The dynamic relationship between digital currency and other financial markets in developed and emerging markets

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Abstract

The paper examines shock spillovers between traditional currencies, digital currencies, and equity markets across emerging and developed economies. In addition, the study examines how connectivity varies across short- and long-term investment horizons to provide insight for asset managers and investors with different investment horizons. The empirical results reveal that Ethereum and Bitcoin, representing digital currencies, are the primary contributors to total return spillover among the three markets over different time frames in developed economies. When contrasting emerging and developed economies, the paper finds that, over the long term, the traditional currency and equity markets in emerging economies play a more significant role in total return spillover compared to those in developed economies. As a result of this research, asset managers and investors will gain invaluable insights regarding optimal asset allocation and investment decisions over short and long term horizons.

Keywords: Spillover, Digital Currency, Return Connectedness, Asset Managers, Stock Market, Currency Market, Emerging Economy, Developed Economy.

1. Introduction

In recent years there has been an emergence of the digital currency, particularly, cryptocurrency. Cryptocurrency is simply a digital currency where records of transactions are stored on a decentralised system with the use of cryptography. The largest cryptocurrency, Bitcoin, was launched in January 2009, however since its inception, hundreds of other cryptocurrencies have emerged, but with Bitcoin remaining the dominant digital currency. Although they were created as a means of transactional use, they have quickly turned into investment and trading vehicles to the point where investors and asset managers are using them for hedging and speculation purposes. For example, Bouri et al. (2017) analyse whether Bitcoin would be an effective hedge or be considered a safe haven before and after its crash of 2013. Urquhart and Platanakis (2020) investigate whether there are benefits to the addition of Bitcoin in a stock portfolio and conclude that adding Bitcoin to portfolios is beneficial owing to the substantially high risk-adjusted returns. Bouri et al.(2020) analyse downside movements in the S&P 500 and whether cryptocurrencies can provide adequate hedges against those downside periods and they find that Bitcoin, Ripple and Stellar are safe havens for all US equity indices while other cryptocurrencies are only safe havens in selected equity sectors.

Many studies focus on the possible linkages between digital currency market and other financial markets. For example, Park et al. (2021) analysed the information flow that occurs between different financial assets and Bitcoin with the use of transfer entropy, and concluded that there exists a considerable flow of information between exchange rates and cryptocurrencies. Corbet et al. (2018) investigate the relationship between a few digital currencies, namely Bitcoin, Litecoin and Ripple with other markets like the bond market, the VIX and Gold, and found evidence of isolation of the cryptocurrencies from these other financial markets.

Many of the above-mentioned studies investigated the relationship between cryptocurrencies and different financial assets, focusing mainly on developed economies. It may not be true that the findings ensuing from these studies, on the link between cryptocurrency and other assets, can be inferred to emerging market economies. It is important to note that markets in different stages of their life cycle may have inherently different attributes that need to be taken into consideration (see Mensah & Alagidede, 2017). More specifically we cannot assume the behaviour of a developed market mimics the behaviour of an emerging market owing to inherent differences like better infrastructure and more mature capital markets. Even though one of the redeeming factors of digital currencies is that they do not have borders, a country's economic situation would however still play a factor in the cryptocurrency market owing to the availability of disposable income to invest in the market, and availability of infrastructure to allow cryptocurrency investing.

In attempting to fill this gap, this study will contribute to the existing literature on the interaction and spillover between the cryptocurrency markets and other financial markets by distinguishing between developed and emerging markets. Furthermore, this study will assess how the spillover between these markets fare in the short and long term. Thus, the contribution of this dissertation is threefold. Firstly, the study makes use of the Diebold and Yilmaz (2014) framework to investigate possible spillover between digital currency, traditional currency and stock exchange markets. The study will investigate whether the directional spillover between these markets differ in developed and emerging economies. Given the difference in financial and economic structures between the two types of economies, this investigation will be informative for investors and policymakers alike. Secondly, the study will distinguish between short- and long-term directional return spillovers between markets. This distinction will be necessary for portfolio managers to decide how and when they can apply portfolio rebalancing or buy-and-hold strategies. Thirdly, the study will attempt to construct a network connectedness between these markets to identify which market serves as a net transmitter or net receiver of return shocks.

Following this introduction, the remainder of this study is structured as follows: Chapter 2 analyses existing literature; Chapter 3 breaks down the selected methodology used; Chapter 4 presents the data and final results obtained; and Chapter 5 finally concludes the study with the necessary references.

2. Literature Review

A number of different studies have analysed the linkages between different markets, be they the digital currency market, the stock market, the traditional currency market, or the bond market, on the link between cryptocurrency and financial assets. Naeem & Kareem (2021) make use of the Time-Varying Optimal Copula (TVOC) to investigate the tail dependence between Bitcoin (BTC) and four green financial assets, namely, the Dow Jones Sustainability

Index, S&P Global Clean Energy Index, ESG Leader Index and S&P Global Green Bonds. They found that while symmetric co-movement was shown by clean energy, there was a significant black-swan event that characterised dependence. They also found that there is diversification potential for clean energy when considering the higher hedge ratio for Bitcoin. Another study that investigates the dependence between cryptocurrency and financial markets using copulas is by Garcia-Jorcano & Benito (2020). They found that under normal market conditions Bitcoin may be used as a hedge for stock markets.

Elsayed et al. (2022) investigate the volatility and return connectedness between financial assets such as stocks, crude oil, gold, bonds and the USD, as well as global uncertainty measures and the VIX from April 2013 until June 2020. With the use of a Vector Autoregression Time-Varying Parameter model as well as network analyses and dynamic connectedness, they find that total spillover indices had reached considerable levels, as well as high volatility and return spillovers during the selected covid period across the different markets. Lahiani et al. (2021) investigate the relationship between digital currencies and stock market indices' returns for some developed and the BRICS from 2016 until 2019. They found that the stock market indices (S&P 500, Nasdaq and DAX 30) all play a role in predicting stock market returns in developed and BRICS countries. Also that Ethereum was a lead predictor of other digital currencies and different stock markets and that Bitcoin futures plays a significant role in shaping the returns of the digital currencies and stock market index returns tail dependence and mean.

Zeng et al. (2020) also study the relationship from January 2012 to June 2019 between Bitcoin and traditional financial assets, namely stock (S&P), gold and oil. They use a method adopted from Diebold and Yilmaz (2009) in a vector autoregressive system that is used to investigate this dynamic interdependence. They find that this connectedness is weak, but by separating negative and positive Bitcoin returns, they find the existence of a spillover effect between Bitcoin and the traditional assets under consideration is asymmetric. They also conclude that connectedness of positive Bitcoin returns are weaker than those of negative Bitcoin returns. Another study that also investigated the causal relationship between Bitcoin and different asset classes is by Bhuiyan et al. (2021). They employ a wavelet approach to understand the lead-lag relationship between Bitcoin and a number of other different asset classes like commodities, gold, stock and bond indices, and currencies. They considered data from January 2014 to November 2019. They conclude that the isolation of Bitcoin from their considered asset classes suggest that Bitcoin can offer diversification benefits to interested investors

Another study that considers the relationship between digital currencies and stock markets is Walid (2021), where, with the use of a quantile regression approach he investigates the effect of Bitcoin prices during specific normal, bear, or bull markets on stock prices. However, instead of using specific country data, he uses data from the closing levels of the S&P Broad Market Indices (BMI). They conclude that the developed market indices are more positively related to realised variance proxy across the normal, bear and bull markets while the same holds true for bear markets in the emerging market indices, as opposed to being negatively correlated in the normal and bull markets.

