Jumps in geopolitical risk and the cryptocurrency market:

The singularity of Bitcoin

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Abstract

Are price discontinuities in cryptocurrencies jointly related to large swings in geopolitical risk? This is a relevant question to answer given recent news from the press that Bitcoin's price jumps are driven by jumps in the level of geopolitical risk index. To answer this question, we examine first the jump incidence of daily returns for Bitcoin and other leading cryptocurrencies via the application of the approach of Laurent et al. (2016) and then study the co-jumps between cryptocurrencies and the geopolitical risk index using logistic regressions. Our dataset is at the daily frequency and covers the period April 30, 2013 to October 31, 2019. The results show that the price behaviour of all cryptocurrencies under study is jumpy but only Bitcoin jumps are dependent on jumps in the geopolitical risk index. This revealed evidence of significant co-jumps for the case of Bitcoin only nicely complements previous studies arguing that Bitcoin is a hedge against geopolitical risk.

Keywords: Geopolitical risk; Bitcoin; Cryptocurrencies; Jumps; GARCH

1. Introduction

Given the importance of geopolitical risk (GPR) for investment decisions and asset allocations (Pástor et al., 2013; 2013; Omar et al., 2017; Caldara and Iacoviello, 2018), the academic literature considers the impact of GPR on financial markets dynamics and asset pricing (e.g., Antonakakis et al., 2017; Balcilar et al., 2018; Cheng and Chiu, 2018; Cunado et al., 2019). Several studies argue that the impact of GPR is not necessarily homogenous across the various asset classes, as it might depend on some characteristics and properties of the asset. For example, the impact is negative on risky assets like equities (Antonakakis et al., 2017) and positive on safe haven assets like gold (Baur and Smales, 2020). Furthermore, it is documented that GPR can predict jumps in the price of US equities (Gkillas et al., 2018).

With the emergence of Bitcoin as a new investment vehicle detached from the global financial system due to its decentralization and independence from governments and central banks, many studies examine the price discovery in the Bitcoin market (e.g., Atsalakis et al., 2019) and assign to Bitcoin valuable diversification and hedging capabilities against conventional assets (Bouri et al., 2017a; Baur et al., 2018; Guesmi et al., 2019; Shahzad et al., 2019), financial uncertainty (Bouri et al., 2017b), and economic policy uncertainty (Demir et al., 2018; Wu et al., 2019). Accordingly, the impact of GPR on Bitcoin prices has been addressed very recently, based on the rationale that during periods of heightened GPR, investors will move away from the financial (equity) market to the Bitcoin market, which leads to an increase in the price of Bitcoin (Aysan et al., 2019). Therefore, heightened levels of GPR are likely to affect positively Bitcoin prices as investors consider Bitcoin as a hedge against global uncertainties. Aysan et al. (2019) examine the ability of GPR to predict the returns and volatility of Bitcoin, implying that Bitcoin is a hedge against global GPR. Al Mamun et al. (2020) focus on the risk-premia nature of Bitcoin, suggesting that GPR and economic uncertainty carry a risk premium, mostly during bear markets. Bouri et al. (2020b) relate the realised correlation between US stock returns and Bitcoin returns with the trade uncertainty of the US and then indicate that Bitcoin is a hedge against the US stock market in the wake of heightened trade policy uncertainty. While the two above studies relate Bitcoin return and volatility to GPR levels, they do not consider the impact of GPR on price discontinuities in leading cryptocurrencies. Given that the price process of cryptocurrencies is characterized by price discontinuities or jumps (Chaim and Laurini, 2018; Bouri et al., 2020a), it is relevant to extend the empirical literature by studying the impact of jumps in the levels of GPR on price jumps in leading cryptocurrencies.

In this study, we address this specific research gap. We use daily data on leading cryptocurrencies and detect jumps via the application of the semi-parametric technique of Laurent et al. (2016). Then, we apply logistic regression analyses to relate jump in the GPR with the jumps in cryptocurrencies.

Our analyses are related to a new strand of literature dealing with GPR and Bitcoin (Aysan et al., 2019; Al Mamun et al., 2020). They are also related to the existing literature associating between GPR and jumps in equities (e.g., Gkillas et al., 2018). In fact, the price process of financial assets exhibits discontinuity (i.e., jumps), and such a discontinuity can occur simultaneously among financial assets leading to the so called cojumps (Lahaye et al., 2011; Maslyuk-Escobedo et al., 2017). The occurrence of jumps in asset prices may explain fat tails in asset returns. Furthermore, the behaviour of jumps and cojumps has important implications to asset allocation, risk management, derivative pricing, and trading (Bormetti et al., 2015).

