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# Is Bitcoin a better safe-haven investment than gold and commodities?

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ABSTRACT

This paper addresses the timely question of whether Bitcoin exhibits a safe-haven property for stock market investments during extreme market conditions and whether such a property is similar to or different from that of gold and the general commodity index. We propose a new definition of a weak and strong safe-haven within a bivariate cross-quantilogram approach. This definition considers the lowest tails of both the safe-haven asset and the stock index. Our sample period spans from 19 July 2010 until 22 February 2018 and focuses on several stock market indices, including those of the US, China, and other developed and emerging economies. Our main results show that, at best, each of Bitcoin, gold, and the commodity index can be considered as a weak safe-haven asset in some cases. Rolling-window predictability analyses generally confirm those results and reveal that the safe-haven roles of Bitcoin, gold, and commodities are time-varying and differ across the stock market indices under study.

## 1. Introduction

The valuable role of gold as an investment asset during stress periods cannot be overstated, and much empirical evidence exists on its safe-haven ability for equities (Areal, Oliveira, & Sampaio, 2015; Baur & Lucey, 2010). To a lesser extent, commodities, in general, act as effective diversifiers against the downside risk in equity markets of advanced and emerging economies (Henriksen, 2018). However, detecting a safe-haven asset becomes difficult in the period after the global financial crisis (GFC), as many studies question the safe-haven ability of gold during that period when the interest-rate bound reached zero, and the financialization of gold (commodity) investing intensified (Baur & Glover, 2012; Bekiros, Boubaker, Nguyen, & Uddin, 2017; Klein, 2017). Interestingly, Bitcoin was released around that time as a solution to the fragile global financial system, and the academic literature draws attention to Bitcoin's role as an investment shelter during stress periods such as the European debt crisis of 2010–13[1] (Luther & Salter, 2017). Several studies apply standard models (e.g., correlation analysis, linear regressions, and GARCH-based techniques) to highlight the very weak correlation between Bitcoin and stock market indices and thereby potential diversification benefits (Baur, Hong, & Lee, 2017; Bouri, Jalkh, Molnár, & Roubaud, 2017; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Brière, Oosterlinck, & Szafarz, 2015; Dyhrberg, 2016a; Guesmi, Saadi, Abid, & Ftiti, 2018). Importantly, press articles[2] often compare the virtues of Bitcoin and gold,[3] although no empirical evidence has yet been documented regarding such a comparison.

This study empirically examines the similarity/dissimilarity between the potential safe-haven properties of Bitcoin, gold, and commodities against a set of global and country stock market indices. In doing so, we focus on the lowest tails of the distribution, rather than the bulk of the distribution, via a quantile-specific approach; we also incorporate a new definition of weak and strong safe-havens that

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[1] https://www.cnbc.com/2015/07/01/greece-is-in-crisis-why-no-love-for-gold-commentary.html.

[2] https://www.forbes.com/sites/rachelwolfson/2018/02/13/digital-gold-vs-real-gold-time-to-use-bitcoin-to-buy-gold/#402e8ef33eef.

[3] Bitcoin is classified as a commodity by the Commodity Futures Trading Commission (CFTC), and has non-political and (virtual) commodity attributes that make it quite similar to gold. In fact, Selgin (2015) argues that Bitcoin has features from commodities (i.e. gold) and can be regarded as synthetic commodity money.

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considers quantile heterogeneity. Specifically, we do not make inferences on the strong safe-haven ability of the asset when only stocks are in the extreme negative state (as in Baur & Lucey, 2010, Bouri, Molnár, et al., 2017 and Bouri, Jalkh, et al., 2017), but instead, we ensure that the strong safe-haven asset is experiencing a similar extreme state capable of partially covering the extreme negative returns in the stock index. We achieve this via the cross-quantilogram of Han, Linton, Oka, and Whang (2016), which allows us to draw a complete-quantile picture of a quantile-to-quantile relation between the stock index and the potential safe-haven asset under study.[4]

Our current study is useful for investors and financial advisors who search for a safe-haven asset, especially during and after the GFC period, when commodities, in general, and gold, in particular, have lost some of their appeal as safe-haven assets and behaved more like risky assets (e.g., Bekiros et al., 2017; Klein, 2017). As such, economic actors can build on our empirical study and portfolio analysis when comparing Bitcoin, gold, and commodities as potential safe-haven assets for stock market indices.

The rest of the paper proceeds as follows. Section 2 sets the background of the analyses. Section 3 presents the methodological approach that is applied as we compare the weak and strong safe-haven abilities of Bitcoin, gold, and the commodity index. Section 4 describes the dataset and discusses empirical results. Section 5 concludes.

## 2. Background information

Introduced by Nakamoto (2008) as a digital cash payment, Bitcoin's anti-government and dependence on mass collaboration have made it a unique digital asset. In particular, the tradability of Bitcoin unit on specialized trading platforms has made it an investment asset (Polasik, Piotrowska, Wisniewski, Kotkowski, & Lightfoot, 2015) with an exponential return, despite its extreme price volatility. The launch of Bitcoin-linked funds by global investment banks increased the accessibility to the Bitcoin market. Importantly, the launch of futures contracts based on Bitcoin prices in late 2017 enhanced the legitimacy of Bitcoin as an investment and moved it closer to the center of the financial world. Such developments suggest that Bitcoin should not be ignored by the investment communities.

It has often been argued that Bitcoin is a shelter from the sovereign risk and the fragility of the global financial system Bouri, Molnár, et al., 2017). This is evidenced during the European debt crisis of 2010–13[5] (Luther & Salter, 2017). The fact that Bitcoin is insulated from economic and financial variables (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018) makes it a valuable diversifier (Bouri, Jalkh, et al., 2017; Bouri, Molnár, et al., 2017; Brière et al., 2015; Dyhrberg, 2016a), especially during stock market downturns (Bouri, Molnár, et al., 2017). Ji, Bouri, Gupta, and Roubaud (2018) uncover the network structure between Bitcoin and several asset classes, including equity indices. They show that Bitcoin is very weakly related to equities, but the relationship is not stable over time and is affected by structural breaks. Guesmi et al. (2018) examine the joint dynamics of Bitcoin and different financial assets via a multivariate GARCH model. They indicate that Bitcoin can offer diversification and hedging benefits for investors.

