FIN30290 Recent Research Topics in Finance

Paper 3

Paper Title: Exploring the Safe-Haven Capabilities of Cryptocurrencies for Global Equity Indices

Paper type: Research Letter

Student's name, surname and ID number
Conor Ryan, 16340116

Date 01/05/2020

I / We declare that all material included in this project is the end result of my/our own work and that due acknowledgement has been given in the bibliography and references to all sources be they printed, electronic or personal.

	Name (print)	*Surname (print)*	*Student Number (print)*	*Signature*
1	Conor	Ryan	16340116	

Please outline here below the type of contribution made by each team member (e.g., 45% of the coding, 20% of the writing, but **you may ignore this table in the case of purely individual submissions**).

	Name and surname	**Student number**	**Type of contribution**
1			
2			

Exploring the Safe-Haven Capabilities of Cryptocurrencies for Global Equity Indices

Abstract

This paper uses the cross-quantilogram method proposed by Han et al. (2016) to examine whether cryptocurrencies are suitable safe-haven investments for three major world stock indices during extreme market conditions. The dataset used consists of daily price observations of each asset from a sample period spanning from August 10th, 2015 to April 27th, 2020. I find that Bitcoin, Litecoin, Stellar and Monero are weak safe-havens for the S&P500, the FTSE 100 and the Nikkei during stress periods. Using a rolling-window methodology I analyse the time-variation in the safe-haven characteristics of each cryptocurrency. I determine that the hedging properties of each cryptocurrency vary over both stock indices and time windows studied.

Research Question:

Are cryptocurrencies viable safe-haven assets and are their hedging properties time-varying?

1. Introduction

In the wake of the COVID-19 pandemic and its incredibly drastic effect on global financial markets, the necessity and desire for safe-haven assets has never been greater. Traditionally, gold is considered the ultimate investment asset during periods of extreme market turbulence and there are numerous empirical analyses of its safe-haven abilities (Baur and Lucey, 2010; Beckmann, Berger and Czudaj, 2014; Bredin, Conlon and Potì, 2015). However, more recent studies by Klein (2017) and Baumöhl and Lyócsa (2017) indicate that the safe-haven properties of gold for equity markets deteriorated significantly both during and after the 2008 global financial crisis (GFC).

This has intensified the hunt for suitable alternative assets that offer investors reduced downside risk for equity investments. Cryptocurrencies first arrived with the advent of Bitcoin, shortly after the GFC, as an alternative to mainstream currencies and is often referred to as “virtual gold”. Cryptocurrencies, as shown by Dyhrberg (2016) and Corbet et al. (2018), possess similar hedging capabilities to gold and are relatively isolated to traditional financial assets making them suitable diversification options for investors and outlines their potential as safe-havens.

Several studies have tested whether Bitcoin is a safe haven for equity markets with varying results. Using dynamic conditional correlations Bouri et al. (2017) explore the safe-haven properties of Bitcoin against world stock indices, bonds and oil and conclude that “Bitcoin is a poor hedge, suitable for diversification purposes only”. They do find however, that Bitcoin serves as a strong safe haven for Asian stocks. A comparison of Bitcoin, gold and general commodities abilities to perform as effective safe-havens is made by Shahzad et al. (2019) and concludes that all three assets are weak safe-havens in certain cases for stock indices.

The aforementioned analyses consider only one cryptocurrency, Bitcoin. However as noted by Bouri et al. (2020) the dominance of Bitcoin in the cryptocurrency market has been consistently waning due to the increased popularity of rival cryptocurrencies such as Ethereum and Ripple. Therefore, I believe it is imperative to also explore the heterogenous safe-haven characteristics of these rival cryptocurrencies.

This study expands on the work of Bouri et al., (2020) by empirically examining the safe-haven properties of several leading cryptocurrencies against the US, UK and Japanese equity markets. Similarly, to Bouri et al. (2020) and Shahzad et al. (2019), I focus on the lowest tails of the return distributions of both the equity indices and cryptocurrencies using a quantile-specific approach. This ensures that inferences of the safe-haven abilities of the cryptocurrencies are only made when both the hedge asset and the stock index are experiencing extreme states. In addition to Bouri et al. (2020) a larger dataset is used producing more statistically robust results and a rolling-window methodology is employed to describe the time-varying nature of each cryptocurrencies hedging characteristics.

This study is useful for equity investors looking to discover new assets to reduce downside risk and to shield their portfolios from market crashes.

2. Data

The dataset used in this study comprises daily closing prices of the eight cryptocurrencies as used in Bouri et al. (2020), namely Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Nem and Monero obtained from https://finance.yahoo.com/, for the period August 10th 2015 to April 27th 2020. The dataset also includes daily closing levels of the S&P 500, FTSE 100 and Nikkei 225 extracted from https://finance.yahoo.com/ and https://www.investing.com/ for the same period. The sample period is restricted due to the availability of cryptocurrency price data prior to August

10th, 2015. This amounts to 1082 daily price observations. Log returns calculated using Eq. (1) below, are used to conduct the empirical analysis.

$$R_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Where Pt and $Pt - 1$ denote the closing prices on days t and $t - 1$, respectively. Descriptive statistics of the returns for each series are shown below.

Table 1. Descriptive Statistics and unit root test results.

	Mean (%)	Median (%)	Std. dev	Skewness	Kurtosis	ADF
BTC	0.161	0.220	4.395	-1.239	15.007	-15.35***
ETH	0.185	-0.140	6.809	0.005	7.925	-30.62***
XRP	0.236	-0.363	7.121	1.228	18.207	-20.94***
Dash	0.156	-0.202	6.019	0.216	7.837	-31.91***
NEM	0.370	-0.031	8.630	2.071	20.683	-33.4***
Stellar	0.089	-0.388	7.563	0.973	11.249	-25.02***
Monero	0.061	-0.129	6.836	0.219	7.406	-15.04***
Litecoin	-0.022	-0.099	6.084	0.709	13.466	-15.46***
SP500	0.031	0.050	1.229	-1.108	23.881	-10.81***
FTSE 100	-0.001	-0.039	1.098	1.289	18.715	-31.72***
Nikkei	-0.014	0.042	1.350	-0.200	5.992	-15.29***

Note: 1 The ADF column displays the test statistics of the Augmented Dickey-Fuller unit root test (Dickey and Fuller, 1979) and their corresponding significance. We reject the null hypothesis at the 1% level of significance in all series.

