look at how the spillover measure of some of the cryptocurrencies (Bitcoin, Dash and Ripple) evolved throughout the years. We have seen how some important event concerning cryptocurrencies have affected the way this asset class transmitted and received volatility to and from other asset classes. The results of the last section further supported our conjecture that cryptocurrencies form their own distinct asset class. Although they have some similarities with other assets, but these links are not strong enough for them to be classified in one of the regular asset classes. Also the links between individual cryptos and other assets showed us, that there are important differences even among cryptocurrencies themselves (with Dash and Ripple having tighter links to commodities than Bitcoin for example).

Also the changes in spillovers we saw at the end of 2017 (and also at the beginning of 2018) suggests that it will be interesting to see how these properties of cryptocurrencies will evolve in the future, and with the market conditions and legal environment changing what role will cryptocurrencies play in our future.
8. References


CRYPTOCURRENCY, CRYPTOCOMMODITY OR CRYPTOSTOCK?