Our results show reasonable evidence that among the five leading cryptocurrencies under study, only Bitcoin jumps are dependent on jumps in the level of GPR. This result is not surprising given the particularity of Bitcoin in hedging global uncertainties (e.g., Bouri et al., 2017b; Demir et al., 2018; Wu et al., 2019), and recent evidence showing that Bitcoin is a hedge against GPR (Aysan et al., 2019).

The rest of the paper is divided into four sections. Section 2 described the dataset. Section 3 provides the methods for detecting jumps and co-jumps. Section 4 presents and discusses empirical results. Finally, Section 5 gives concluding remarks and opens paths for further research.

2. Data

This study uses two sets of daily data. The first covers the GPR index of Caldara and Iacoviello (2018)[1], which is widely used in the existing literature (Balcilar et al., 2018; Cunado et al., 2019). This GPR index reflects the tensions among countries, military conflicts, terrorist attacks, and threats of war as counted by their news in leading newspapers from around the globe. The second

[1] The data is sourced from https://www2.bc.edu/matteo-iacoviello/gpr.htm

set includes the price index of Bitcoin, Ethereum, Ripple, Litecoin, and Stellar[2]. Table A1 presents market value of the five cryptocurrencies. Notably, the sample period involving GPR and Bitcoin (Litecoin) is from April 30, 2013 to October 31, 2019, giving 2,369 daily observations. For the other cryptocurrencies, the sample period varies according to their price availability (See Table 1). To conduct the empirical analyses, we use the daily log returns of Bitcoin and other leading cryptocurrencies, whereas the levels of the GPR index are employed since the GPR is stationary at levels (See Table 1). The summary statistics of Bitcoin returns and the geopolitical risk index are tabulated in Table 1. All series have non-zero skewness and excess kurtosis, and their Jarque-Bera statistics imply the non-normal distribution of the series. The ARCH statistics show the presence of heteroskedasticity in both series, which points to the appropriateness of applying GARCH-based techniques for detecting jumps in the price process. The test statistics of augmented Dickey-Fuller (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) indicate that the null hypothesis of stationarity is rejected at conventional levels, which confirms the stationarity of the series. The Pearson pairwise correlation between GPR and the return of each of the five cryptocurrencies is given in Table 2. It is very weak and fluctuate between positive and negative values.

Table 1. Summary statistics

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP	ARCH-LM	ρ	N
GPR	127.823	83.448	1.639	7.551	3104***	-9.205***	-40.844***	93.889***	1	2,369
Bitcoin	0.002	0.043	-0.162	10.607	5722***	-48.568***	-48.719***	31.963***	0.005	2,369
Ethereum	0.003	0.073	-3.404	72.820	315572***	-41.982***	-41.672***	22.213***	-0.003	1,539
Ripple	0.002	0.074	2.053	32.231	82485***	-45.281***	-46.181***	24.375***	0.024	2,272
Litecoin	0.001	0.065	1.706	28.161	63639***	-47.509***	-47.671***	33.805***	-0.017	2,369
Stellar	0.001	0.076	1.957	19.089	21765***	-40.622***	-40.629***	39.235***	0.001	1,905

Notes: This table gives summary statistics of daily data: return series of Bitcoin, Ethereum, Ripple, Litecoin, and Stellar, as well as the level series of the GPR index. The ADF and PP tests are conducted with an intercept. The ARCH-LM is the heteroskedasticity test of Engle (1982) up to 10 lags. ρ denotes the Pearson correlation coefficient between the GPR index and the returns of each of the five cryptocurrencies. N denotes the number of daily observations. The start of the sample period is April 30, 2013 for GPR, Bitcoin and Litecoin, August 8, 2015 for Ethereum, August 5, 2013 for Ripple August 6, 2014 for Stellar. For all series, the sample period ends at October 31, 2019. Significance at 1% level is indicated by ***.

[2] Price data are collected from https://coinmarketcap.com/. The five leading cryptocurrencies account for more than 81% of the total market value of all cryptocurrencies and attract most of the trading activity.

3. Methodology

3.1. Testing for jumps

To date-stamped jumps in the data series, we apply the semi-parametric approach of Laurent et al. (2016)[3], which allows us to test for additive jumps in AR-GARCH models[4].