The very weak relation between Bitcoin and other financial assets might be because Bitcoin does not share many common price determinants with those financial assets (Bouoiyour, Selmi, Tiwari, & Olayeni, 2016; Kristoufek, 2015). In fact, Bitcoin price depends less on economic and financial variables (Kristoufek, 2015) and more on a unique set of characteristics, such as attractiveness (Kristoufek, 2015), energy prices (Li & Wang, 2017), user anonymity (Ober, Katzenbeisser, & Hamacher, 2013), computer programming enthusiasts, and illegal activity (Yelowitz & Wilson, 2015).

Compared to the high status of gold, Bitcoin has a great deal of ground to gain in terms of acceptance, history, tangibility, intrinsic value, low volatility, and consumption. However, Bitcoin and gold share many characteristics. First, both Bitcoin and gold have non-political attributes and are regulated as commodities, especially in the US where Bitcoin is classified as a commodity by the CFTC. Second, no central authority can control or adjust their mining and transactions (Baur et al., 2017), which makes them both independent of inflation. Third, both Bitcoin and gold do not generate cash-flows and are instead produced in a process called "mining".[6] Specifically, the supply of Bitcoin is limited to no > 21 million coins, as dictated by its protocol. Fourth, the inverted asymmetric reaction to positive and negative news is present in both gold (Baur, 2012) and Bitcoin (Bouri, Azzi, & Dyhrberg, 2017). Finally, in emerging countries, where strict regulations on capital flows exists (e.g. China), Bitcoin is used to move money out of the country. This has been accentuated by the scrutiny of the Chinese government over the gold physical market, which has made Bitcoin an ideal alternative to gold.

So far, a limited number of studies have considered Bitcoin, gold, and other commodities (e.g. crude oil). Importantly, this scant empirical literature covers gold and Bitcoin markets (Bouoiyour & Selmi, 2015; Bouri, Molnár, et al., 2017; Corbet et al., 2018; Dyhrberg, 2016a; Kristoufek, 2015), without making a comparable analysis between their roles against stock market indices. Furthermore, Guesmi et al. (2018) use GARCH-based models that are not suitable for detecting the tails of the distribution of Bitcoin returns with that of the stock market indices. Furthermore, Guesmi et al. (2018) neither conduct a time-varying approach while assessing the role of Bitcoin nor compare the safe-haven ability of Bitcoin to that of gold and the commodity index. Those research gaps are also relevant to Bouri, Jalkh, et al. (2017) and Bouri, Molnár, et al. (2017) who apply standard models based on regressions augmented by dummy variables capturing extreme negative returns in global and regional stock indices and find evidence that Bitcoin is a very useful diversifier.

In this study, we extend the above-mentioned literature by comparing the safe-haven roles of Bitcoin, gold and the commodity index against a set of global and country stock market indices (world, developed, emerging markets, China, and the US). The rich sample covers countries with the most influential institutional investors, the longest history in stock market activities, and the largest economy and market capitalization. It also allows us to capture potential heterogeneity between developed and emerging stock indices and between the largest developed economy, the US, and the largest emerging economy, China. Interestingly, China is an important player in the Bitcoin market, and its government has recently intensified its regulations on the activities of Bitcoin exchanges. This paper also considers the time-variability in the safe-haven properties of Bitcoin, gold, and commodities, which can be comparable to the focus of Li and Lucey (2017), which, using a different

[4] As explained in Section 3, Bitcoin, gold, and commodities can be labelled as strong safe-havens if there is an evidence of negative predictability from the stock index to the (safe-haven) asset (Bitcoin, gold, or commodities) in the low quantiles of both the stock and the safe-haven asset. Otherly said, extreme negative stock returns are followed by future positive Bitcoin/gold/commodities returns, when the markets are in stress. In contrast, an asset is labelled as a weak safe-haven if the lowest returns distribution of the stock index fails to predict the lowest returns distribution of the (safe-haven) asset. It is important to note that if one asset (asset to be hedged) is in bearish state (at the 0.05 quantile) then the other asset (asset used to hedge) is expected to be in bearish state as well (at the 0.05 quantile) – same day or the next day. To have two markets in two entirely different states (one in bearish and the other in bullish) is a rare scenario, as financial markets are known to co-boom and co-crash. We, therefore, only focus on the lowest quantiles of both assets while examining the safe haven properties.

[5] https://www.cnbc.com/2015/07/01/greece-is-in-crisis-why-no-love-for-gold-commentary.html.

[6] Obviously, the physical mining of gold differs from the digital-based mining of Bitcoin (Bouri, Jalkh, et al., 2017).

approach, considers the time varying safe-haven properties of gold, silver, platinum, and palladium against adverse stock and bond market conditions.

## 3. Methodology

Within the literature related to asset risk management, the extreme quantiles of the return distribution attract substantial attention from scholars and investors. In fact, focusing on the extreme lower quantiles allows for estimating potential losses under extreme conditions, i.e. at the tail of return distribution, such as at the lowest 5% or 10% of quantiles. As extreme tail (negative) events are common in the equity market, it is important for investors to have an asset that can rise in value (i.e. has a negative correlation in lowest quantiles) to offset the extreme downside risk of equity indices.