3. Methodology

I employ the cross-quantilogram approach of Han et al. (2016) to test the safe-haven properties of eight cryptocurrencies for US, UK and Japanese equity markets. I use the definitions of a strong and weak safe-haven asset proposed by Shahzad et al. (2019). An asset is considered a strong safe-haven if there is evidence of negative significant predictability from a stock index to that asset in the low quantiles of both the asset and the index returns. This imposes that extreme negative stock returns are followed by positive returns in the strong safe-haven asset. Concurrently, an asset is a weak safe-haven if there is no significant predictability between the stock index and the asset in the low quantiles of index and asset returns.

The cross-quantilogram is an extension by Han et al. (2016) of the univariate quantilogram proposed by Linton and Whang (2007), which was developed to test for directional predictability of a stationary time series at varying quantiles. The cross-quantilogram is a highly flexible and advanced method that estimates the lead-lag correlation between series for different quantiles and lags simultaneously, while also providing a corresponding hypothesis test for directional predictability in quantiles from one series to another.

I denote the stationary time series $x_{i,t}, i = 1{,}2$, and $t = 1,2, \dots, \tau$, where index i represents either the returns of one of the eight cryptocurrencies or a corresponding equity index. The time series $x_{i,t}$, is assumed to be strictly stationary with unconditional distribution function $F_i(.)$, unconditional density function $f_i(.)$ and corresponding unconditional quantile $q_i(\alpha_i) = \inf\{v: F_i(v) \geq \alpha_i\}$ for $\alpha\_i \in (0{,}1)$.

The cross-quantilogram for an α-quantile with k lags is given below by equation (2).

$$\rho_\alpha(k) = \frac{E[\Psi_{\alpha 1}\left(x_{1,t} - q_1(\alpha_1)\right)\Psi_{\alpha 2}\left(x_{2,t-k} - q_2(\alpha_2)\right)]}{\sqrt{E[\Psi_{\alpha 1}^2\left(x_{1,t} - q_1(\alpha_1)\right)]}\sqrt{E[\Psi_{\alpha 2}^2\left(x_{2,t-k} - q_2(\alpha_2)\right)]}} \tag{2}$$

Where $k = 1,2, \dots, \Psi_\alpha\ (\mu) = I[\mu < 0] - \alpha$ is a hit function and $I(.)$ denotes the indicator function. The sample cross-quantilogram given the unconditional sample quantile $\hat{q}_i(\alpha_i)$,of $x_{i,t}$, is defined below in Eq. (3).

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t-k+1}^{\tau} \Psi_{\alpha 1}(x_{1,t} - q_1(\alpha_1))\Psi_{\alpha 2}(x_{2,t-k} - \hat{q}_2(\alpha_2))}{\sqrt{\sum_{t=k+1}^{\tau} \Psi_{\alpha 1}^2(x_{1,t} - \hat{q}_1(\alpha_1))}\sqrt{\sum_{t-k+1}^{\tau} \Psi_{\alpha 2}^2(x_{2,t-k} - \hat{q}_2(\alpha_2))}} \tag{3}$$

Eq. (3) is used to calculate the magnitude of the directional dependence between two time series. For example, if we let $x_{1,t}$ be the returns of Bitcoin and $x_{2,t}$ the returns of the Nikkei index, the value of $\hat{p}_\alpha(1) = 0$ implies that if the return of the Nikkei index is below or above a given quantile $\hat{q}_2(\alpha_2)$ at time $t-1$, it does not inform the predictability of whether Bitcoin's return is higher or lower than the quantile $q_1(\alpha_1)$ on the next trading day.

The recommended quantile version of the Ljung-Box test statistic in Eq. (4) is used to statistically test the directional predictability from event $\{x_{2,t-k} \leq q_{2,t-k}(\alpha_2): k = 1,2,\ldots,\rho\}$ to event $\{x_{1,t} \leq q_{1,t}(\alpha_1)\}$.

$$\hat{Q}_\alpha^{(p)} = \frac{T(T+2)\sum_{k-1}^{p} \hat{p}_\alpha^2(k)}{T-k} \tag{4}$$

The formal hypothesis test is shown below.

$$H_0: p_\alpha(1) = p_\alpha(2) = \cdots = p_\alpha(\rho)$$

$$H_1: \exists k, p_\alpha(k) \neq 0, k = 1,2,\ldots,\rho$$

I obtain the critical values for the Ljung-Box statistics using the stationary bootstrapping procedure described by Politis and Romano (1994) in order to carry out inference testing.

This study firstly considers the directional dependence of a given pair of returns series between all pairwise quantiles within $\{0.05,0.1,\ldots,0.4\}$ up to a number of lags, $\rho \in \{1,5,10\}$. The choice of lag parameter ρ corresponds to studying whether there is a spill-over from the stock index to the cryptocurrency within the following ρ trading days. The results are presented in the form of heatmaps where the x-axis corresponds to the quantile of the given market index returns and the y-axis corresponds to the quantile of the chosen cryptocurrency's returns.

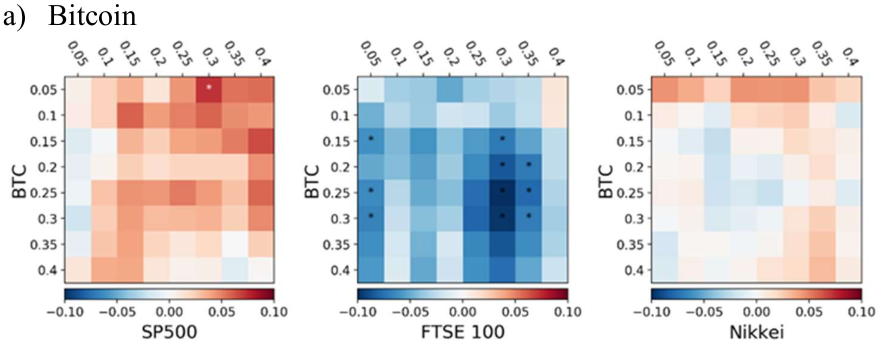
Lastly, I employ a rolling-window methodology in order to examine the time-variation in the hedging characteristics of the cryptocurrencies on the three indices returns. The window size is set to 1 year to evaluate the annual changes in directional predictability from stock indices to the cryptocurrency returns.