A time series (r_t) is described by an AR(1)-GARCH(1,1) model:

$$r_t = \mu_t + \alpha\, r_{t-1} + \sigma_t z_t\, ;\; z_t \sim i.i.d.\; N(0,1) \tag{1}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

where μ_t is the conditional mean, σ_t^2 is the conditional variance, $\sigma_t z_t$ is the residual term (ε_t), and z_t is the white noise process. After adding an independent jump component $a_t I_t$ to r_t, we can write the following:

$$r_t^* = r_t + a_t I_t \tag{3}$$

where r_t^* is the observed returns, I_t is a binary variable that equals 1 if there is a jump on day *t* and 0 otherwise (I_t is generated by an outlier process, namely the Poisson process), and a_t represents the jump size. In this regard, Laurent et al. (2016) show that the next period conditional variance (σ_{t+1}^2) is not impacted by $a_t I_t$[5].

Then, the estimates of μ_t and r_t, $\tilde{\mu}_t$ and $\tilde{\sigma}_t$ are obtained based on the bounded innovation propagation (BIP)-AR(1) and the BIP-GARCH(1,1) respectively described in Muler et al. (2009) and Muler and Yohai (2008)[6]. As argued by Laurent et al. (2016), these estimates are robust to potential jumps $a_t I_t$. Considering the standardized return is calculated as follows:

$$\tilde{J}_t = \frac{r_t^* - \tilde{\mu}_t}{\tilde{\sigma}_t} \tag{4}$$

[3] As indicated by Laurent et al. (2016), this test is comparable to the non-parametric tests of Lee and Mykland (2008) and Andersen et al. (2007). It has been applied in recent studies such as Collet and Ielpo (2018), and Bouri et al. (2020a).
[4] Notably, our estimated results are not sensitive to the choice between the AR-GARCH and AR-GARCH-GJR models.
[5] For more information, the readers are referred to the original work of Laurent et al. (2016).
[6] Further details regarding the auxiliary specification for the conditional variance are given in Laurent et al. (2016).

To detect the presence of jumps, we test the null hypothesis $H_0: a_t I_t = 0$, against the alternative $H_1: a_t I_t \neq 0$. We reject H_0 if $\max_T |\tilde{J}_t| > g_{T,\lambda}$, where $\max_T$ is the maximum of $|\tilde{J}_t|$ for $t = 1, \dots, T$, and $g_{T,\lambda}$ is the critical value. When H_0 is rejected, an alternative binary variable is suggested as follows:

$$\tilde{I}_t = I(|\tilde{J}_t| > g_{T,\lambda}) \tag{5}$$

where I(.) is the indicator function, and $\tilde{I}_t$ takes the value of 1 if there is a jump on day *t* and 0 otherwise.

3.2. Testing for co-jumps

Based on the results of the detected jumps, we employ logistic regressions[7] to study the co-jumping behaviour between the GPR and cryptocurrencies' return series.

$$\text{logit}(p) = log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X + \epsilon_t \tag{6}$$

where p is the probability of a jump in the GPR index; (1-p) is the probability that jump in GPR index did not occur; and X is a jump in the cryptocurrency. In Equation (6), both dependent and independent variables take a value of 1 when there is a jump and 0 otherwise[8]. The distribution of the residual term (ϵ_t) pursues the logistic regression.

4. Empirics

4.1. Results for jumps

The plots of the jumps are given in the Appendix Figure 1A, while some key statistics of the jumps are presented in Table 2. Based on Table 2, we date-stamp 31 in the GPR index. Regarding the cryptocurrencies under study, the most jumpy cryptocurrencies are Litecoin (80), Ripple (74), and Bitcoin (71), representing 3.38%, 3.26% and 3.00% of days. Conversely, Ethereum is the least

[7] Previous studies apply logistic regressions to detect evidence of cojumps (e.g., Maslyuk-Escobedo et al., 2017; Bouri et al., 2020a).
[8] Given that all cryptocurrencies are traded 24 hours and seven days a week, it is relevant to assume that the cryptocurreny market digests and responds to geopolitical events on the same day.

jumpy cryptocurrency with only 38 jumps, representing 2.47% of days (Compared to Bitcoin and Litecoin, Ethereum data are limited to around four years and three months (i.e., 1,539 observations). Many jumps take place in 2016-2017. The above evidence of infrequent large price changes among leading cryptocurrencies concords with previous studies (Chaim and Laurini, 2018; Bouri et al., 2020), suggesting the need to consider jumps when modelling the price process of leading cryptocurrencies. This is a major concern as the occurrence of jumps can make the tails fatter.