The studies touched on above are but a small and refined section of the literature focused on the relationship between digital currencies and different financial assets. They considered different digital currencies and financial assets, different data periods and different methodologies. One such study is Yoon et al. (2019) who make use of a network spillover methodology to analyse the market connectedness among different stock markets, the bond market, currency and commodities, with data considered from December 1999 to June 2016. They find that the S&P 500 is the largest contributor to the return spillover shock of other stock markets. Furthermore, that different asset classes, such as bonds, currency, oil and gold, all reduce total spillover, which in turn offers a diversification benefit to asset managers. While this study considers the potential relationship between different asset markets, it does not consider digital currencies which have, in their own right, become quite a sizeable market. In addition, from the available literature we find, to our knowledge, that no study considers the return spillover connectedness among digital currencies, the stock market and traditional currencies, while at the same time considering an emerging economy versus a developed economy viewpoint. Also, we don't, to the best of our knowledge, find literature that considers this relationship but with different time horizons such as shorter-term return spillover connectedness and longer-term return spillover connectedness. The lack of available literature to provide these insights allows this analysis, therefore, to be undertaken.

3. Methodology

3.1. Generalized Variance Decomposition (GVD) and Network Connectedness

As mentioned earlier, we will employ the Diebold & Mariano (2014) modelling framework that uses a Vector Autoregressive type methodology which considers the Generalized Variance Decomposition (GVD) connectedness index. What this methodology does is create an invariant variance decomposition of the variables, allowing us to calculate comparable pairwise forecast errors, to show the effects of shocks to the path of our selected variables. This will allow us to analyse any potential spillover connectedness between our selected markets. We make use of a stationary VAR(p) defined as

$$y_t = \sum_{i=1}^{P} \theta_i \, y_{t-1} + \varepsilon_t \tag{1}$$

where our parameter y_t is the $Nx1$ vector of endogenous variables, θ_i constitutes the NxN autoregressive coefficient matrices, and finally, as usual, ε_t corresponds to the independent and identically distributed error vectors. According to the Wold's decomposition theorem, Equation 1 can be transformed in a moving average form, defined as: However, for our sake:

$$y_t = \sum_{i=0}^{\infty} \alpha_i \, \varepsilon_{t-i} \tag{2}$$

where our parameter y_t is the Nx1 vector of endogenous variables, α_i constitutes the NxN autoregressive coefficient matrices of α that observe the following recursion:

$$\alpha_i = \theta_1 \alpha_{i-1} + \theta_2 \alpha_{i-2} + \cdots + \theta_p \alpha_{i-p} \tag{3}$$

with $\alpha_i = 0$ for $i < 0$ and α_0 is an NxN identity matrix.

The variance decomposition may help to derive the forecast error variance of each variable into elements related to the various shocks in the system. Furthermore, a spillover index can be constructed based on total forecast error variance. Using H-step ahead forecast, the spillover index is constructed as:

$$\delta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i \alpha_h \Sigma \, e_j)^2}{\sum_{h=0}^{H-1} (e_i \alpha_h \Sigma \, \alpha_h e_j)} \tag{4}$$

where Σ denotes the variance matrix of ε (vector of errors), e_i is an $Nx1$ vector with 1 on the i^{th} element or being zero otherwise, σ_{jj} is the standard deviation in the j^{th} equation of the error term. Now our connectedness index consists of an NxN matrix $\delta(H) = [\delta_{ij}(H)]$, where each entry will show us the contribution of variable *j* to the forecast-error variance of variable *i*.

We note that the own-variable and cross-variable variance contribution do not sum up to 1 under the usual generalised variance decomposition, therefore with the use of its row sum, we normalise each entry of the variance decomposition matrix, expressed by:

$$\delta_{ij}(H) = \frac{\delta_{ij}(H)}{\sum_{j=1}^{N} \delta_{ij}(H)} \tag{5}$$

where $\sum_{j=1}^{N} \delta_{ij}(H) = 1$, and $\sum_{i,j=1}^{N} \delta_{ij}(H) = N$. We use $\delta_{ij}(H)$ to provide us an immediate measure from *j* to *i* at horizon H of a pairwise directional connectedness. Going forward, for ease of understanding, we convert the notation of equation (4) to $C_{i\leftarrow j}(H)$ to indicate transmission from *j* to *i*. Now using this degree from the two connectedness we find the net pairwise directional connectedness given by:

$$C_{ij} = C_{i\leftarrow j}(H) - C_{j\leftarrow i} \tag{6}$$

This measure assists us in identifying which market is receiving and which is giving the spillover, which is an extremely component of this analysis. We note here that the 'giver' is the dominant information transmitter. Now to investigate how all markets contribute to the spillover of a single market, i.e., calculate total directional connectedness, we will aggregate pairwise connectedness over all markets. The total directional connectedness to market *i* from all markets is defined as:

$$C_{i\leftarrow *}(H) = \frac{\sum_{j=1,j\neq i}^{N} \delta_{ij}(H)}{\sum_{ij=1}^{N} \delta_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \delta_{ij}(H)}{N} \times 100 \tag{7}$$

Now using the same logic, by aggregating total directional connectedness from market *i* to all other markets we calculate the contribution of market *i* to the shocks of all other markets:

$$C_{*\leftarrow i}(H) = \frac{\sum_{j=1,j\neq i}^{N} \delta_{ji}(H)}{\sum_{ij=1}^{N} \delta_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \delta_{ji}(H)}{N} \times 100 \tag{8}$$

From these two pairwise directional indices, we can construct a total direction connectedness, defined as:

$$C_i(H) = C_{*\leftarrow i}(H) - C_{i\leftarrow *}(H) \tag{9}$$

This establishes how important market *i* is to the system, as equation (11) lets us know how market *i* is giving or receiving spillover to/from the other markets. Finally, to measure the magnitude of all aggregate pairwise connections, we apply the following formula which aggregates all pairwise connectedness measures:

$$C(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \delta_{ij}(H)}{\sum_{i,j=1}^{N} \delta_{ij}(H)} \times 100 = \frac{\sum_{i,j=1}^{N} \delta_{ij}(H)}{N} \times 100 \tag{10}$$

We use this measure to compare the aggregation of all connectedness to all pairwise connectedness, which includes the off-diagonal elements in our generalised variance decomposition matrix. Therefore, this measures how the entire system is integrated as a whole as our index captures the total information flow between all the markets.

An important connection we make is that variance decompositions are in fact also networks, that is, a variance decomposition matrix D is essentially our network adjacency matrix A, and this describes the entire set of connectedness measures. Understanding this allows us to use variance decompositions and network connectedness together. It's important we understand that our variance decomposition networks D are not filled with weights instead of the 0-1 entries. We also note that these links differ regarding direction, i.e., the strength of the link ij will not be the same as ji in most instances, implying that the adjacency matrix A is not symmetric. Also, the sum of each row is 1 since they are shares of the variance. Therefore, we can denote our diagonal elements as $A_{ij} = 1 - \sum_{j=1,j\neq i}^{N} A_{ij}$, and we observe that these diagonals are no longer equal to zero. Our node degrees are now found by summing up our weights in the 0-1 range.

We define our node degrees as 'to' which corresponds to the row sum and 'from' which corresponds to the column sum. The 'to' degree is the probability distribution of the 'to' degrees across the different nodes, defined as $\delta_i^{to} = \sum_{i=1,i\neq j}^{N} A_{ij}$, which is a univariate distribution with (0,N) support. The 'from' degree, which is also a univariate distribution, however with (0,1) support is the probability distribution of the 'from' degrees and is described as $\delta_i^{from} = \sum_{j=1,j\neq i}^{N} A_{ij}$. Summarising our measures, the 'from' degree is $C_{i\leftarrow\cdot}$ and the 'to' degree is $C_{\cdot\leftarrow j}$ which was weighted with our variance decomposition network D. Finally, our total connectedness measure, defined as C, is the mean degree of our variance decomposition network D, acknowledging that since the sum of all rows equals the sum of all columns, we can use either 'to' or 'from' degrees.

3.2. Hodrick-Prescott Filter

The final tool in our study methodology is the use of the Hodrick-Prescott Filter, which we will use to extract the cyclical aspect of our data to analyse shorter-term results and then follow that with extracting the trend aspect of our data to analyse potential longer-term results. Hodrick & Prescott (1981) initially introduced the Hodrick-Prescott (HP) Filter with the intention of estimating business cycles, however, we note that this only ended up being published in 1997 once the HP Filter had gained mass notoriety in the economics space.