The ability of three assets (Bitcoin, gold, and the commodity index) to act as strong or weak safe-havens for stock markets at different quantiles is examined via the bivariate cross-quantilogram of Han et al. (2016).[7] This advanced cross-quantilogram technique offers flexibility in estimating the lead-lag relation between time series at different lags and quantiles, simultaneously. In addition, the rolling-window approach of directional predictability from stock returns to safe-haven assets is used to capture any potential time-changing role of three assets against stock markets.

### 3.1. Defining weak and strong safe-haven

Based on the above argument and in an extension of the definition of a safe-haven proposed in Baur and Lucey (2010), we differentiate between a strong and a weak safe-haven asset as follows. An asset is labelled a strong safe-haven if there is evidence of predictability from a stock index to that asset in the low quantiles of both the stock and the asset returns, and the sign of this predictability is negative. This ensures that extreme negative stock returns are followed by future positive returns in the (safe-haven) asset, i.e. the movement of the (safe-haven) asset in the opposite direction of that of the stock index ensures that the losses occurring in stock investments are counterbalanced. In contrast, an asset is labelled a weak safe-haven if there is no evidence of predictability from a stock index to that asset in the low quantiles of both the stock and the asset returns.

### 3.2. The cross-quantilogram

Let us consider two stationary time series as $\{x_{i,\ t}, t \epsilon Z\}$, $i = 1, 2$. In the present study, $x_{1,\ t}$ and $x_{2,\ t}$ represent the stock index and Bitcoin/gold/commodity, respectively. The density and distribution functions of series $x_{i,\ t}$ are labelled as $f_i(\cdot)$ and $F_i(\cdot)$. The quantile of $x_{i,\ t}$ is represented as $q_i(\propto_i) = inf\{v : F_i(v) \geq \alpha_i\}$ for $\alpha_i \epsilon\ (0,1)$, and the expression of two-dimensional series of quantiles are represented by $(q_1(\propto_1)\ q_2(\propto_2))^{\tau}$, for $\alpha \equiv (\propto_1, \propto_2)^{\tau}$.

The cross-quantilogram for $\alpha$-quantile with $k$ lags can be written as:

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

for $\mathrm{k} = 0, \pm 1, \pm 2, \ldots$, and where $\Psi_a(\mu) \equiv 1[\mu < 0]$, $1(\cdot)$ denotes the indicator function and $1[x_{i,\ t} \leq q_i(\alpha_i)]$ is the quantile exceedance process. At different quantiles, the serial dependence between two time series is captured through Eq. (1). In the present framework, we assess the predictability of safe haven assets' returns through the stock returns by $\rho_\alpha(1)$. Thus, $\rho_\alpha(1) = 0$ implies that the stock returns below or above a quantile $q_{ret}(\alpha_{ret})$ at time $t$, does not provide useful information for predicting whether the safe haven assets' returns will be lower or higher than the quantile $q_{SHA}(\alpha_{SHA})$ on the next trading day. Contrary to this, $\rho_\alpha(1) \neq 0$ suggests a one-day directional predictability from stock returns to safe haven assets' returns at $\alpha = \alpha_{ret}(\alpha_{SHA})$. In Eq. (2), cross-quantilogram of the sample counterpart is estimated as:

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

In the above formula, the $\widehat{q}_i(\alpha_i)$ represents the unconditional sample quantile of $x_{i,\ t}$, as defined in Han et al. (2016). We utilize a quantile version of the Ljung-Box-Pierce statistic as:

$$\widehat{Q}_\alpha^{(p)} = \frac{T(T+2)\sum_{k=1}^{p}\widehat{\rho}_\alpha^{\,2}(k)}{T-k} \tag{3}$$

As the asymptotic distribution of cross-quantilogram contains noise under the null hypothesis of no directional predictability, Han et al. (2016) use the stationary bootstrap (SB) of Politis and Romano (1994) to approximate the distribution of the testing statistic under the null hypothesis that can then be used for the statistical inference. This is in fact a portmanteau test $\widehat{Q}_\alpha^{(p)}$ for directional predictability from one time series to the other for up to $p$ lags over the quantile pair $\alpha = (\alpha_1, \alpha_2)$. Unlike the usual bootstraps, this test is a block bootstrap procedure that permits us to handle inherent serial dependence in the data by allowing random block lengths. Suppose that $B_{\mathrm{Ki},\ \mathrm{Li}} = \{(x_{1,\ t}x_{2,\ t-k})\}_{t=k_i}^{L_i-1}$ is the $i$-th block with length $L_i$ starting from $K_i$. Then $L_i$ indicates an independent and identically distributed variable with $\Pr(L_\mathrm{i} = \mathrm{s}) = \gamma(1-\gamma)^{s-1}$, $\mathrm{s} = 1,2, \ldots$ for $\gamma \in (0,1)$. Finally, in this framework, $K_i$ is an *iid* sequence drawn from a uniform distribution $\{1,2, \ldots T\}$. We replace the pair $(x_{1,\ t}x_{2,\ t-k})$ by $(x_{1,\ j}x_{2,\ j-k})$ with $j = k + (t \bmod (T-k))$, where mod denotes the modulo operator,[8] because the upper limit $B_{ki,\ Li}$ may exceed the sample size $T$, when $t > T$. Further, in order to obtain the bootstrapped confidence interval, we construct and conduct a pseudo re-sampling based on the sequence of blocks and employ the cross-quantilogram and its associated portmanteau.