Table 2. Statistics of jumps

	GPR	Bitcoin	Ethereum	Ripple	Litecoin	Stellar		
Panel A: Number of date-stamped jumps							**TJY**	**AJ**
2013	1	5	NA	3	9	NA	**18**	**3.00**
2014	7	11	NA	11	11	6	**46**	**7.67**
2015	4	10	6	11	16	8	**55**	**9.17**
2016	4	15	6	8	10	14	**57**	**9.50**
2017	5	10	12	18	18	14	**77**	**12.83**
2018	7	11	6	13	8	6	**51**	**8.50**
2019	3	9	8	10	8	5	**43**	**7.17**
TJ	**31**	**71**	**38**	**74**	**80**	**53**	***347***	
Panel B: % of days with jumps								
2013	0.04%	0.21%	-	0.13%	0.38%	-		
2014	0.30%	0.46%	-	0.48%	0.46%	0.31%		
2015	0.17%	0.42%	0.39%	0.48%	0.68%	0.42%		
2016	0.17%	0.63%	0.39%	0.35%	0.42%	0.73%		
2017	0.21%	0.42%	0.78%	0.79%	0.76%	0.73%		
2018	0.30%	0.46%	0.39%	0.57%	0.34%	0.31%		
2019	0.13%	0.38%	0.52%	0.44%	0.34%	0.26%		
TJ %	**1.31%**	**3.00%**	**2.47%**	**3.26%**	**3.38%**	**2.78%**		

Notes: NA denotes periods with no data. TJ (total number of jumps). TJY (total number of jumps per year). AJ (average number of jumps per year). TJ % (total number of jumps as a percentage of the total number of observations). Panel A provides the number of date-stamped jumps. Panel B presents the percentage (%) of days with jumps. Notably, the start of the sample period is April 30, 2013 for Bitcoin and Litecoin, August 8, 2015 for Ethereum, August 5, 2013 for Ripple August 6, 2014 for Stellar.

4.2. Results for co-jumps

To examine whether jumps in GPR occur contemporaneously with jumps in cryptocurrencies, we run regression (6)[9]. Results are reported in Table 3.

Table 3. The impact of GPR jumps on the jumps in cryptocurrencies[10]

	GPR jumps	Constant	McFadden R^2
Bitcoin jumps	1.775***	-3.525***	0.019***
Ethereum jumps	0.773	-3.718***	0.001
Ripple jumps	0.881	-3.407***	0.001
Litecoin jumps	0.096	-3.354***	0.000
Stellar jumps	0.565	-3.571***	0.000

Notes. Results are from the estimation of Equation (6), with the coefficient covariance computed using the Huber-White method. Significance at 1% level is indicated by ***.

They show that the occurrence of jumps in the GPR index significantly increases the likelihood of jumps in Bitcoin, suggesting that the jump behaviour of Bitcoin is dependent on the jump behaviour in the GPR index. However, the jump behaviour of other cryptocurrencies (Ethereum, Ripple, Litecoin, and Stellar) is independent of the jump behaviour in the GPR index.

Our results are not surprising given the dominance of the Bitcoin market over the cryptocurrency market (around 60% of the total market share of all cryptocurrencies), and, importantly, the hedging and safe haven ability of Bitcoin against financial uncertainty (Bouri et al., 2017b) and economic uncertainty (Fang et al., 2019; Wu et al., 2019). The fact that Bitcoin is dependent on the jumps in GPR points to the possibility of using Bitcoin as a shelter and an alternative to the ineffectiveness of traditional economic and financial systems (Bouri et al., 2017b) in times of heightened geopolitical risk (Aysan et al., 2019) such as Brexit, Venezuela Sanctions, the salient US-Iranian conflict in the Middle East, and the US-China trade tensions (Bouri et al., 2020b). Accordingly, investors tend to move to Bitcoin during periods of heightened geopolitical events.

[9] We also added the lagged variable of the GPR jumps while estimating Equation (6). However, the estimated results remain qualitatively the same. The results are available upon request from the authors.

[10] Notably, a low value for the McFadden R2 in logistic regressions doesn't jeopardize the trustworthiness of the estimated model. In fact, to the presence of intrinsic randomness prevents the value of the McFadden R2 to attain 1. In other words, a low value for the McFadden R2 in logistic regressions is not a problem as it simply illustrates the fact that, in practice, there is a difficulty in predicting a binary event with near certainty (https://thestatsgeek.com/2014/02/08/r-squared-in-logistic-regression).

This result also reflects potential effects of contagion between the safe-haven digital asset (Bitcoin) and GPR, which allows for traders in the Bitcoin market to predict jumps based on the occurrence of jumps in the GPR index. Bouri (2020a) show that the formation of jumps in Bitcoin is related to the occurrence of jumps in some leading cryptocurrencies. We show here that only the formation of jumps in Bitcoin is related to jumps in GPR. Furthermore, our above results are comparable to the existing literature that associate the price discontinuity (i.e., jump) in equity prices to GPR (e.g., Gkillas et al., 2018), which has important implications regarding portfolio and risk management as well as derivative pricing (Bormetti et al., 2015).