The HP Filter makes use of the idea that a time series, x_t, can in fact be broken down into two components namely, a non-stationary long-run secular trend, τ_t, as well as a shorter-run stationary cyclical component, c_t. This equation is illustrated as:

$$x_t = \tau_t + c_t \tag{11}$$

$$Observed\ series, x_t = long\ run\ trend\ component, \tau_t + cyclical\ component, c_t \tag{12}$$

The Hodrick-Prescott Filter extracts the different components with the use of a penalty, by solving the following:

$$min_{\tau_t} \sum_{t=1}^{T} (x_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \tag{13}$$

where $\sum_{t=1}^{T}(x_t - \tau_t)^2$ corresponds to the goodness of fit, and $\lambda . \sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$ corresponds to the penalty incurred for deviations. Our lambda parameter, λ, is in control of the smoothing the created trend series namely τ_t. What this means is that as our lambda parameter tends to 0, $\lambda \rightarrow 0$, the trend component then approximates the actual time series, x_t, while as our lambda parameter approaches infinity, $\lambda \rightarrow \infty$, the trend component approaches linearity to converge to a solution of least squares. Our minimisation formula, Equation 14, aims to maximise the trend component of the time series, or can be interpreted as minimising the cyclical component by ensuring that the trend components gradient is minimised.

4. Data, Estimation and Discussion of Results

In this chapter, we present and discuss the results obtained after implementing the earlier methodology. We begin by describing the data, then presenting and discussing our results and finally interpreting our robustness tests.

4.1. Data

As mentioned earlier, one of the contributions of this study is to distinguish between emerging and developed countries' economies in assessing the cross-transmission of shocks or spillover of cryptocurrency and other financial markets. The rationale behind the selection of the USA as the chosen developed country is quite straightforward. The USA is unequivocally the largest and most important economy in the world[1]. Regarding emerging economies, we chose South Africa, given that, as of July 2021, this country has been a key contributor to digital currencies with the use of the index value of global cryptocurrency adoption per country[2]. The data used for stock market indices are the All-Share Index (ALSI) for South Africa and the S&P 500 for the United States. For currencies, we use the rand per unit of the USD (USDZAR) for South Africa while for the USA we make use of the Dollar Index which is a measure of the USD value vs a basket of currencies used by USA trade partners. The data sample selected is from 10 November 2017 to 09 September 2022 to data availability and the importance to assess how the cross-transmission fares during the COVID-19 crisis. The final decision on the selection of our digital currencies was predominantly based on the market capitalisation value of the digital currencies, as well as their potential real world long-term application, which lead to the decision to perform this analysis on Bitcoin, Ethereum and Ripple.

For all our variables under consideration we source the price (index) data from Thomson Reuters Eikon and Yahoo Finance. We calculate our returns as per the below, where R_t is our return and P_t is our price:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{14}$$

We now take a further step into analysing the data by looking into the descriptive statistics. Table 1 below tabulates the results of this. We observe that across the digital currencies only Bitcoin and Ethereum have positive average returns over our selected period, albeit Ethereum being extremely closer however positive, nonetheless. We find that Ripple over the period had, in fact, negative average returns which may be expected with all the issues surrounding the digital currency, due to the legal battles with the U.S. SEC mentioned earlier. As expected, we also observe the maximum and minimum values across all digital currencies are considerably high, along with them having a comparatively high standard deviation, which aligns with the expected volatility that digital currencies face. We then analyse the selected stock market indices and observe positive averages for both the ALSI and S&P 500 with the latter being higher. We also note similar standard deviations as well as similar minimums and maximums

[1] https://www.focus-economics.com/countries/united-states

[2] https://www.statista.com/chart/26757/cryptocurrency-adoption-world-map/#:~:text=Among%20developed%20countries%2C%20cryptocurrency%20use,also%20registered%20as%20heavy%20users

over the selected period, which were likely during the pandemic phase. Finally, looking at the traditional currencies we observe similar means but as one would expect we find higher maximums and lower minimums along with higher standard deviation for USDZAR compared to the USDX. Based on the p-values for the Jarque-Bera (J-B) test, we reject normality for all variables. We also consider the Augmented Dicky-Fuller (ADF) test to check for stationarity, and we find that they all reject the null hypothesis, therefore confirm all series are stationary. We find that these views align with what one would expect for an emerging market versus developed market comparison.

Table 1: Summary Statistics

	Mean	**Max**	**Min**	**Std. Dev.**	**Skew**	**Kurt**	**J-B**	**ADF**
BTC	0.06	22.51	-46.47	4.46	-0.90	11.89	7113.20**	-9.82**
ETH	0.00	23.47	-55.07	5.57	-1.05	10.01	5144.50**	-9.73**
XRP	-0.02	60.69	-55.05	7.00	0.54	14.98	11094.00**	-9.59**
ALSI	0.01	9.05	-10.23	1.29	-0.56	9.59	4587.50**	-10.51**
USDZAR	0.01	3.96	-2.89	0.98	0.29	0.48	27.45**	-10.21**
SP500	0.04	8.97	-12.77	1.35	-0.97	14.96	11184.00**	-9.83**
USDX	0.01	1.59	-1.69	0.39	0.17	1.05	60.32**	-11.10**

Source: Author's calculations

*Notes: J-B refers to the Jarque-Bera test used for normality. ADF is the statistic of the Augmented Dickey Fuller unit root test. We note that the ** refers to the rejection of the null hypothesis of normality and unit root.*

4.2. Empirical results

In this chapter, based on the methodologies described in Chapter 3, we will analyse the data at the level, then evaluate how the cross-transmission of shocks fares for the cyclical and trend components of the time series to evaluate results from both a short- and long-term perspective. Finally, we perform robustness tests to ensure the validity of our analysis.

4.2.1. Analysis of spillover with data at level

In this section we investigate the return spillover connectedness index from one variable to the next as well as the net-pairwise spillover effects, for the two different countries with the data at level. We begin by tabulating our results for the emerging country, South Africa, below:

Table 2: South Africa Total Spillover Index

From (*j*)						
To (*i*)	BTC	ETH	XRP	ALSI	USDZAR	**From**
BTC	49.10	32.21	15.78	1.95	0.96	50.90
ETH	30.31	46.06	20.51	1.82	1.32	53.94
XRP	17.55	24.70	55.17	1.59	0.98	44.83
ALSI	4.39	4.90	2.89	82.48	5.33	17.52
USDZAR	1.74	2.77	2.11	5.73	87.65	12.35
To	53.98	64.58	41.30	11.09	8.59	179.54
All	103.09	110.64	96.47	93.57	96.23	**Total**: 35.91%

Source: Author's calculations

Table 3: South Africa Net-Pairwise Spillover Index

From (*j*)

To (*i*)	BTC	ETH	XRP	ALSI	USDZAR
BTC	0	1.90	-1.77	-2.44	-0.78
ETH	-1.90	0	-4.19	-3.08	-1.45
XRP	1.77	4.19	0	-1.3	-1.13
ALSI	2.44	3.08	1.3	0	-0.40
USDZAR	0.78	1.45	1.13	0.40	0
Net	3.09	10.62	-3.53	-6.42	-3.76
Conclusion	**Net transmitter**	**Net transmitter**	**Net Recipient**	**Net Recipient**	**Net Recipient**

Source: Author's calculations

In Table 2 we observe that the total spillover reaches 35.91% in South Africa, which implies a moderate level of connectedness across our selected variables in the country. When considering the directional spillovers transmitted 'To' we observe that Ethereum transmit the most shocks to other markets. At 64.58% it is the largest contributor to the other markets, closely followed by Bitcoin with 53.98%. We also observe that USDZAR at 8.59% and the ALSI at 11.09% are the lowest contributors to the total return spillover to other markets, while they receive 12.35% and 17.52% of contributions from other markets.