## 4. Results

### 4.1. Data

We use daily spot prices data for Bitcoin, ounce of gold, and the S&P Goldman Sachs Commodity Index (S&P GSCI). We use similar data for five Morgan Stanley Capital International (*MSC*I) stock indices: world, developed, emerging markets, China, and the US. Following Bouri, Molnár, et al. (2017), we use the CoinDesk price index as a representative of the Bitcoin prices (https://www.coindesk.com). It lists the average price of Bitcoin against the US$ from leading trading platforms from around the globe. As for the rest of the data, it was collected from DataStream. Our sample is from 19 July 2010 to 22 February 2018, where the starting point represents the day when Bitcoin prices become available. Our empirical analysis is conducted with continuously compounded (i.e., log) returns. We present in Table 1 summary statistics of the daily return series, along with some additional statistics. Unsurprisingly, Bitcoin has the highest Sharpe ratio as well as the highest mean return and standard deviation. In contrast, gold has a much lower Sharpe ratio, while that of the commodity index is negative. Bitcoin and gold have quite similar high values for the kurtosis and

[7] The approach of Han et al. (2016) is particularly suitable to the aim of our study, given evidence of heterogeneity in the return characteristics of gold (e.g., Shahzad, Raza, Shahbaz, & Ali, 2017) and Bitcoin (Balcilar, Bouri, Gupta, & Roubaud, 2017; Kristoufek, 2013). Importantly, it adds to the quantile approach adopted in Baur and Lucey (2010) by providing a more complete picture of the relation between the stock index (world, developed, and emerging stock indices as well as the stock indices of the US and China), that would make more refined inferences on the safe-haven abilities of Bitcoin, gold, and commodities.

[8] For any positive integers a and b, the modulo operation a mod b is equal to the remainder, on division of a by b.

**Table 1**
Descriptive statistics and unit root tests.

| | Mean (%) | Std. dev. (%) | Sharp ratio | Skewness | Kurtosis | ADF | KPSS |
|---|---|---|---|---|---|---|---|
| Bitcoin | 0.591 | 6.549 | 0.090 | −0.017 | 12.044 | −42.80*** | 0.137 |
| Gold | 0.006 | 1.011 | 0.006 | −0.820 | 11.174 | −45.10*** | 0.157 |
| Commodities | −0.023 | 1.174 | −0.020 | −0.197 | 5.639 | −46.02*** | 0.259 |
| World | 0.034 | 0.813 | 0.041 | −0.606 | 8.114 | −39.19*** | 0.159 |
| Developed | 0.019 | 0.945 | 0.020 | −0.534 | 7.887 | −39.19*** | 0.065 |
| Emerging | 0.012 | 0.951 | 0.013 | −0.415 | 6.110 | −35.15*** | 0.053 |
| USA | 0.077 | 1.650 | 0.047 | −3.377 | 7.192 | −48.17*** | 0.110 |
| China | 0.023 | 1.261 | 0.019 | −0.183 | 6.182 | −41.89*** | 0.054 |

Notes: The table presents the descriptive statistics and unit root tests for six return series. The sample period is from 19 July 2010 till 22 February 2018. ADF and KPSS tests present empirical statistics of the Augmented Dickey-Fuller unit root test (Dickey and Fuller, 1979) and KPSS (Kwiatkowski et al., 1992) stationarity test, respectively.