Results

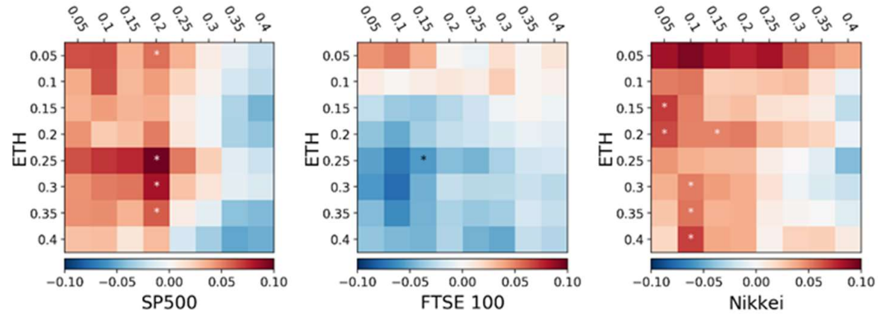
The results of the directional predictability from all pairwise quantiles of stock index returns to each of the eight cryptocurrency returns for lags of 1,5 and 10 are shown in Fig.1, Fig.3 and Fig.4 respectively (Fig. 3 and Fig.4 are included under the appendices for brevity). The magnitude of predictability is shown via a colour scale with red indicating (highly negative), white (uncorrelated) and blue (highly positive). The significance of predictability at the 95% is shown using stars.

Panel A: SP500 **Panel B: FTSE100** **Panel C: Nikkei**

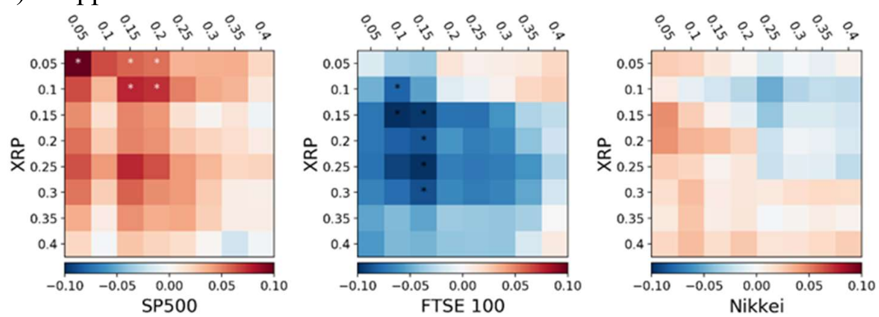
a) Bitcoin



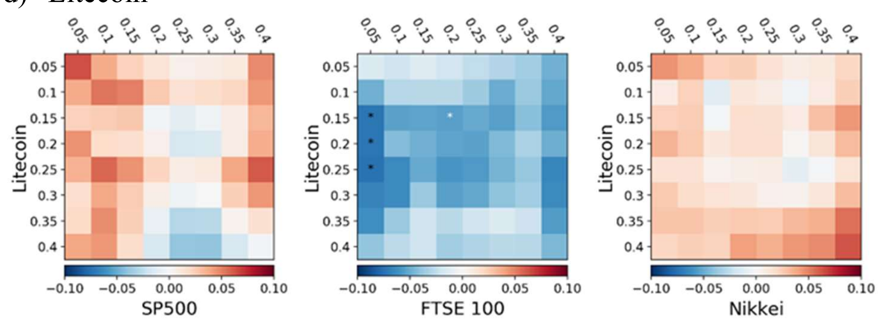
b) Ethereum



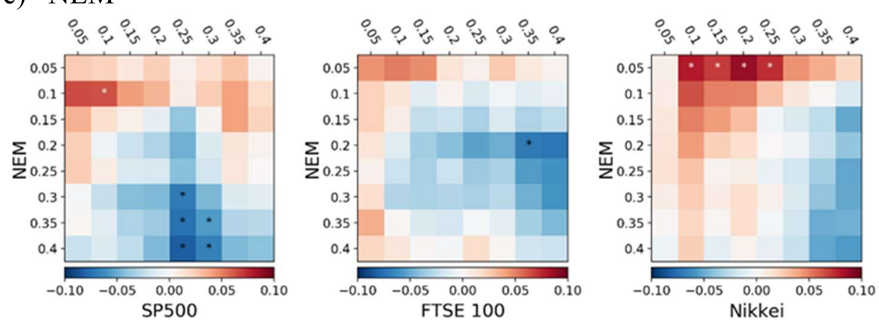
c) Ripple



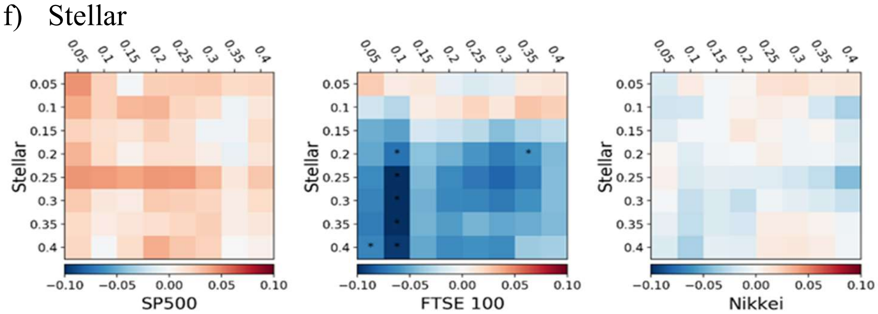
d) Litecoin



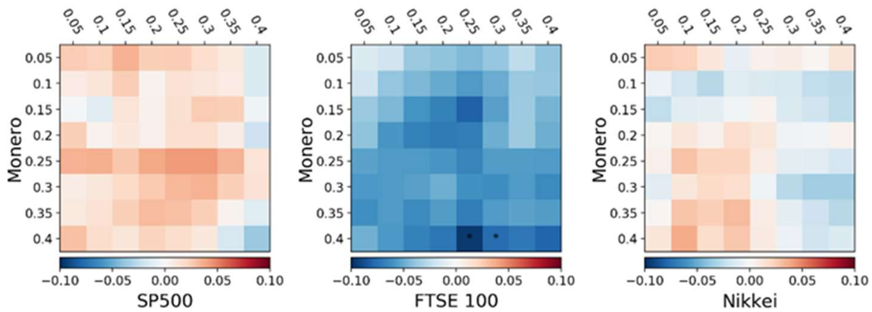
e) NEM



f) Stellar



g) Monero



h) Dash

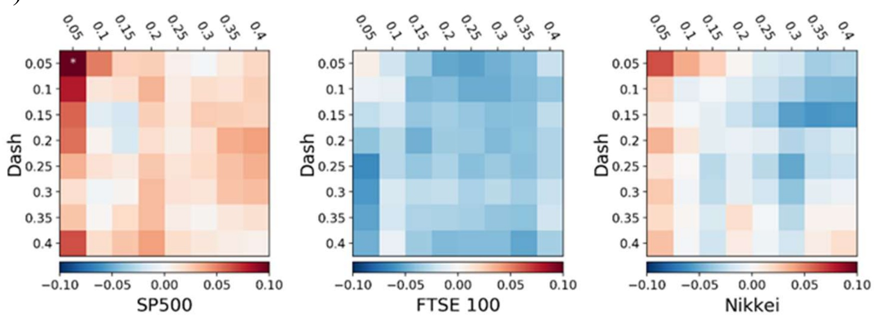


Fig. 1 Directional Predictability from stock indices to cryptocurrencies using 1-day lag.