4.3. Robustness analysis

In this section, we check the robustness of results to the choice of the data. First, we rerun the jump and co-jumps analyses using the main component of the GPR index, called threat[11], and the five cryptocurrencies under study. The results, reported in Table 4, show that only the jump behaviour of Bitcoin is dependent of the jump behaviour of both GPR indices.

Table 4. The impact of GPR-threat jumps on the jumps in cryptocurrencies

	GPR-threat jumps	Constant	McFadden R^2
Bitcoin jumps	1.565***	-3.511***	0.006**
Ethereum jumps	0.688	-3.425***	0.000
Ripple jumps	0.303	-3.395***	0.000
Litecoin jumps	0.071	-3.320***	0.000
Stellar jumps	0.397	-3.308***	0.000

Notes. Results are based of Equation (6), with the coefficient covariance computed using the Huber-White method. Significance at 1% level is indicated by ***.

Furthermore, one reviewer indicates that the conclusion about the hedging character of Bitcoin against the GPR index could stand if it could be proven that when geopolitical risk fluctuations increase, then Bitcoin fluctuations decrease. Therefore, we conduct a regression analysis involving geopolitical risk fluctuations and Bitcoin fluctuations and the results are reported in Table 5. They

[11] Figure A.2 in the Appendix shows the plot of jumps in the GPR-threat index.

uncover an inverse association, which confirms earlier evidence on the hedging ability of Bitcoin against the GPR index.

Table 5. The impact of GPR fluctuations on the fluctuations in Bitcoin

	GPR fluctuations	Constant	Prob(Wald F-statistic)
Bitcoin fluctuations	-0.000***	0.002***	0.0068

Notes: The coefficient covariance is computed using the Huber-White method. Significance at 1% level is indicated by ***.

5. Concluding remarks

In this study, we detect the presence of jumps in the geopolitical risk index and the returns of five leading cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Litecoin, and Stellar. Then, we try to jointly relate the occurrence of jumps in cryptocurrencies with that in the geopolitical risk index using logistic regressions. Based on the estimated results, Bitcoin is the only cryptocurrency having its price jumps positively dependent on jumps in the level of geopolitical risk. This result provides evidence supporting the possibility of using Bitcoin as a shelter to political risk. This finding is useful to participants in the cryptocurrency market and has implications regarding risk and portfolio management. Further research on the impact of geopolitical events on the cryptocurrency market under various market states can further give insights into the capability of geopolitical risks to move cryptocurrency prices.

References

Al Mamun, M., Uddin, G. S., Suleman, M. T., & Kang, S. H. (2020). Geopolitical risk, uncertainty and Bitcoin investment. Physica A: Statistical Mechanics and its Applications, 540, 123107.

Antonakakis, N., Gupta, R., Kollias, C., & Papadamou, S. (2017). Geopolitical risks and the oil-stock nexus over 1899–2016. Finance Research Letters, 23, 165-173.

Atsalakis, G. S., Atsalaki, I. G., Pasiouras, F., & Zopounidis, C. (2019). Bitcoin price forecasting with neuro-fuzzy techniques. European Journal of Operational Research, 276(2), 770-780.

Aysan, A. F., Demir, E., Gozgor, G., & Lau, C. K. M. (2019). Effects of the geopolitical risks on Bitcoin returns and volatility. Research in International Business and Finance, 47, 511-518.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? Journal of International Financial Markets, Institutions and Money, 54, 177-189.

Baur, D.G. & Smales, L. A. (2020). Gold and Geopolitical Risk. Available at SSRN: https://ssrn.com/abstract=3109136

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2018). Geopolitical risks and stock market dynamics of the BRICS. Economic Systems, 42(2), 295-306.

Bormetti, G., Calcagnile, L. M., Treccani, M., Corsi, F., Marmi, S., & Lillo, F. (2015). Modelling systemic price cojumps with Hawkes factor models. Quantitative Finance, 15(7), 1137-1156.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017a). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters, 20, 192-198.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017b). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23, 87-95.

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. Finance Research Letters, 29, 178-183.

Bouri, E., Roubaud, D., & Shahzad, S. J. H. (2020a). Do Bitcoin and other cryptocurrencies jump together? The Quarterly Review of Economics and Finance, 76, 396-409.

Bouri, E., Gkillas, K., & Gupta, R. (2020b). Trade Uncertainties and the Hedging Abilities of Bitcoin. Economic Notes, https://doi.org/10.1111/ecno.12173

Caldara, D., & Iacoviello, M. (2018). Measuring geopolitical risk. FRB International Finance Discussion Paper, (1222).