*** Indicates significance at 1% level or better.

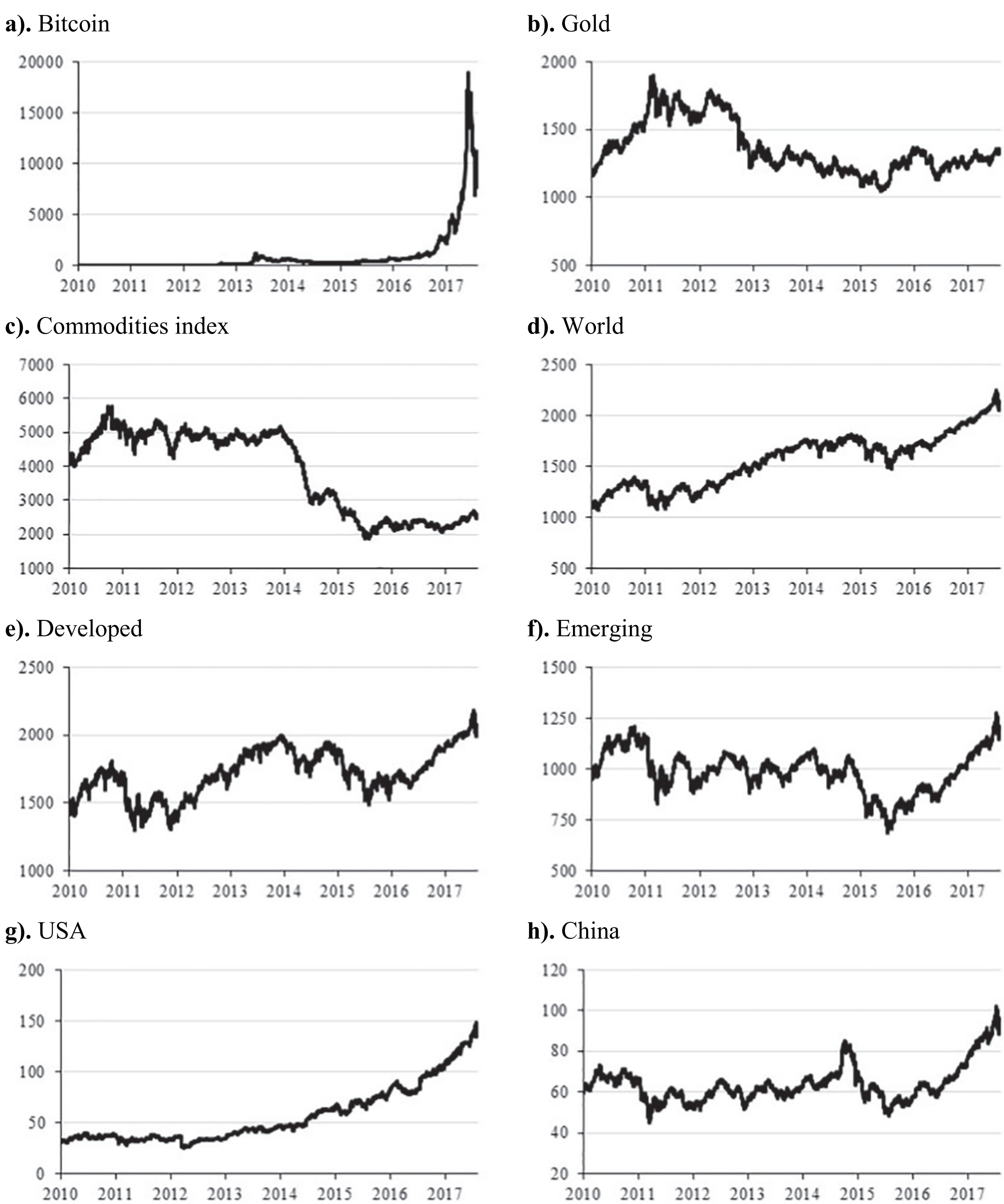


**Fig. 1.** Time series plots of the stock markets and potential safe haven assets.

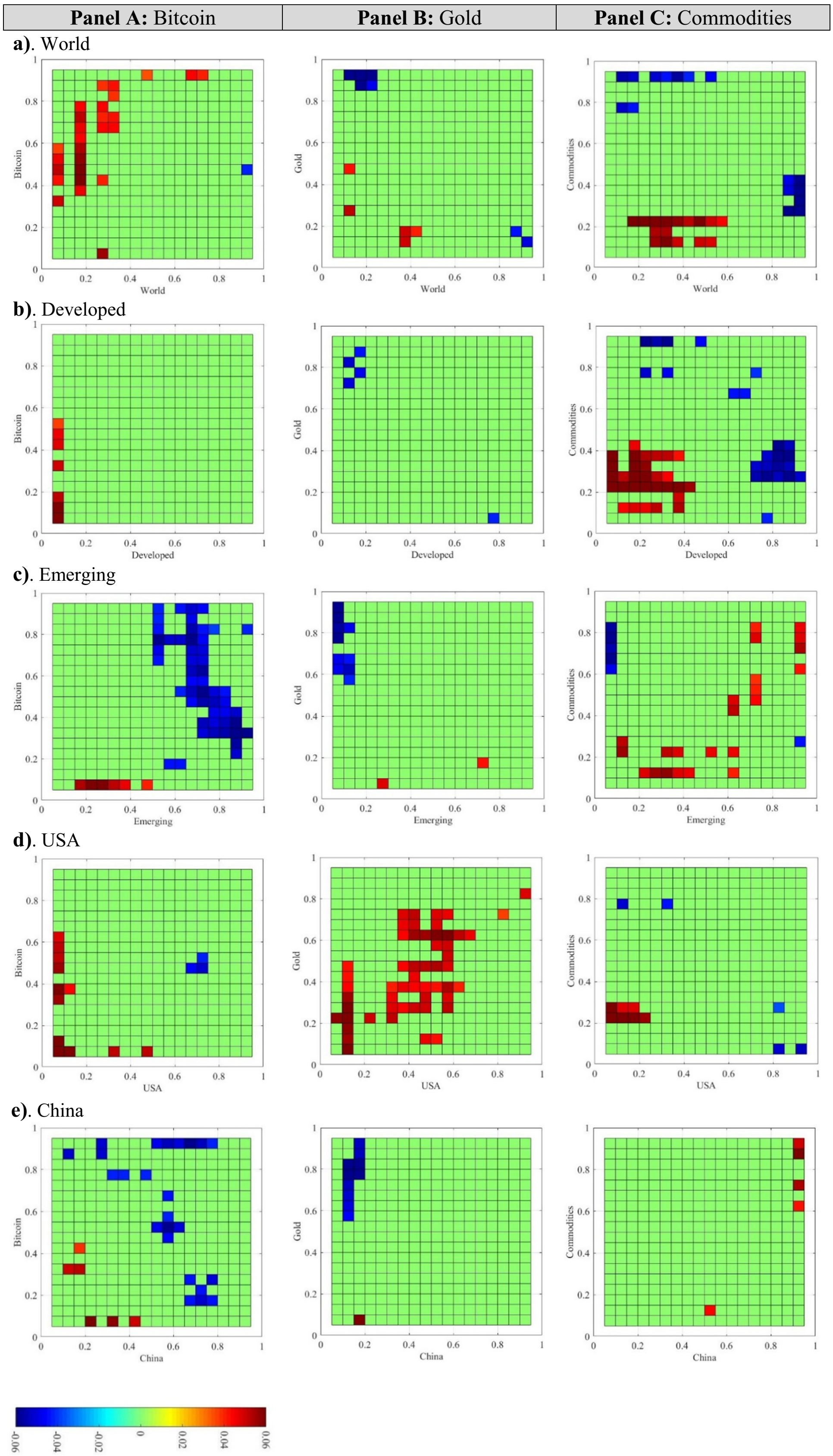


**Fig. 2.** Predictability of safe-haven quantiles through the cross-quantilogram – full sample.
Note: These figures show the significant directional predictability of the safe-haven asset returns from the selected stock market returns for various quantiles. The color bar, shown at the right-side, illustrates the magnitude of the cross-correlations when it is significant and indicates causal flows from the stock market returns to the safe-haven asset returns. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