To determine whether a cryptocurrency is a strong or weak safe-haven for a given stock index we analyse the top-left portion of the heatmaps above. A cryptocurrency is a strong safe-haven if this area of the heatmap is blue and contains a significance star (significant negative directional predictability in the low quantiles of both asset and index).

Bitcoin cannot be considered a strong safe-haven for any of the three equity markets studied. We do find however, that Bitcoin is a weak safe-haven for each index which, while using a significantly larger dataset complements the results of previous studies (e.g. Shahzad et al., 2019; Dyhrberg, 2016; Corbet et al., 2018)

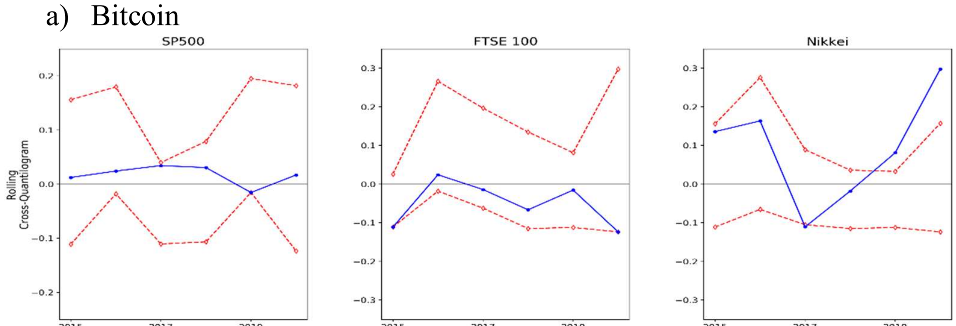
We observe that Ripple is a strong safe-haven asset for the FTSE 100 index and is the only strong safe-haven asset across any index and day-lag parameter. Interestingly, Ripple is not even a weak safe-haven when we consider the S&P 500 index outlining the heterogeneity possible in safe-haven characteristics within assets.

Overall, I find that Bitcoin, Litecoin, Stellar, Monero and to a lesser extent Ethereum are weak safe-havens across all three stock markets. This mirrors the results of (Bouri, Et al., 2020) while adding robustness to their results by examining multiple quantiles and markets. This result is of practical use to investors or financial advisors who can choose between either of these five cryptocurrencies to shield themselves from extreme losses in each of the studied markets. I also find that Dash is a weak safe-haven for the FTSE 100 and Nikkei whereas NEM is a weak safe-haven for the FTSE 100 only.

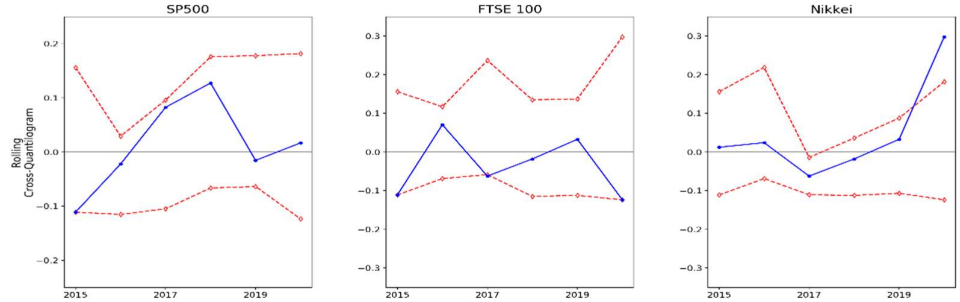
As outlined in the methodology section, I also explore how the safe-haven characteristics of the cryptocurrencies vary over time. The results of the rolling-window analysis using a low quantile of 0.1 for both the cryptocurrency and equity index are shown in Fig. 2 below. The dashed red lines represent the upper and lower bounds of the Ljung-Box critical values at the 95% level obtained via stationary bootstrap. The solid blue line corresponds to the sample cross-quantilogram test statistic using a 1-day lag.