Chaim, P., & Laurini, M. P. (2018). Volatility and return jumps in bitcoin. Economics Letters, 173, 158-163.

Cheng, C. H. J., & Chiu, C. W. J. (2018). How important are global geopolitical risks to emerging countries? International economics, 156, 305-325.

Collet, J., & Ielpo, F. (2018). Sector spillovers in credit markets. Journal of Banking & Finance, 94, 267-278.

Cunado, J., Gupta, R., Lau, C. K. M., & Sheng, X. (2019). Time-varying impact of geopolitical risks on oil prices. Defence and Peace Economics, 1-15.

Demir, E., Gozgor, G., Lau, C. K. M., & Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. Finance Research Letters, 26, 145-149.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association, 74(366a), 427-431.

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? International Review of Financial Analysis, 61, 29-36.

Gkillas, K., Gupta, R., & Wohar, M. E. (2018). Volatility jumps: The role of geopolitical risks. Finance Research Letters, 27, 247-258.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. International Review of Financial Analysis, 63, 431-437.

Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. Journal of Applied Econometrics, 26(6), 893-921.

Laurent, S., Lecourt, C., & Palm, F. C. (2016). Testing for jumps in conditionally Gaussian ARMA–GARCH models, a robust approach. Computational Statistics & Data Analysis, 100, 383-400.

Maslyuk-Escobedo, S., Rotaru, K., & Dokumentov, A. (2017). News sentiment and jumps in energy spot and futures markets. Pacific-Basin Finance Journal, 45, 186-210.

Omar, A. M., Wisniewski, T. P., & Nolte, S. (2017). Diversifying away the risk of war and cross-border political crisis. Energy Economics, 64, 494-510.

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. Journal of financial Economics, 110(3), 520-545.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

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

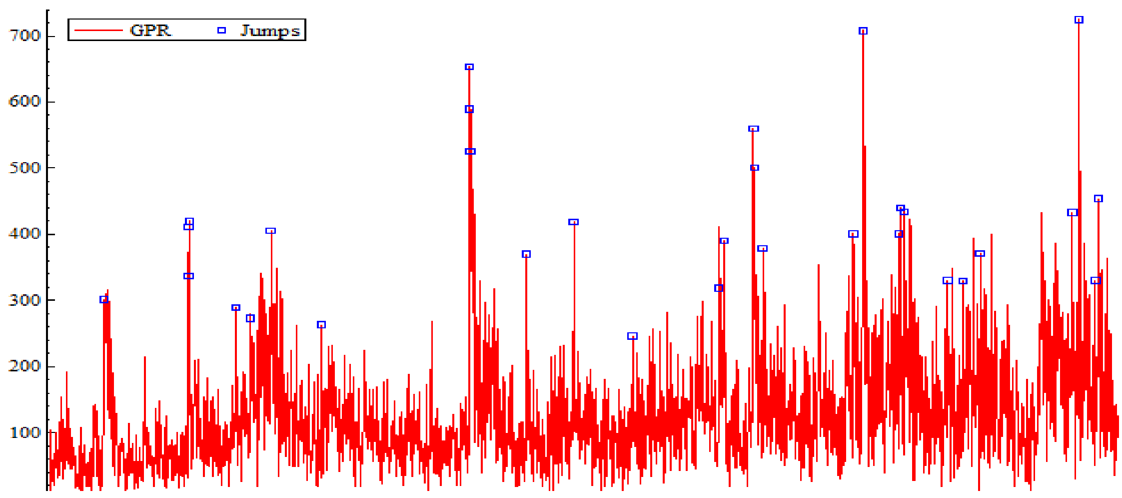
Wu, S., Tong, M., Yang, Z., & Derbali, A. (2019). Does gold or Bitcoin hedge economic policy uncertainty? Finance Research Letters, 31, 171-178.

Table A1. Market value of the five cryptocurrencies

Ranking	Name	Market Value
1st	Bitcoin	154,115,667,122
2nd	Ethereum	19,788,003,410
3rd	Ripple	11,430,331,072
6th	Litecoin	3,703,168,290
10th	Stellar	1,449,205,009

Note: The data is based on the rank of the five cryptocurrencies within the first largest 20 cryptocurrencies (https://coinmarketcap.com).