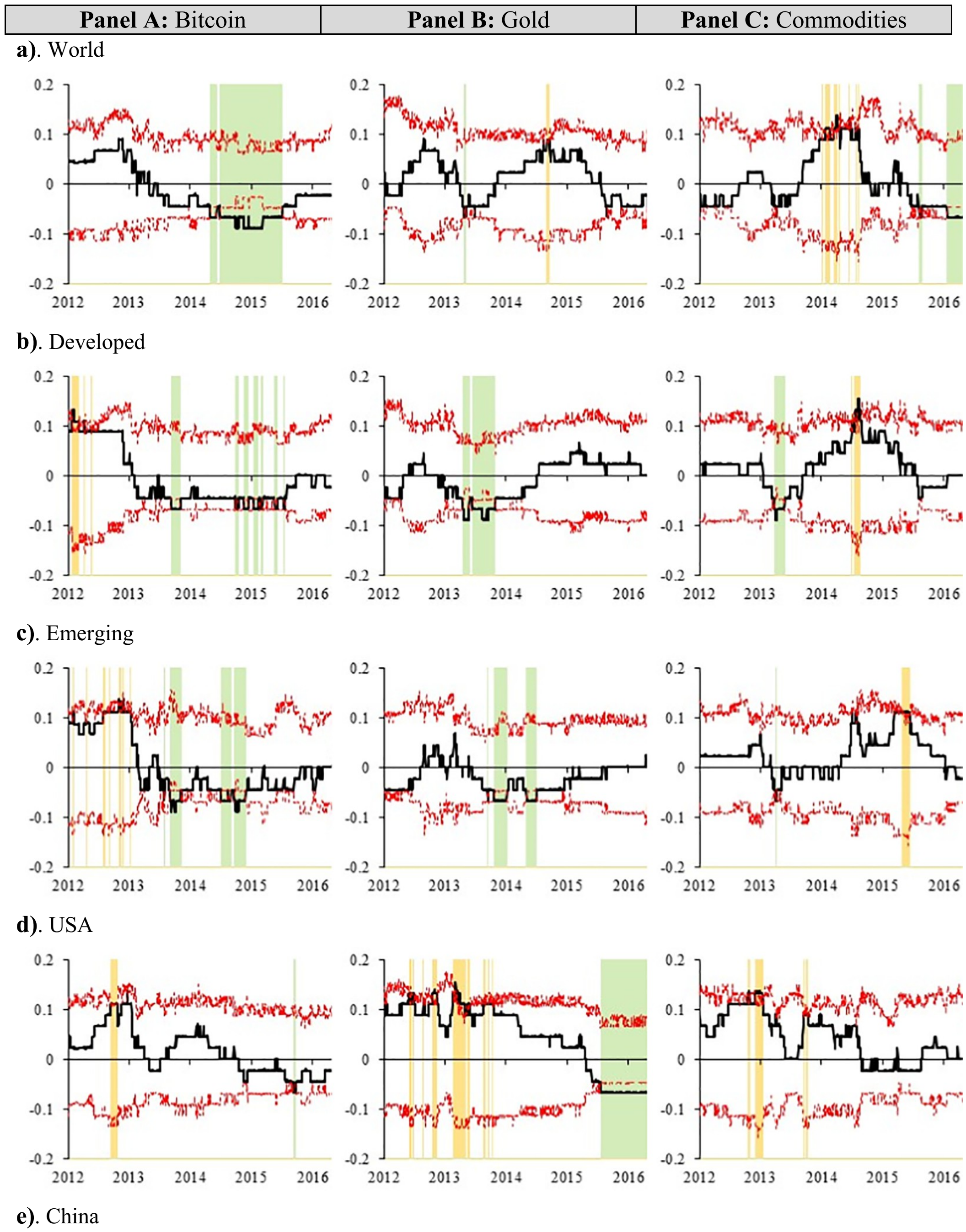


**Fig. 3.** Rolling window directional predictability from stock returns to safe-haven assets.
Notes: The figures show the 1-day rolling quantile (α = 0.10) spillovers from the stock market indices to the safe-haven assets. The sequence of cross-correlations starts on 20 June 2012 as a 500-day rolling window is used to obtain its evolution over time. Black lines are the rolling (500-day fixed rolling-window) cross-quantilogram while red lines are 95% bootstrapped confidence intervals for the null hypothesis of no predictability based on 1000 bootstrapped replicates. Shaded green (yellow) area shows negative (positive) predictability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

negative skewness. However, gold has a greater negative skewness than Bitcoin, suggesting that gold is more characterized by frequent small gains and a few extreme losses. We checked the stationarity of the return series with augmented Dickey-Fuller (ADF) and Kwiatkowski–-Phillips–Schmidt–Shin (KPSS) tests and show evidence of stationarity in all cases. Time series plot of each asset prices is given in Fig. 1. We can see that Bitcoin experienced a more substantial price spike than in other assets, during most of the sample periods, especially during 2016 and 2017. This has helped Bitcoin to exhibit the highest Sharpe ratio. However, from December 2017, the Bitcoin market experienced a price crash on news of regulatory crackdown in Asia and Russia which weighs on investor sentiment. This was coupled by signs of an overheating Bitcoin market in which prices increased by > 200% in the last three months of 2017, suggesting an unsustainable bubble.

### 4.2. Results from the cross-quantilogram

The results of the directional predictability from all quantiles of the stock market returns to the returns of each of the three assets, Bitcoin, gold, and commodities, are given in Panels A, B, and C of Fig. 2,

**Table 2**
Summary of rolling-window directional predictability from stock returns to safe-haven assets – lowest quantile (10%).

| Predictability of | Predictability from | No predictability | Negative | Positive |
|---|---|---|---|---|
| Bitcoin | World | 78.6% | 21.4% | 0.0% |
| | Developed | 85.8% | 11.9% | 2.2% |
| | Emerging | 87.9% | 9.6% | 2.4% |
| | USA | 97.8% | 0.7% | 1.4% |
| | China | 91.4% | 7.7% | 0.8% |
| Gold | World | 95.8% | 3.6% | 0.6% |
| | Developed | 91.2% | 8.8% | 0.0% |
| | Emerging | 93.1% | 6.9% | 0.0% |
| | USA | 65.8% | 27.7% | 6.5% |
| | China | 97.1% | 0.0% | 2.9% |
| Commodities | World | 89.3% | 8.0% | 2.8% |
| | Developed | 94.7% | 3.0% | 2.2% |
| | Emerging | 95.6% | 1.8% | 2.6% |
| | USA | 96.4% | 0.0% | 3.6% |
| | China | 99.1% | 0.0% | 0.9% |