Panel A: SP500 **Panel B: FTSE100** **Panel C: Nikkei**

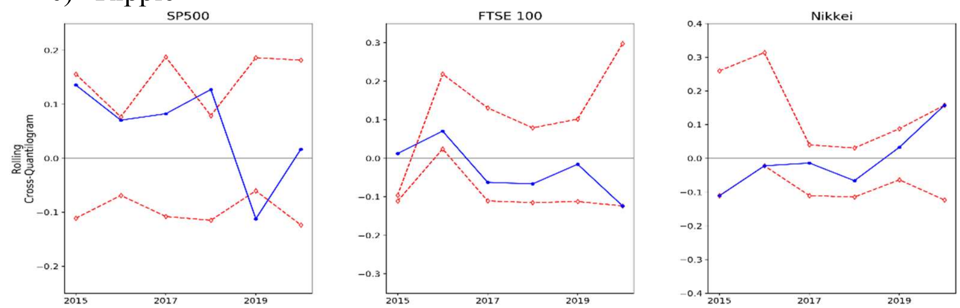
a) Bitcoin



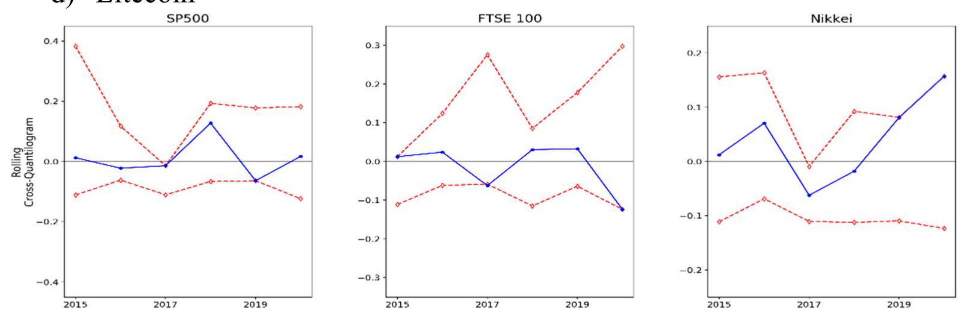
b) Ethereum



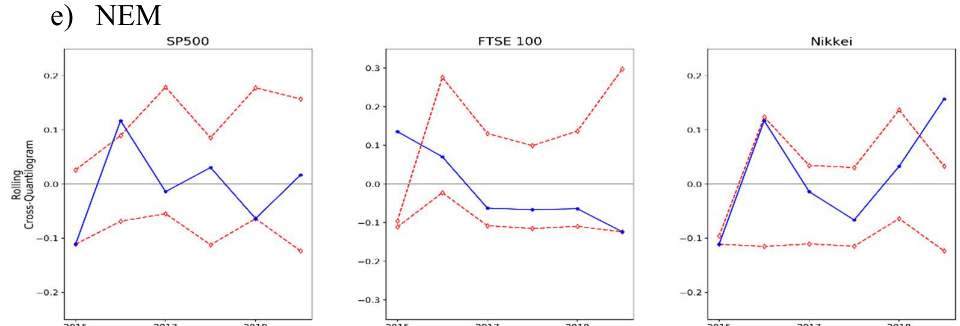
c) Ripple



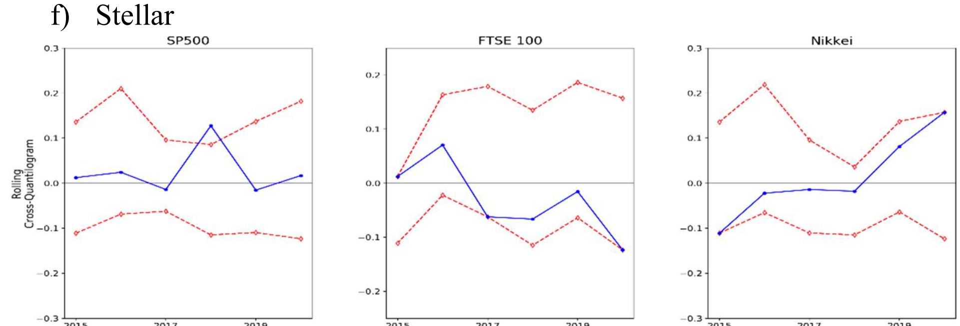
d) Litecoin



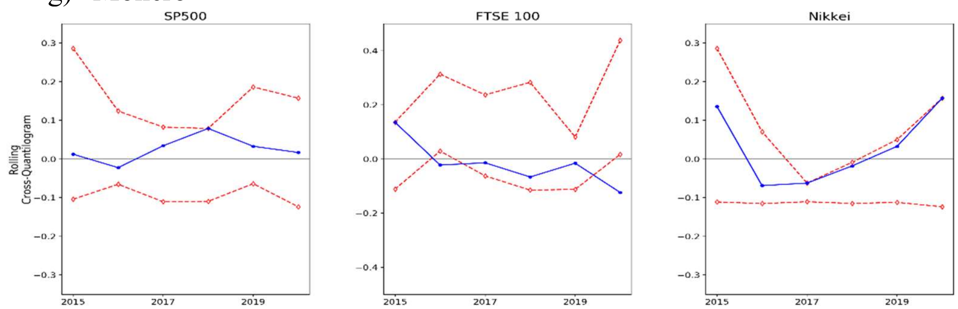
e) NEM



f) Stellar



g) Monero



h) Dash

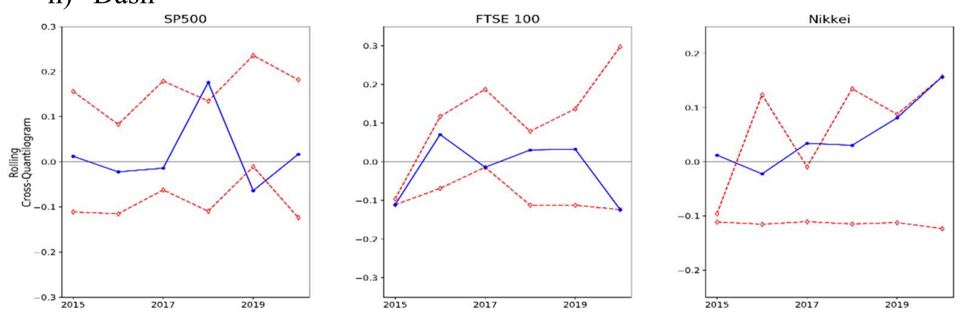


Fig. 2 Rolling-Window directional predictability from equity indices to cryptocurrencies Using 1-day lags, quantile = 0.1 and annual window size.

The above results indicate that the safe-haven properties of all cryptocurrencies studied vary across time and market index. This is similar to the results obtained by (Shahzad et al., 2019) and complements (Bouri, Et al., 2020) by analysing the time-varying properties of multiple cryptocurrencies as safe-haven assets for equity investors.

Overall, only Litecoin and Monero maintain either strong or weak safe-haven status across all markets and time windows. Concurrently, significant negative directional predictability from the FTSE 100 to Monero in 2020 indicates Monero is a strong safe-haven during this window. Importantly, we observe that while some assets namely, Ripple, Monero and Dash display strong safe-haven properties at some time window in the sample, none consistently sustain these properties.

Regarding US equities, we note that Bitcoin, Ethereum, Litecoin, and Monero are weak but reliable safe-havens while both Dash and Ripple are strong safe-havens in 2019. Monero is clearly the best safe-haven asset for the FTSE 100 index, indicated by significant negative directional predictability in both 2016 and 2020. The results are less clear for developed Asian stocks with several assets performing as weak safe-havens across the studied period. Interestingly, Bitcoin, is the worst performer in terms of safe-haven capabilities when applied to the Nikkei index.

Conclusion

Inspired by the work of (Bouri, Et al., 2020), this study aims to explore the safe-haven characteristics of cryptocurrencies and determine how these properties vary with time. After the global financial crisis of 2008 the ability of traditional safe-haven assets such as gold, to shelter investors from extreme market conditions was severely questioned (Baumöhl and Lyócsa, 2017). With the recent outbreak of the COVID-19 pandemic, investor portfolios have been decimated again, further intensifying the hunt for alternative safe-havens.