With the total return spillovers considered, we now delve deeper into the table and analyse the individual effects each of our selected variables have on each other to obtain further insight. Our linkages find that Bitcoin returns affect both Ethereum and Ripple, 30.31% and 17.55% respectively, but have extremely limited influence on the ALSI and USDZAR, at 4.39% and 1.74% respectively. Our results also indicate that the inverse is also true with Ethereum and Ripple returns affecting Bitcoin, 32.21% and 15.78% respectively, and the ALSI and USDZAR also having a very limited influence on Bitcoin with 1.95% and 0.96% respectively. In summary these results suggest that the traditional currency and stock markets' index are influenced to a lesser extent by digital currencies. We note as well that the inverse is also true, in that our traditional currency and stock market index have little effect on our digital currency returns. It can be inferred from the individual linkages that the total spillover of 35.91% is mostly attributed to cross-transmission of shocks among the digital currencies.

In addition to the total spillover considered in Table 2, we also consider the net-pairwise spillover explained earlier. Table 3 above illustrates that this net-pairwise spillover could possibly exist between our selected variables. Validating our results from Table 2, we observe here that the two predominant digital currencies, Bitcoin and Ethereum, are net transmitters (positive net values) with 3.09% and 10.62% respectively, while the smallest digital currency Ripple, the stock market index (ALSI) and the traditional currency (USDZAR) are net recipients (negative net values) of return spillover shock from others with -3.53%, -6.42% and -3.76% respectively. We note that Ethereum is the largest contributor again, with 10.62% of the return shock in other markets being attributed to Ethereum. We do however acknowledge that in the grand scheme of things, neither of the markets are strong contributors to each other's return spillover.

We now investigate the developed economy i.e., USA's markets by tabulating the total spillover index as well as the net-pairwise spillover index below and analysing the results.

Table 4: USA Total Spillover Index

From (*j*)						
To (*i*)	BTC	ETH	XRP	S&P 500	USDX	**From**
BTC	47.79	31.14	15.51	4.07	1.49	52.21
ETH	29.26	44.77	20.14	4.22	1.62	55.23
XRP	17.54	24.68	54.61	2.22	0.96	45.39
S&P 500	7.62	8.23	3.59	77.12	3.44	22.88
USDX	2.35	2.79	1.54	7.02	86.30	13.70
To	56.77	66.84	40.77	17.53	7.51	189.42
All	104.56	111.61	95.38	94.65	93.81	**Total**: 37.88%

Source: Author's calculations

Table 5: USA Net-Pairwise Spillover Index

From (*j*)					
To (*i*)	BTC	ETH	XRP	S&P 500	USDX
BTC	0	1.88	-2.03	-3.55	-0.86
ETH	-1.88	0	-4.54	-4.01	-1.17
XRP	2.03	4.54	0	-1.37	-0.58
S&P 500	3.55	4.01	1.37	0	-3.58
USDX	0.86	1.17	0.58	3.58	0
Net	4.56	11.60	-4.62	-5.35	-6.19
Conclusion	**Net transmitter**	**Net transmitter**	**Net Recipient**	**Net Recipient**	**Net Recipient**

Source: Author's calculations

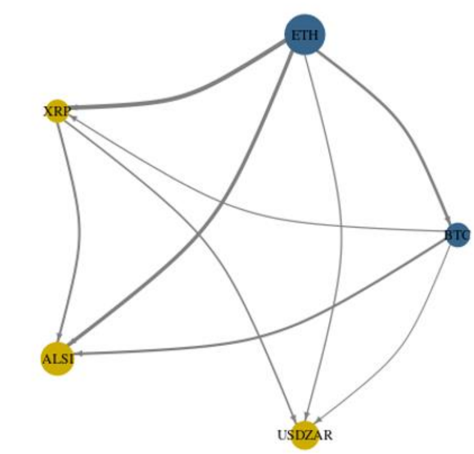
From Table 4 above we observe that the total spillover reaches 37.88%, somewhat similar to the emerging economy, South Africa, which across, here as well, only implies a moderate level of connectedness. We also observe Ethereum to be the largest contributor to the markets in terms of directional spillovers transmitted 'To' at 66.84%, slightly higher than in the emerging economy, Bitcoin at 56.77% is also slightly higher, and Ripple at 40.77%, which, interestingly enough, is slightly lower when compared to the emerging economy. As with the USDZAR, the USDX is the lowest contributor to the total return spillover with 7.51%, implying that the traditional currency has very little effect on the other variables, yet we note that the USA stock market index (S&P 500) return spillover contribution is considerably higher than that of the emerging economy stock market index, 17.53% vs 11.09%, which implies that the S&P 500 has a greater effect on the digital currencies and the traditional currency. This is not entirely surprising considering possible high integration between different markets in the developed country.

As with the emerging economy, it is important that we analyse the individual spillover effects between our variables to further our understanding and find the main contributors to the overall spillovers. We observe that Bitcoin returns affect both Ethereum and Ripple at a reasonable level of 29.26% and 17.54% respectively – almost to similar levels as the emerging economy. While we also see a similar level with regards to the traditional currency of 2.35% for the USA and 1.74% for South Africa, we observe a considerable relative increase from 4.39% for South Africa to 7.62% for the USA, which implies that Bitcoin returns has a greater influence on the stock market index returns. This effect holds for Ethereum as well with the influence on the developed economy's stock market index being almost double the influence of the emerging economy (8.23% vs 4.90%). Similarly, we find that the S&P 500 has again almost double the influence on Bitcoin (4.07%) and Ethereum (4.22%), while Ripple (2.22%) is almost similar to the effect that the ALSI has on our digital currencies. We do however note that these return spillover influences are still incredibly low. As with our emerging economy we find that our digital currencies linkages are all relatively high among each other, although there is very little relation between them and our stock market index and traditional currency. With regards to the comparison of emerging economy and developed economy we do however observe that while the traditional currency (USDX) has a similar effect between both economies, the stock market index (S&P 500) for the developed economy is more greatly influenced by Bitcoin and Ethereum more specifically, admittedly a low degree.

We now consider the net-pairwise spillover for our developed economy, the USA, illustrated in Table 5 above. Similarly, validating the results from Table 4, we observe here that Bitcoin and Ethereum are net transmitters with 4.56% and 11.60% respectively, also observing that these net spillover values are higher for the developed economy compared to the emerging economy, while Ripple, S&P 500 and USDX are all net recipients of return spillover shocks from others with -4.62%, -5.35% and -6.19% respectively. In this case Ethereum is the largest contributor again, with 11.60% of the return shock in other markets being attributed to Ethereum, but as opposed to the emerging economy here the traditional currency (USDX) contributes the second most compared to the emerging economy, where the stock market index (ALSI) is second. In summary, here as well, we observe that neither of the markets are strong contributors to each other's return spillover based on the net's values, which aligns with the emerging economy's results.

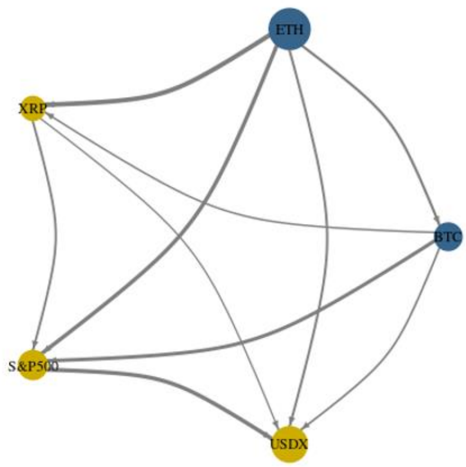
To obtain further insights into the connectedness we consider an additional component namely network graphs. We make use of Diebold and Yilmaz (2014) network topology approach, which presents our total return directional connectedness, considering both the 'To' and the 'From' connectedness, as well as the net pairwise return directional connectedness for our selected variables. From our figure below we again observe how Bitcoin and Ethereum are the net transmitters (blue nodes) and Ripple, the stock market and the traditional currency are net recipient (gold nodes). We also note that Ethereum is the largest contributor with the largest sized node as a net transmitter. It is also worth noting how the stock markets are both full recipients from the other variables (all inward arrows). Furthermore, we observe how Ethereum

Figure 1: South African Network Graph



Source: Author's calculations

Figure 2: USA Network Graph



Source: Author's calculations

does not receive any net return spillover from the other variables, while it does transmit to all variables with Bitcoin, the largest digital currency, included.