Notes: This table provides the summary of rolling-window estimates shown in Fig. 2. The values show the percentages of no or significant (negative/positive) directional predictability from stock returns to safe-haven assets (Bitcoin, gold and commodities).

respectively. For example, in the first figure of Panel A, the quantiles of world and Bitcoin are displayed on x- and y- axis, respectively. The magnitude (positive/negative causality spillovers) is shown through the color scale from blue (highly negative) through green (uncorrelated) to red (highly positive).[9]

As indicated in the Methodology section, in the framework of the cross-quantilogram analysis, Bitcoin/gold/commodities is a weak safe-haven for the stock market indices if the lowest left corner of the heat-map is green, meaning that no dependence exists among the lower quantiles (at the 0.05 quantile); in addition, Bitcoin/gold/commodities is a strong safe-haven if the lower left-corner of the heat-map is blue (or light blue), i.e. the coefficients are negative, which would suggest that extreme negative stock returns are followed by future positive Bitcoin/gold/commodities returns in next periods.

Overall, the blue color is absent from the lower left-corner of the heat-map in all cases and for all pairs. This suggests that Bitcoin, gold, and commodities cannot be regarded as a strong safe-haven for any of the stock indices under study. Instead, green and, to a lesser extent, red colors are omnipresent in the lower left-corner of the heat-map, suggesting that Bitcoin, gold, or commodities can be, at best, regarded as a weak safe-haven. Specifically, green colors dominate the lower left-corner of the heat-map of world stocks-Bitcoin, world stocks-gold, world stocks-commodities suggesting the absence of predictability in extreme lower quantiles for Bitcoin, gold, and commodities and the world stock index. This finding suggests that Bitcoin, gold, and commodities are each a weak safe-haven for the world stock market. For the case of the developed stock markets, gold exhibits the only weak safe-haven property, given that the extreme negative stock returns in developed countries are uncorrelated with the extreme future gold returns in next periods. In contrast, there is a red color in the lower left-corner of the heat-map of both stock-Bitcoin and stock-commodities for the case of developed markets; i.e. there is evidence of positive predictability, implying that neither Bitcoin nor commodities is a weak/strong safe-haven asset for the developed stock markets. For the case of emerging markets, gold and commodities act as a weak safe-haven, whereas Bitcoin exhibits no such property. In the US, only commodities can be regarded as a weak safe-haven for local stock market, given extreme negative US stock returns are uncorrelated with extreme commodities returns in next periods. For the case of China, both Bitcoin and commodities exhibit a weak safe-haven property against movements in the Chinese stock market, whereas gold does not have such a property, as it has evidence of positive predictability in some extreme lower quantiles of both gold and Chinese stocks.

It is a common finding in financial literature that the relationship between financial assets is dynamic and subject to change over time and any conclusion drawn based on full sample analysis might be misleading. We therefore re-estimate the desired relationship in a rolling-window framework, using a fixed window of 500 days. In doing so, we only focus on the quantile-level of interest, which is the lowest quantile of both distributions (=10%). The results of the rolling-window cross-quantilogram analysis (Fig. 3) show that the directional predictability from stock returns to each of Bitcoin, gold, and commodities varies across time and across the different stock indices under study. This finding suggests time-varying safe-haven properties, which can be partially comparable to that found in Li and Lucey (2017) regarding gold and stock market indices. Specifically, the directional predictability from world, developed, emerging, and Chinese stock markets to the Bitcoin market exhibits a negative behavior around 2015, suggesting a strong safe-haven role. Gold exhibits quite a different negative predictability that is mostly found in the US around 2016–07, suggesting that gold is the most preferred safe-haven asset against movements in US equities. Finally, commodities display less evidence of negative predictability in all cases. The summary of these rolling-window estimates in percentage terms is shown in Table 2. The latter confirms the safe-haven roles of three considered assets.

Finally, we examine the robustness of our findings using different rolling-window sizes (400 days and 600 days) and slightly different quantile levels (the 5% and 15% quantiles). For robustness check and to conserve space, we only show the directional predictability from world stock market returns to the Bitcoin returns (see Fig. 4); other results are available from the authors on request. The results shown in Fig. 4 confirm our main findings, that Bitcoin is generally a weak safe-haven asset for the world stock investment and a strong safe-haven during 2015, are not sensitive to rolling-window sizes and quantile levels.

## 5. Concluding remarks

Within the cross-quantilogram of Han et al. (2016) and in the spirit of Baur and Lucey (2010), we uncover the similarity/dissimilarity in the safe-haven properties of Bitcoin, gold and commodities against extreme movements in some global and country stock market indices from 20 July 2010 until 22 February 2018. The employed approach considers heterogeneity across the different quantiles, so a more in-depth analysis of safe-haven property is explored.

Our main results reveal that Bitcoin, gold, and commodities have a similarity in their weak safe-haven properties for the world stock market index, which is not the case for the developed, emerging, US, and Chinese stock markets. In fact, gold is the only weak safe-haven asset in developed stock markets, whereas both gold and commodities play that role in emerging stock markets. Interestingly, Bitcoin shares with commodities the weak safe-haven property in China, whereas commodities are the only weak safe-haven asset in the US. Further, the rolling window analyses point toward a time-varying safe-haven property for Bitcoin, gold, and commodities that also differs across the stock market indices under study.