Using daily data from eight cryptocurrencies and three equity indices I determine whether cryptocurrencies are suitable hedges for market turbulence using the cross-quantilogram approach of (Han, Linton, Oka and Whang, 2016). The initial time-static results indicate that while none of the studied cryptocurrencies display strong safe-haven capabilities, several are found to be weak safe-havens across the US,UK and Japanese stock markets, including Bitcoin, Litecoin and Monero.

I then employ the rolling-window cross-quantilogram approach as implemented by (Shahzad et al., 2019) and find that the safe-haven properties of the cryptocurrencies are time-varying. In contrast to the initial time-constant results we observe a greater disparity in the hedging capabilities of cryptocurrencies across markets. Litecoin and Monero are found to consistently perform as safe-haven assets for each of the equity indices, with the latter exhibiting fleeting strong safe-haven behaviour in relation to the FTSE 100. The safe-haven abilities of the remainder of the cryptocurrencies are found to be less consistent indicating they are less reliable hedging options for investors.

The implications of these findings are of concern to any equity investor searching for assets to reduce the downside risk of their portfolios. These results are most applicable to periods of extreme market stress. Examining the practical performance of cryptocurrencies to hedge against the COVID-19 crash could be an interesting avenue of research. Further analysis is also required to explore the time varying relationship of spillovers between cryptocurrencies and specific market sectors.

References

1. Baumöhl, E. and Lyócsa, Š., 2017. Directional predictability from stock market sector indices to gold: A cross-quantilogram analysis. *Finance Research Letters*, 23, pp.152-164.
2. Baur, D. and Lucey, B., 2010. Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review*, 45(2), pp.217-229.
3. Beckmann, J., Berger, T. and Czudaj, R., 2014. Does Gold Act as a Hedge or a Safe Haven for Stocks? *SSRN Electronic Journal*,
4. Bouri, E., Hussain Shahzad, S. and Roubaud, D., 2020. Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance*, 75, pp.294-307.
5. Bouri, E., Molnár, P., Azzi, G., Roubaud, D. and Hagfors, L., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, 20, pp.192-198.
6. Bredin, D., Conlon, T. and Potì, V., 2015. Does gold glitter in the long-run? Gold as a hedge and safe haven across time and investment horizon. *International Review of Financial Analysis*, 41, pp.320-328.
7. Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, pp.28-34.
8. Dyhrberg, A., 2016. Hedging capabilities of bitcoin. Is it the virtual gold?. *Finance Research Letters*, 16, pp.139-144.

9. Grobys, K., 2020. When Bitcoin Has the Flu: On Bitcoin's Performance to Hedge Equity Risk in the Early Wake of the COVID-19 Outbreak. *SSRN Electronic Journal*,.

10. Han, H., Linton, O., Oka, T. and Whang, Y., 2016. The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series. *Journal of Econometrics*, 193(1), pp.251-270.

11. Klein, T., 2017. Dynamic correlation of precious metals and flight-to-quality in developed markets. *Finance Research Letters*, 23, pp.283-290.

12. Linton, O. and Whang, Y., 2007. The quantilogram: With an application to evaluating directional predictability. *Journal of Econometrics*, 141(1), pp.250-282.

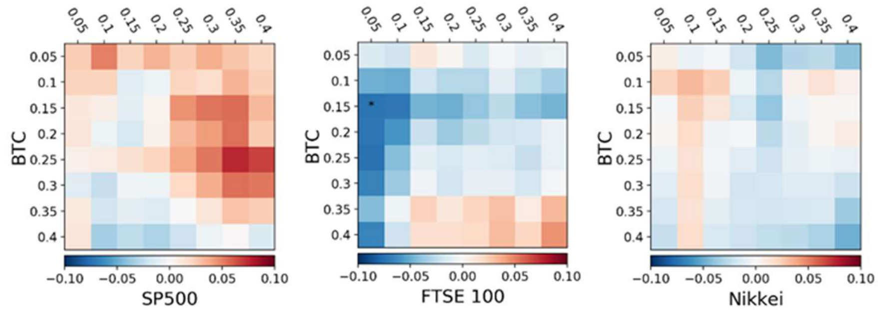
13. Shahzad, S., Bouri, E., Roubaud, D., Kristoufek, L. and Lucey, B., 2019. Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*, 63, pp.322-330.

14. GitHub. 2020. *Wangys96/Cross-Quantilogram*. [online] Available at: <https://github.com/wangys96/Cross-Quantilogram> [Accessed 29 April 2020].