Considering that most of the analysis on return spillover so far has been from a static viewpoint, we now consider the time-varying total spillover index with the use of a rolling window and present these results graphically below. We calculate the dynamic spillover with the use of the forecast error variance decomposition, again on 4-ahead forecasts with the total spillover indices being estimated with the use of a 200-day rolling window.

Figure 3: Total spillover index with 200-day Rolling Window

In Figure 3 above we illustrate the total spillover index with a 200-day rolling window. We plot the results for the emerging market in black and the developed market in red. As can be observed both the emerging and developed economy follow the same general trend, although it appears there is more sensitivity to spillovers for the developed economy. For both countries though, with regards to the spillover index, we observe considerable variation during the period 2020 and 2021. We can conclude that crises magnify total spillover across markets, and that this is apparent in both emerging and developed economies. This high spillover implies possible contagion between these markets during global crisis periods.

4.2.2. Analysis of spillover with trend component

In this section we analyse the spillover by, with the use of the Hodrick-Prescott filter, considering only the trend component of the data to evaluate a longer-term viewpoint which is more applicable to ‘buy-and-hold’ strategies. Unlike in Chapter 4.2.1 where we analysed each value of each table, in this section we will present the results for both countries then summarise our findings. Below we tabulate the total spillover and net-pairwise spillover indices and the display the network plots for both countries.

Table 6: South Africa Trend Total Spillover Index

From (*j*)						
To (*i*)	BTC	ETH	XRP	ALSI	USDZAR	**From**
BTC	53.33	30.01	16.54	0.07	0.04	46.66
ETH	31.70	39.41	28.34	0.06	0.49	60.59
XRP	22.21	33.81	43.80	0.03	0.15	56.20
ALSI	0.91	0.39	0.21	95.16	3.33	4.84

USDZAR	0.01	0.12	0.79	3.78	95.41	4.59
To	54.83	64.21	45.89	3.94	4.01	172.88
All	108.17	103.62	89.69	99.10	99.42	**Total**: 34.58%

Source: Author's calculations

Table 2: South Africa Trend Net-Pairwise Spillover Index

From (*j*)					
To (*i*)	BTC	ETH	XRP	ALSI	USDZAR
BTC	0	-1.69	-5.67	-0.84	0.03
ETH	1.69	0	-5.47	-0.33	0.37
XRP	5.67	5.47	0	-0.18	-0.64
ALSI	0.84	0.33	0.18	0	-0.45
USDZAR	-0.03	-0.37	0.64	0.45	0
Net	8.17	3.74	-10.32	-0.9	-0.69
Concl.	**Net transmitter**	**Net transmitter**	**Net Recipient**	**Net Recipient**	**Net Recipient**

Source: Author's calculations

Table 8: USA Trend Total Spillover Index

From (*j*)						
To (*i*)	BTC	ETH	XRP	S&P 500	USDX	**From**
BTC	56.4	30.49	12.40	0.11	0.61	43.60
ETH	36.10	42.12	20.61	0.41	0.76	57.88
XRP	25.21	32.87	41.15	0.50	0.27	58.86
S&P 500	0.01	0.26	0.28	99.31	0.15	0.69
USDX	0.06	0.07	0.03	0.87	99.02	0.98
To	61.32	63.70	33.32	1.89	1.78	162.01
All	117.71	105.82	74.47	101.20	100.80	**Total**: 32.40%

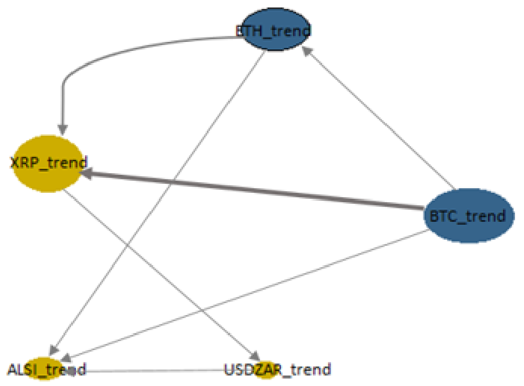
Source: Author's calculations

Table 9: USA Trend Net-Pairwise Spillover Index

From (*j*)					
To (*i*)	BTC	ETH	XRP	S&P 500	USDX
BTC	0	-5.61	-12.81	0.1	0.55
ETH	5.61	0	-12.26	0.15	0.69
XRP	12.81	12.26	0	0.22	0.24
S&P 500	-0.1	-0.15	-0.22	0	-0.72
USDX	-0.55	-0.69	-0.24	0.72	0
Net	17.77	5.81	-25.53	1.19	0.76
Conclusion	**Net transmitter**	**Net transmitter**	**Net Recipient**	**Net Transmitter**	**Net Transmitter**

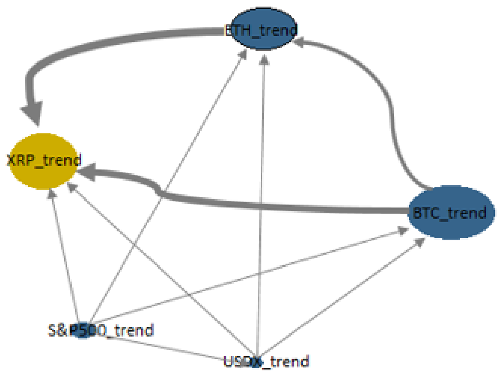
Source: Author's calculations

Figure 4: South Africa Trend Network Plot



Source: Author's calculations

Figure 5: USA Trend Network Plot



Source: Author's calculations

In summary, the results of the trend analysis show a significant net cross-transmission of the digital currency markets with other markets compared to our level analysis. This increasing connectedness signifies the growing integration between the digital currency market and other markets, such as equity markets, in the long term. Moreover, digital currencies continue to play a dominant role as sources of shock transmission to other markets in our network.

Also consistent with both economies, developed and emerging, we find that the digital currencies' spillover contribution to the stock market is less than the spillover contribution of the traditional currency to the stock market, which is a natural expectation considering how traditional currency is mostly used for stock market purchases as opposed to the use of digital currencies. For both economies over the longer term, Bitcoin contributes the most return spillover over other cryptocurrency. This finding is understandable given the long-term perspective and importance of bitcoin as a cryptocurrency. This is largely owing to reasons such as, Bitcoin being the first mainstream digital currency; it having arguably the most secure network; and many altcoins essentially being Bitcoin clones, etc.[3] For these reasons Bitcoin has always been the leading currency in the digital space, and thus over this longer-term period being the most influential. Ripple contributes the lowest return spillover for both economies, which is as we expect since it's the smallest of the three digital currencies and as explained earlier, this could be useful for asset managers when determining which digital currency to add to their portfolio.

Over the longer-term analysis we also observe a few differences between the emerging and developed economies. The first apparent difference is that the stock market and traditional currency are net transmitters as opposed to net recipients. This is somewhat in line with expectations since over the years, the USA stock market and traditional currency have been powerhouses and would certainly have an effect on the remaining markets in our network. The mutual influences of digital and traditional currencies as well as stock markets in the network may have an impact on how asset managers should optimise portfolios constituted of these assets.

We also find in the comparison between the emerging and developed economy that the total directional spillover is higher for our emerging economy, which is in contrast to the results we obtained when considering level dataset. It may be observed from the results presented in Table

[3] https://www.commpro.biz/why-does-bitcoin-have-such-a-big-influence-on-other-cryptocurrencies/

9 that the traditional currency contributed to the increasing spillover in the network. The findings reflect the importance of the traditional currency, especially its growing impact on stock returns in emerging economies. The declining importance of the traditional currency in developed economies may be due to the high digitalisation of their economies.

As the final step of our analysis for our trend set of data, we now plot the dynamic spillover, making use of the forecast error variance on 4-ahead forecasts and using a 200-day rolling window.