Figure A1. Plots of jumps

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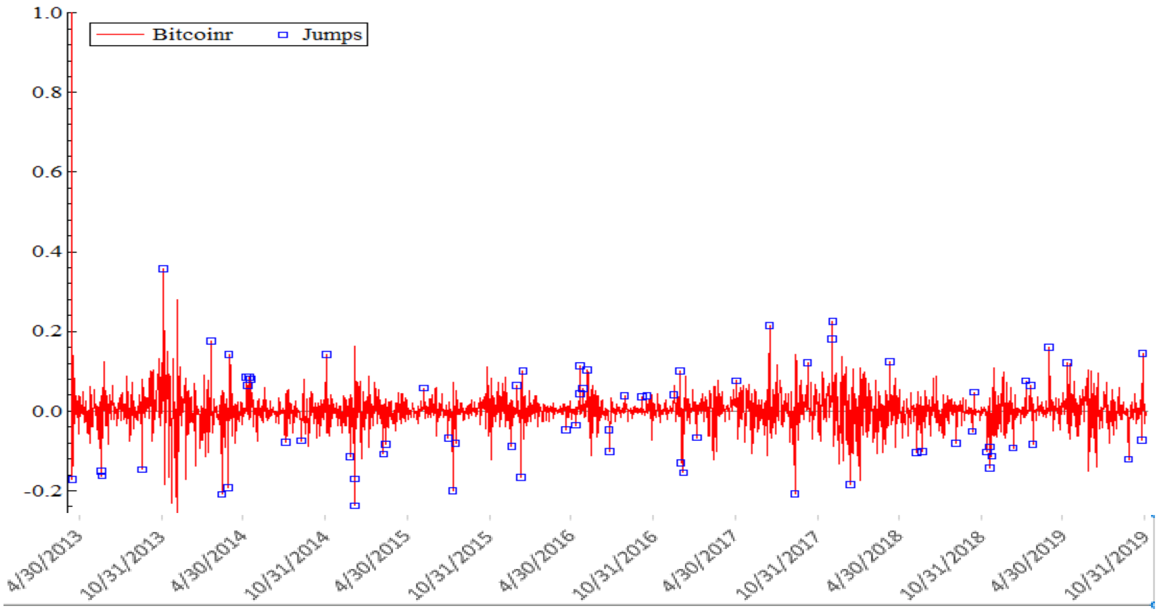
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