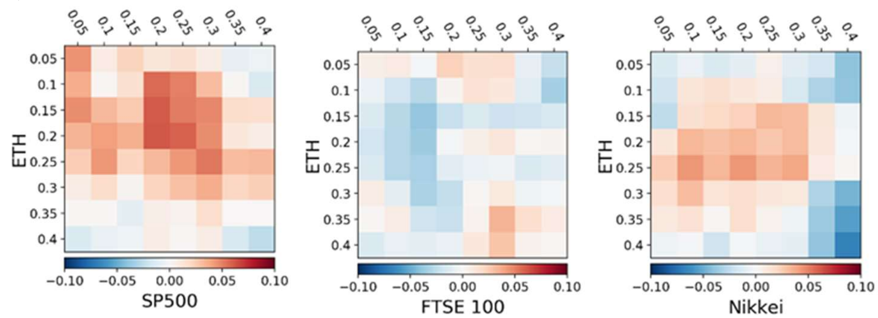
Appendices

Panel A: SP500	Panel B: FTSE100	Panel C: Nikkei

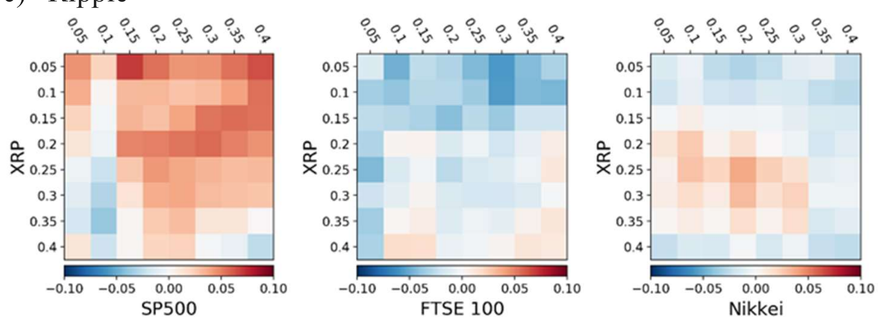
a) Bitcoin



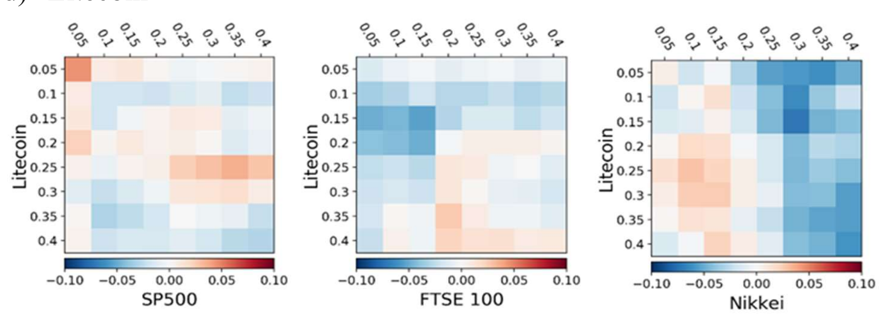
b) Ethereum



c) Ripple



d) Litecoin



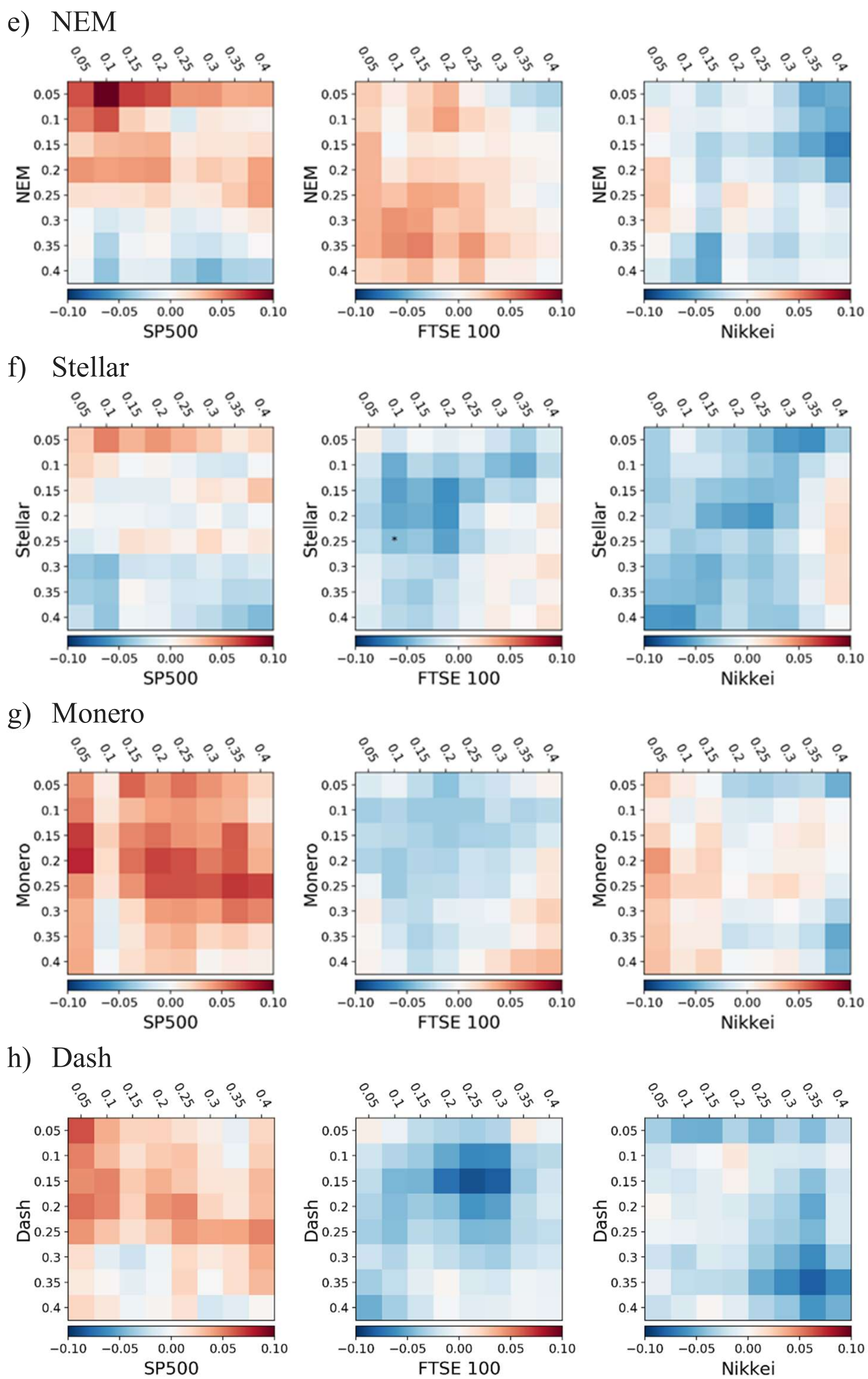
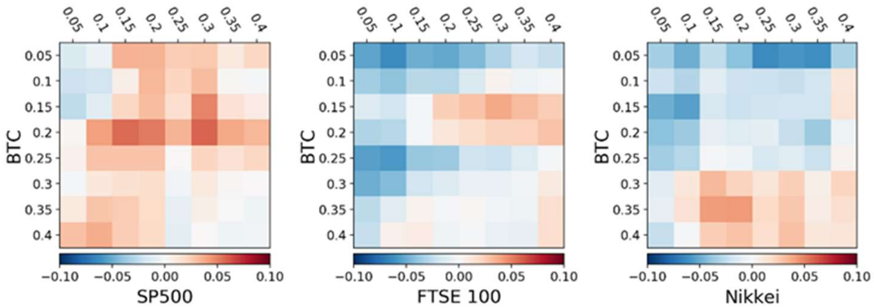


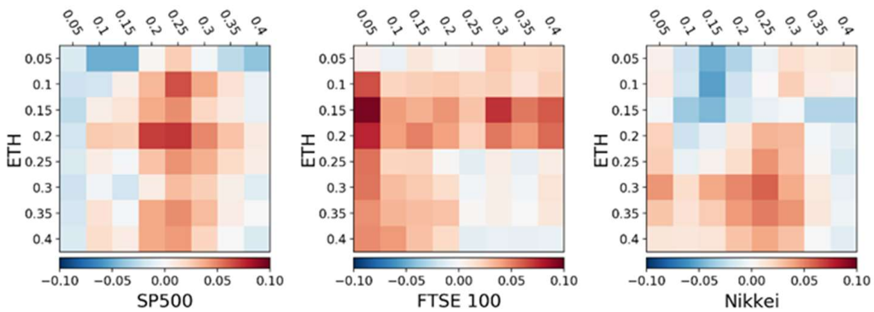
Fig. 3 Directional Predictability in quantiles from stock market indices to cryptocurrencies using 5-day lags.