It is observed for Figure 6 that the total spillover for South Africa is relatively lower than the

Figure 6: Total Spillover Index with 200-day Rolling Window for Trend set of data

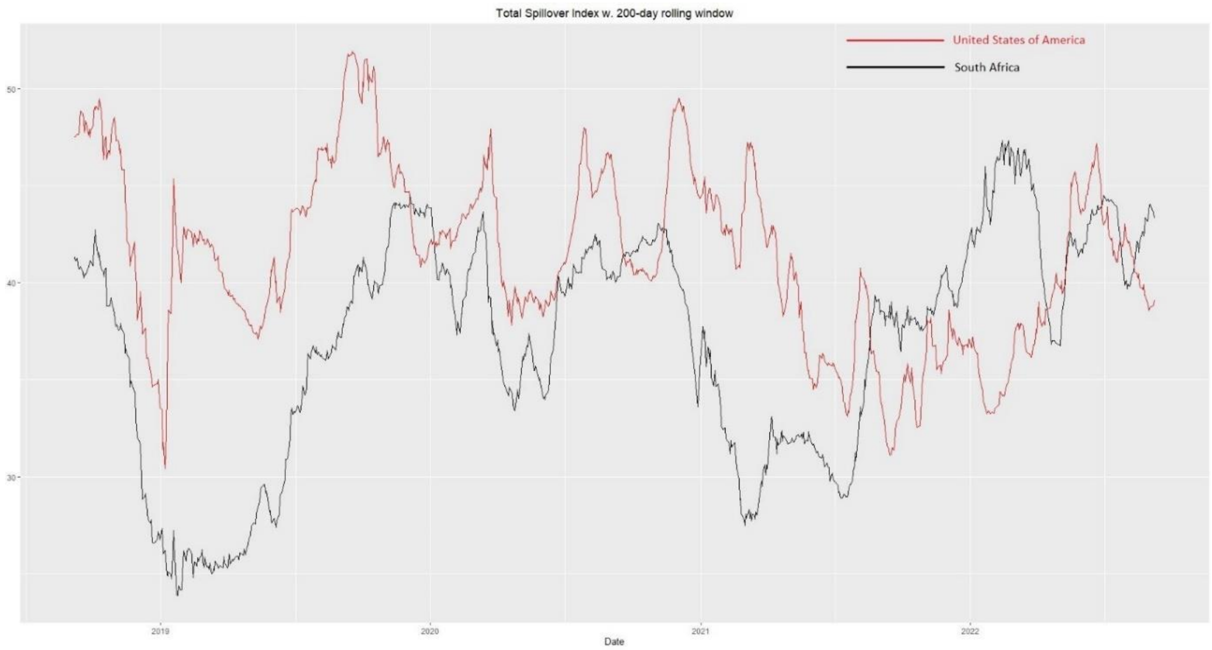
USA during normal market conditions, which we consider the periods before the 2020 coronavirus pandemic, and after around mid-2021 when the markets began to return to levels of normality. The increase in spillover in South Africa in late 2021 and in 2022 may be attributed to the adoption of cryptocurrency as an official means of payment, affecting different transactions.

4.2.3. Analysis of spillover with cyclical component

We now considering only the cyclical component of the data to evaluate a shorter-term viewpoint which is more applicable to 'rebalancing' strategies. Again, unlike in Chapter 4.2.1 in this section we will present the results for both countries then summarise our findings. Below we tabulate the total spillover and net-pairwise spillover indices and the display the network plots for both countries.

Table 10: South Africa Cycle Total Spillover Index

From (*j*)						
To (*i*)	BTC	ETH	XRP	ALSI	USDZAR	**From**
BTC	49.12	32.25	15.71	1.96	0.95	50.88
ETH	30.23	46.19	20.46	1.84	1.28	53.81
XRP	17.55	24.72	55.19	1.63	0.92	44.81
ALSI	4.28	4.83	2.90	82.64	5.34	17.36
USDZAR	1.60	2.63	1.83	5.71	88.24	11.76



To	53.65	64.43	40.90	11.13	8.49	178.6
All	102.78	110.62	96.09	93.77	96.73	**Total**: 35.72%

Source: Author's calculations

Table 3: South Africa Cycle Net-Pairwise Spillover Index

From (*j*)					
To (*i*)	BTC	ETH	XRP	ALSI	USDZAR
BTC	0	2.02	-1.84	-2.32	-0.65
ETH	-2.02	0	-4.26	-2.99	-1.35
XRP	1.84	4.26	0	-1.27	-0.91
ALSI	2.32	2.99	1.27	0	-0.37
USDZAR	0.65	1.35	0.91	0.37	0
Net	2.79	10.62	-3.92	-6.21	-3.28
Concl.	**Net transmitter**	**Net transmitter**	**Net Recipient**	**Net Recipient**	**Net Recipient**

Source: Author's calculations

Table 4: USA Cycle Total Spillover Index

From (*j*)						
To (*i*)	BTC	ETH	XRP	S&P 500	USDX	**From**
BTC	47.82	31.18	15.43	4.04	1.53	52.18
ETH	29.17	44.91	20.08	4.20	1.65	55.09
XRP	17.53	24.71	54.64	2.21	0.91	45.36
S&P 500	7.53	8.16	3.54	77.34	3.42	22.66
USDX	2.06	2.52	1.36	6.98	87.08	12.92
To	56.30	66.57	40.41	17.43	7.51	188.22
All	104.12	111.48	95.05	94.77	94.58	**Total**: 37.64%

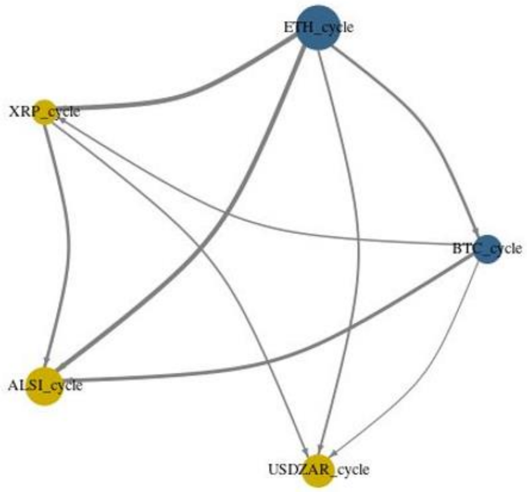
Source: Author's calculations

Table 5: USA Cycle Net-Pairwise Spillover Index

From (*j*)					
To (*i*)	BTC	ETH	XRP	S&P 500	USDX
BTC	0	2.01	-2.1	-3.49	-0.53
ETH	-2.01	0	-4.63	-3.96	-0.87
XRP	2.1	4.63	0	-1.33	-0.45
S&P 500	3.49	3.96	1.33	0	-3.56
USDX	0.53	0.87	0.45	3.56	0
Net	4.11	11.47	-4.95	-5.22	-5.41
Conclusion	**Net transmitter**	**Net transmitter**	**Net Recipient**	**Net Recipient**	**Net Recipient**