The results mirror the findings of prior studies showing that Bitcoin is a valuable stock diversifier (Bouri, Jalkh, et al., 2017; Bouri, Molnár, et al., 2017; Brière et al., 2015; Corbet et al., 2018; Dyhrberg, 2016a, 2016b; Guesmi et al., 2018). However, some other studies have questioned the diversification benefits of Bitcoin (e.g., Chowdhury, 2016) and raised some doubts concerning the prospects of Bitcoin as an alternative asset. In fact, there are still mixed views on whether or not Bitcoin has an intrinsic value and whether its exponential price growth is characterized by an irrational bubble (Bouoiyour et al., 2016; Kristoufek, 2013; Li & Wang, 2017). Importantly, it seems that the link between Bitcoin and stock markets is still weak, likely because the two

[9] See the color bar provided at the end of Fig. 2.

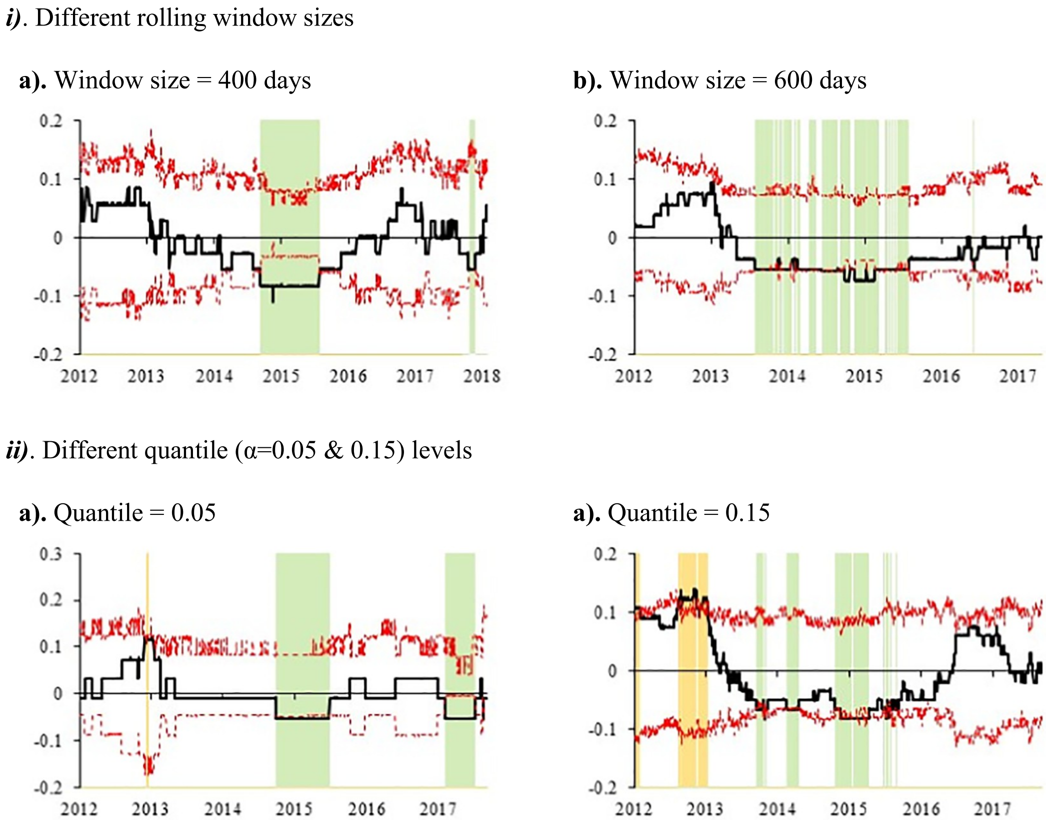


**Fig. 4.** Robustness checks - rolling window directional predictability from World stock returns to Bitcoin returns.
Notes: These figures show the rolling quantile spillovers from the World stock market index returns to the Bitcoin returns. Black lines are the rolling cross-quantilogram, while red lines are 95% bootstrapped confidence intervals for the null hypothesis of no predictability based on 1000 bootstrapped replicates. Shaded green (yellow) area shows negative (positive) predictability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

markets have different pools of investors (Filtz, Polleres, Karl, & Haslhofer, 2017). Financial institutions are not very excited about making direct investments in Bitcoin due to various legal, taxing, and accounting issues (Tan & Low, 2017). Importantly, and unlike the equity markets that involve institutional investors, most participants in the Bitcoin market are young and unexperienced individual investors who seem to depart from rationality while processing information and making trading decisions (Bouri, Gupta, & Roubaud, 2018). As such, they pushed Bitcoin prices several thousand percent in just a few years, whereas the prices of gold and commodities underwent very mild trends. Another factor that explains the weak relationship between Bitcoin and stock markets is that the price determinants in each of the two markets is different, as documented by Kristoufek (2015) and Bouoiyour et al. (2016).

The particularity of our analyses stems from its uncovering time-variability and non-linearity of the relationship between Bitcoin/gold/commodities and the stock markets. Especially, the cross-quantilogram approach allows us to draw a complete-quantile picture of a quantile-to-quantile relation between the stock index and the potential safe-haven asset under study. Despite the significance of our results, we should not expect investors to easily consider Bitcoin as an alternative investment to high-status assets such as gold and commodities. In fact, Bitcoin still has a long way to go in order to catch gold in terms of history, price stability, and accessibility. So, a word of caution is warranted here. The status of Bitcoin in the international financial market is far from being solved, despite the launch of the Bitcoin futures contracts by the CME and CBOE in December 2017, which added some legitimacy to Bitcoin and may ultimately help manage its price volatility.

Based on our analyses, investors and traders now have strong empirical evidence that Bitcoin has some of the virtues of gold and commodities against extreme down movements in the world stock market index. However, stock investors in developed markets have no choice other than gold as a safe-haven asset, given that Bitcoin fails to offer such a property. Interestingly, Chinese investors can consider Bitcoin as a safe-haven asset despite the restrictions taken by the Chinese government against Bitcoin exchanges and trading activities. However, it is not clear whether the exchange rate of the different countries under study has affected our analyses. This would open the door for future research considering potential interplay across foreign exchange rates, Bitcoin, gold, commodities, and stock markets.

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