Panel A: SP500 **Panel B: FTSE100** **Panel C: Nikkei**

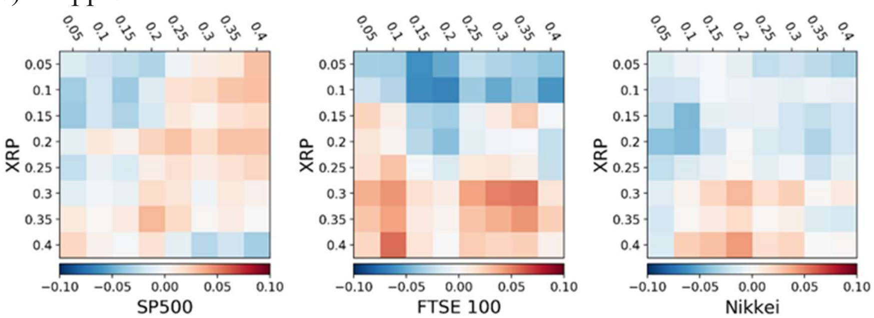
a) Bitcoin



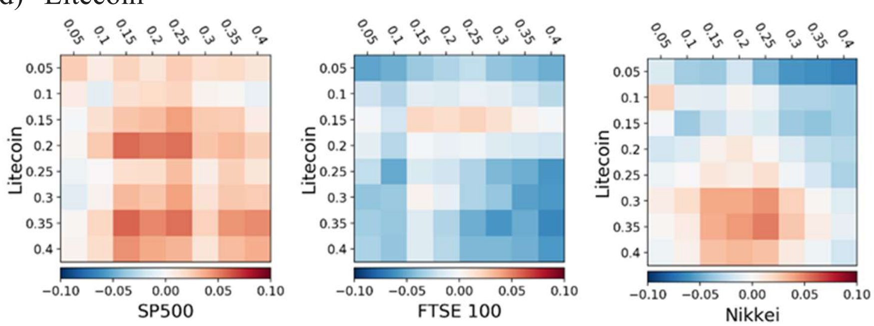
b) Ethereum



c) Ripple



d) Litecoin



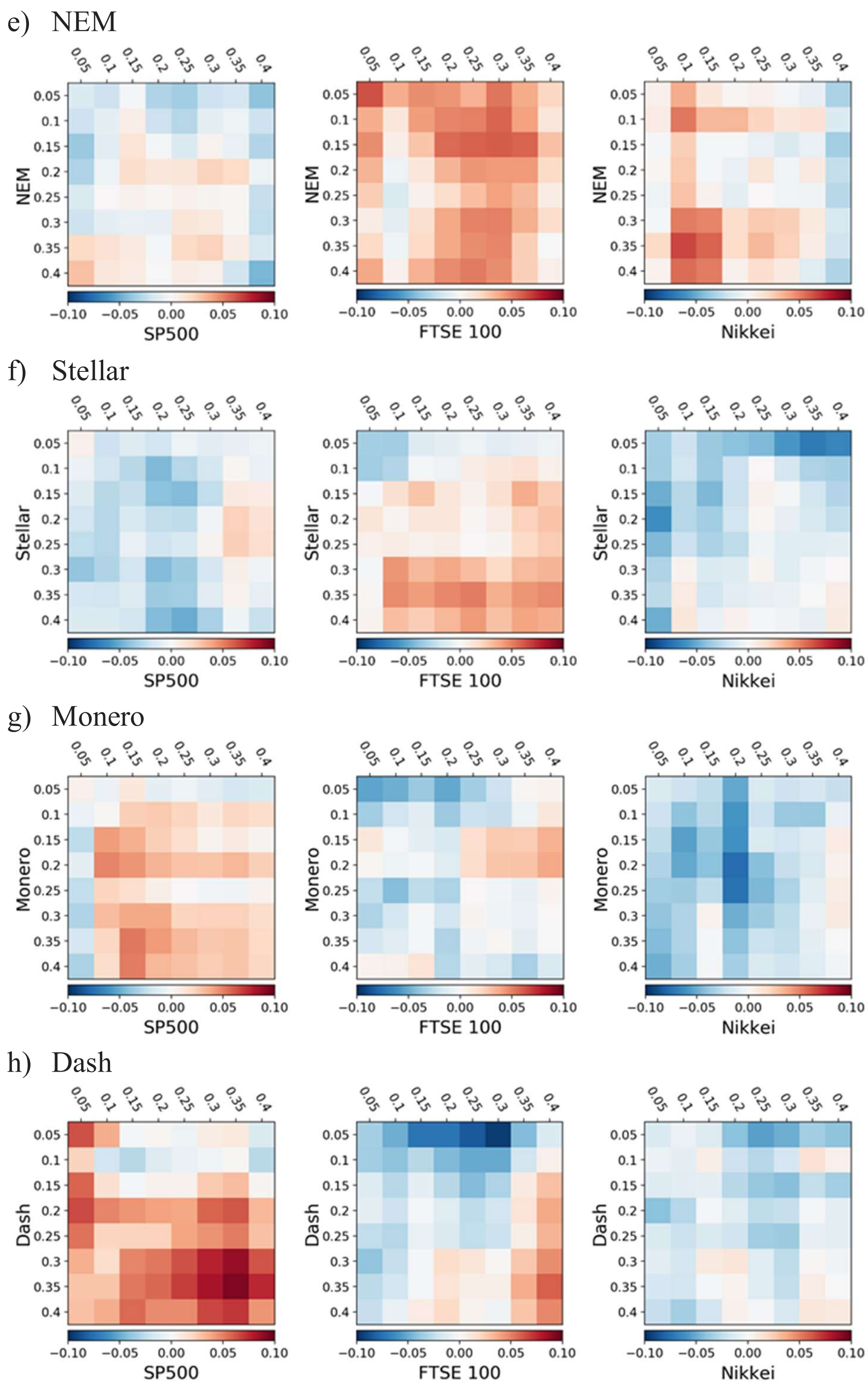


Fig. 4 Directional Predictability in quantiles from stock market indices to cryptocurrencies using 10-day lags.