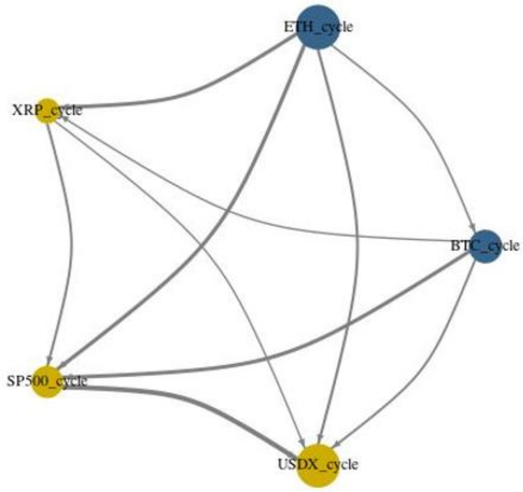
Source: Author's calculations

Figure 7: South Africa Cycle Network Graph



Source: Author's calculations

Figure 8: United States of America Cycle network plot

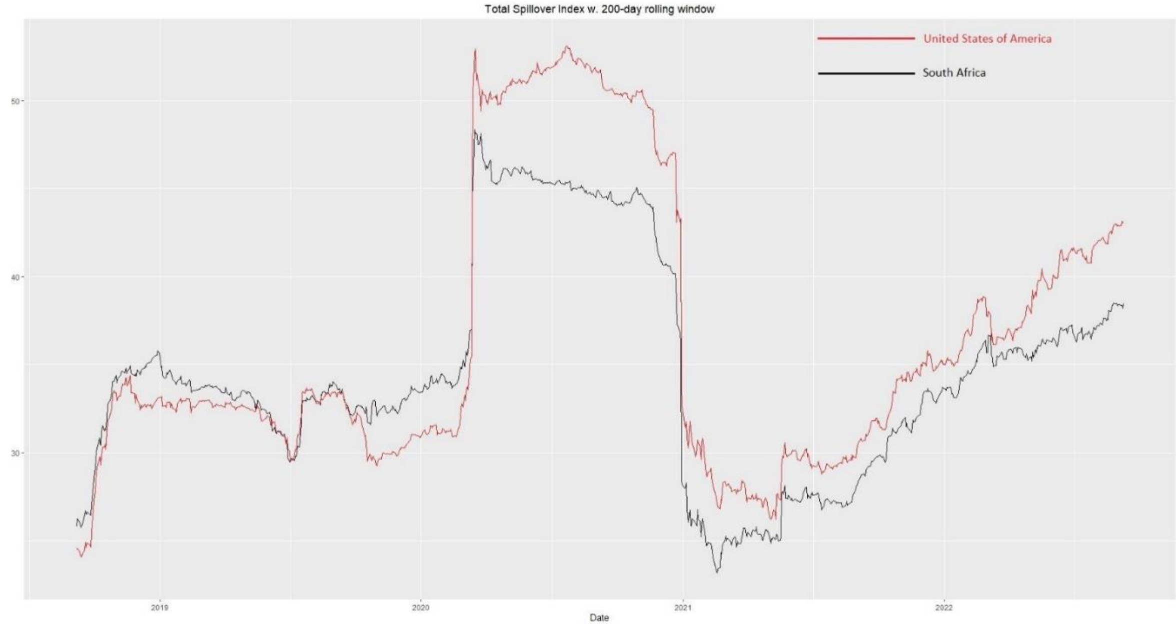


Source: Author's calculations

In summary, we find that the cyclical components mimic our level results. This is in line with Mpoha and Bonga-Bonga (2021) who find that return series are dominated short-term cycles of 2 to 4 days. Moreover, digital currency remains the dominant net transmitter of shocks in the network, especially in the short term. Despite the dominance of Bitcoin and Ethereum as the net transmitters of shocks, the two digital currencies alternate their dominance in the short term and long term. Bitcoin dominates the network as the net transmitter of shocks in the long term. This is certainly due to its popularity over the years. Ethereum influences the network as the dominant net transmitter of shocks in the short term. These findings have an implication for asset managers in allocating assets in an optimal portfolio in that connectedness based on long-term analysis should guide asset managers on how to apply buy-and-hold strategies while the short-term analysis should provide insight on how initially to allocate to portfolios when adopting the portfolio rebalancing strategy. With the buy-and-hold strategy, Bitcoin should be preferred to Ethereum as the leading digital currency asset in a portfolio, while this choice should be given to Ethereum in an initial portfolio when adopting rebalancing strategy.

We now plot the dynamic spillover for the cyclical component of the emerging economy and developed economies' data with the use of 4-ahead forecast error variance and using a 200-day rolling window and display these results below.

Figure 1: Total Spillover Index with 200-day Rolling Window for Cyclical Set of Data



Source: Author's calculations

From Figure 9 we observe that the total spillover for both the emerging and developed economy, when looking at only the cyclical component of the data, move almost in tandem over our selected time period. We also observe that our total spillover index is extremely responsive to periods of market turmoil, like the coronavirus pandemic, as can be seen during the periods of early 2020 and post the normalising of the market, post early 2021. We also find that our developed economies' spillover is more sensitive than the emerging economy to large market volatility.

4.3. Robustness Tests

An important concept in the analysis of results is to test whether conclusions obtained hold under different assumptions. This is where robustness tests come into play. In order to test the robustness of our results we consider a couple of options. The first being to consider the H-step ahead error variance decomposition forecast, as done above, but considering different forecast horizons, namely two, five and ten. The second is to consider different rolling windows while holding the forecast horizon constant. We consider the 200- and 250-day rolling windows. We present the results for both countries below:

Figure 20: South Africa Return Spillover

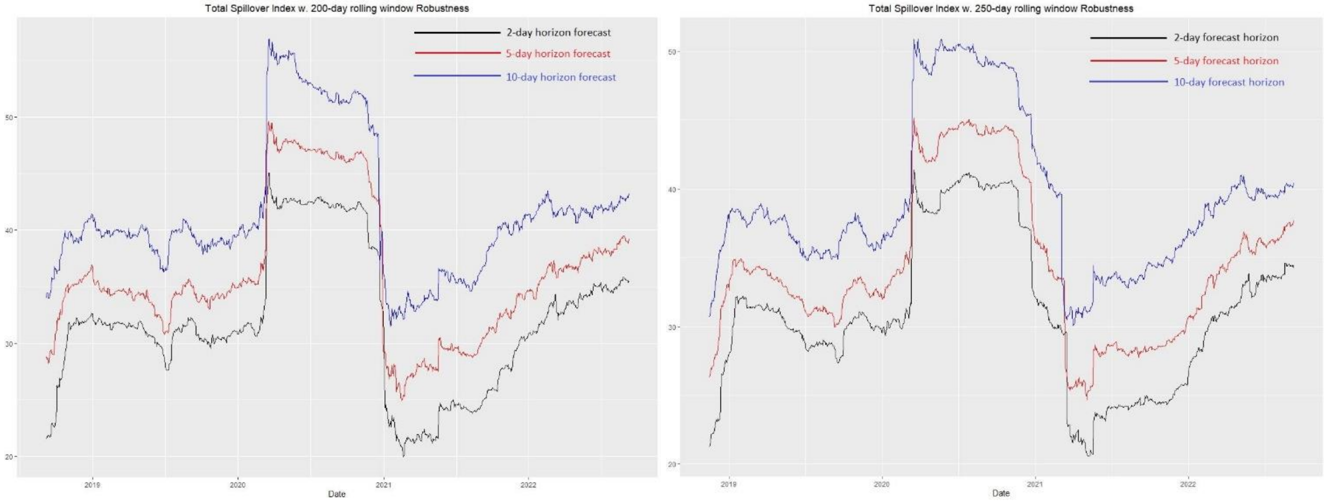
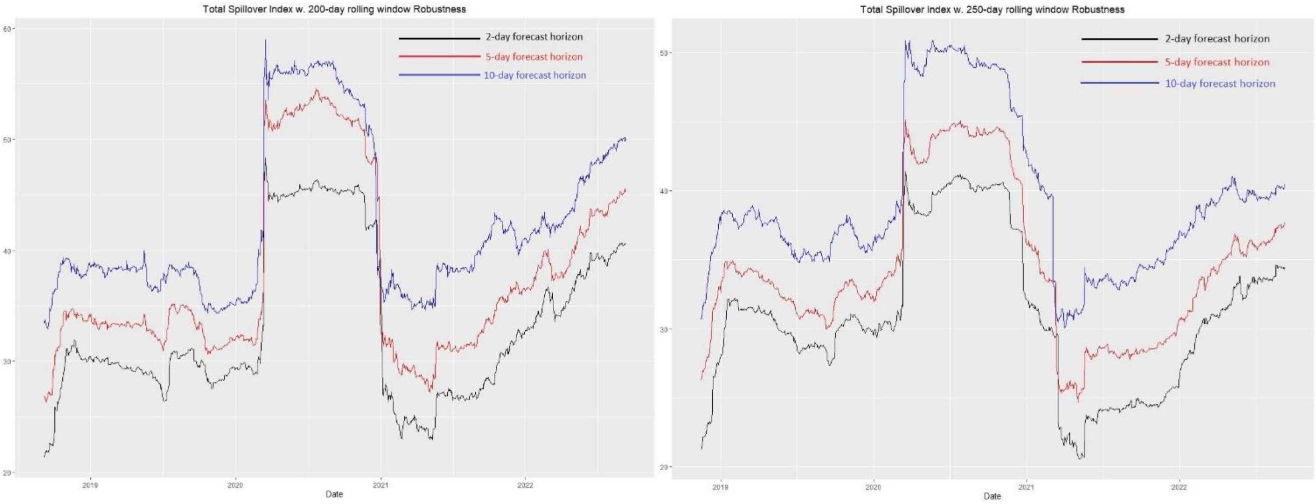


Figure 31: USA Return Spillover



The total spillovers obtained with the different scenarios display the same pattern with the increasing trend at the outset of COVID-19. The results support the contagion among the different asset and markets in the network. These results are consistent with Chau & Deemsomsak (2014), Kang, McIver & Yoon (2017) and Antonakakis & Kizys (2015) who all concluded that total spillover between selected markets, regardless of size of selected window or selected horizon forecast, are similar across the different scenarios.

5. Conclusion

This study investigated the spillover and return network connectedness between a number of different markets. We performed this analysis from the viewpoint of investigating any potential differences in return network connectedness between an emerging economy and a developed economy, namely South Africa and the USA, representing emerging and developed economies, respectively. We also add an additional layer to our analysis where we consider the shorter- and longer-term directional spillover effects for both the developed and emerging economy. This is of particular importance to investors and asset managers as generally longer- and shorter-term investment strategies differ. The markets we considered were the digital currency market (Bitcoin, Ethereum and Ripple), the traditional currency market (USDZAR and US Dollar Index) and stock market (All-Share Index and the S&P 500 index).

To perform this analysis, we made use of the Diebold & Yilmaz (2014) Vector Autoregressive methodology that uses the general variance decomposition connectedness index. The benefit of this methodology is that while it examines the relationship between our selected markets, it also provides insight into the two-way directional relationship. We considered the total spillover indices, net-pairwise spillover indices and network graphs for the level set of data. In line with expectations, we found that the total return spillover is higher for the developed country when compared to the emerging one, which is likely due to factors such as technological advancement, more market integration, etc. We also found that the stock market in the developed economy contributes more to the total spillover than the stock market in the emerging economy, easily explainable by the S&P 500 being the leading stock market index in the world and therefore having more of an impact on the different markets. This is useful for asset managers as when shocks occur to the stock markets across the world, they can rebalance their portfolios with the knowledge that the spillover into other markets would be more for the developed economy than the emerging economy. We also found that the total return spillover of the traditional currency in our network of markets was not very high, and this result was consistent across both the developed and emerging economy, implying that asset managers could possibly employ similar investment strategies for both.

We found some consistent results across both the emerging and developed countries in that the spillover contribution by the digital currencies was less than the spillover contributions from the traditional currencies for the stock markets, which as explained was in line with our expectations since traditional currencies are the primary means of purchasing stocks in the market. The implication of which for asset managers is that particular attention should be paid to shocks in the traditional currency market when compared to the digital currency market, because the spillover would be more considerable and thus require more pronounced rebalancing of their portfolios. We also considered the total return spillover with the use of a 200-day rolling window and found that both the emerging and developed countries followed the same general trend, which for asset managers means that similar investment strategies could be employed. We did also however find that during times of crisis the total return spillover was highly sensitive, with the developed economy being more sensitive than the emerging, the implication being that for asset managers, in times of high volatility, further rebalancing of portfolios would be required in developed markets portfolios.

We then considered our data from two different perspectives namely, a longer-term viewpoint and a shorter-term viewpoint. The logic behind this is that investors and asset managers usually employ different investment strategies for different time horizons and this analysis aims to inform them on these decisions. We found that in the shorter term a number of our results mimicked the results of the level set of data, which is somewhat expected, considering we used daily data for the analysis. We did however find contrasting results in our longer-term analysis. The first and most apparent was the total return spillover of the emerging economy being higher than that of the developed economy and we note that this was supported by our 200-day rolling window total spillover analysis. This is not an entirely unexpected result as over the longer term we would expect the developed economies' markets to be a lot more stable than that of the emerging one. We also found that for our developed economy, the traditional currency and stock market play a net role of being net transmitters, as opposed to net recipients in previous results, which is entirely plausible considering that both those markets have been dominant markets in the world and would therefore naturally affect others. We do however acknowledge that these net return spillovers were quite close to zero and therefore very close to net neutral. This implies that investors and asset managers when considering longer-term investments would need to construct their portfolios with the understanding that owing to the emerging markets’ higher spillover, more rebalancing of their portfolios would be required than for the developed economy.

Finally, a possible extension to this study could be to consider not only the return spillover, but also the volatility spillover for the developed and emerging economy. One could also incorporate additional markets into this analysis, such as the bond market or even the commodity market considering commodities like gold, silver or even oil.

References

Bhuiyan Rubaiyat Ahsan, Afzol Husain, Changyong Zhang , (2021) A wavelet approach for causal relationship between bitcoin and conventional asset classes, *Resources Policy* 71 (2021) 101971

Bouri, E., Balcilar, M., Gupta, R., Roubaud, D., 2017. Can volume predict bitcoin returns and volatility? A quantiles-based approach. *Econ. Model*. 64, 74–81.

Bouri, E., Lucey, B., & Roubaud, D. (2020). Cryptocurrencies and the downside Risk in equity investments. *Finance Research Letters*, 33, Article 101211.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28–34.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182, 119–134.

Elsayed Ahmed H.,Giray Gozgor, Chi Keung Marco Lau (2022) , Risk transmissions between bitcoin and traditional financial assets during the COVID-19 era: The role of global uncertainties, *International Review of Financial Analysis* 81 (2022) 102069

Garcia-Jorcano, Laura and Benito, Sonia, (2020), Studying the properties of the Bitcoin as a diversifying and hedging asset through a copula analysis: Constant and time-varying, Research in International Business and Finance, 54, issue C, number S0275531920300192.

Lahiani, A. Jeribi, A. Jlassi, N, B. Nonlinear tail dependence in cryptocurrency-stock market returns: The role of Bitcoin futures, *Research in International Business and Finance*, https://doi.org/10.1016/j.ribaf.2020.101351

Mariana, C. D., Ekaputra, I. A., & Husodo, Z. A. (2021). Are Bitcoin and Ethereum safe-havens for stocks during the Covid-19 pandemic? *Finance Research Letters*, 38, Article 101798.

Mensah, J. O., & Alagidede, P. (2017). How are Africa’s emerging stock markets related to advanced markets? Evidence from copulas. *Economic Modelling*, 60, 1-10.

Naeem M.A., Karim, S (2021) Tail Dependence between bitcoin and green financial assets, *Economics Letters*, Park Sangjin, Kwahngsoo Jang, Jae-Suk Yang, (2021), Information flow between bitcoin and other financial assets, *Physica A* 566 (2021) 125604

Ting Zeng a, Mengying Yang, Yifan Shen (2020) , Fancy Bitcoin and conventional financial assets: Measuring market integration based on connectedness networks, *Economic Modelling* 90 (2020) 209–220

Trabelsi, N. (2018). Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes? *Journal of Risk and Financial Management*, 11(4), 66.

Urquhart, A. & Platanakis, E., (2020). Should investors include bitcoin in their portfolios? A portfolio theory approach. *The British Accounting Review,* 52(4), Article 100837.

Walid Ahmed M.A., How do Islamic equity markets respond to good and bad volatility of cryptocurrencies? The case of Bitcoin, *Pacific-Basin Finance Journal* 70 (2021) 101667

Yoon S.M, Mamun M.A, Salah Uddin G., Kang S.H, (2019), Network connectedness and net spillover between financial and commodity markets, *The North American Journal of Economics and Finance, Volume 48*, 2019, Pages 801-818, ISSN 1062-9408, *https://doi.org/10.1016/j.najef.2018.08.012*.