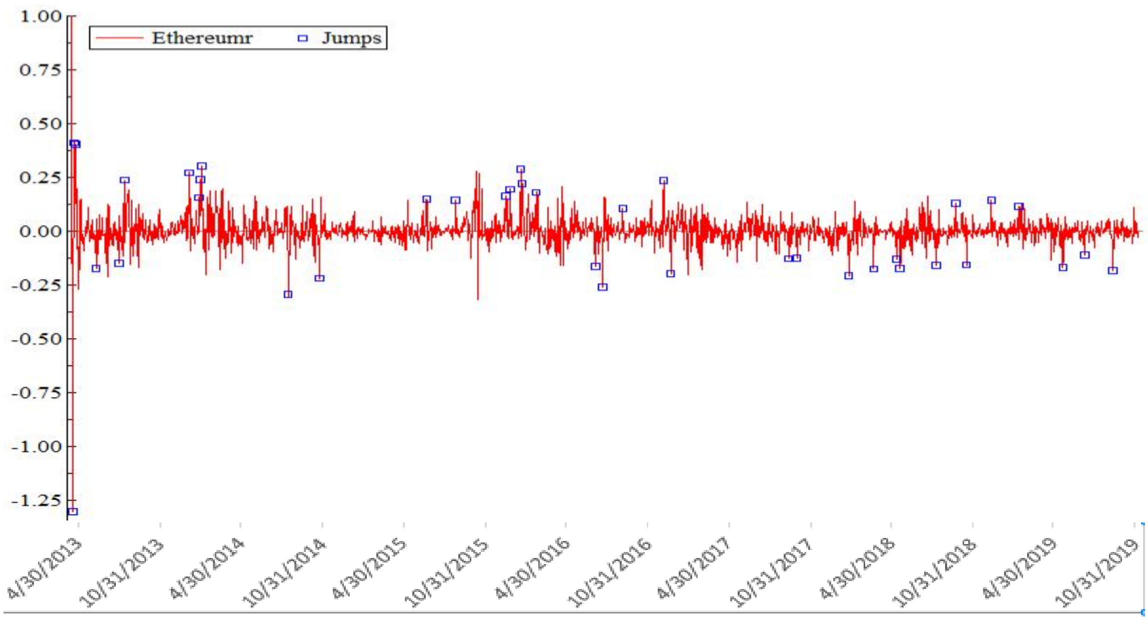
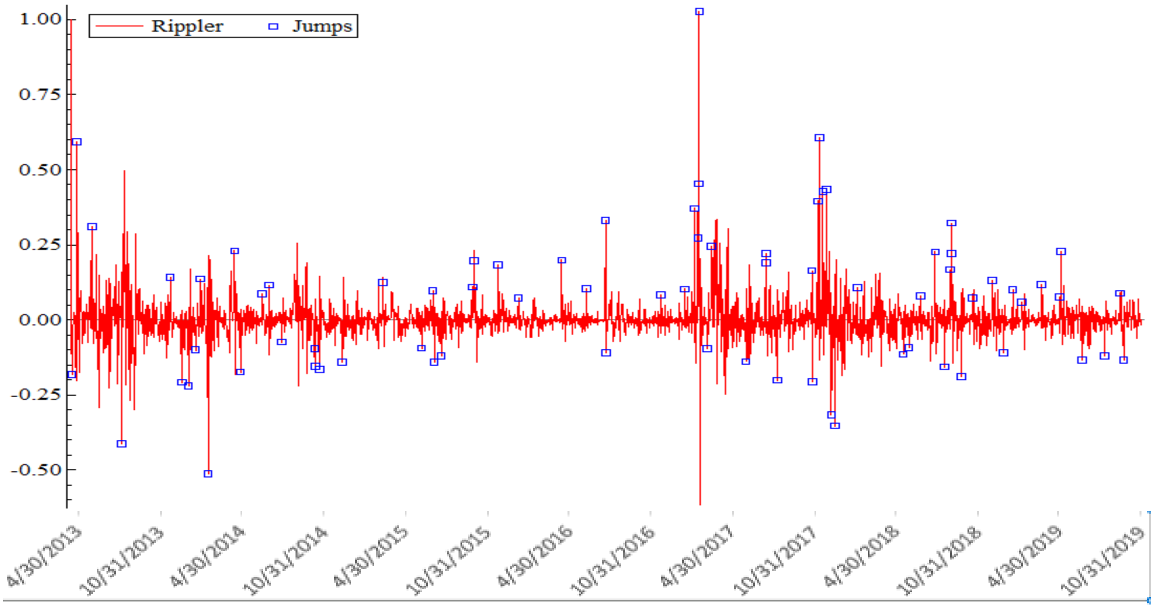
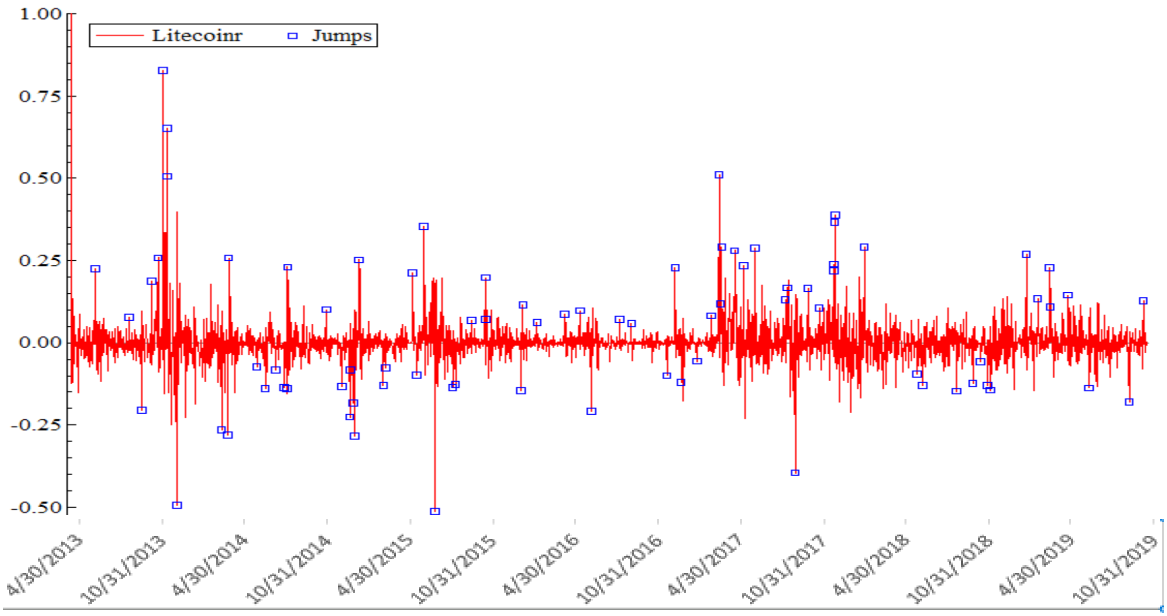

Ethereumr
Jumps
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00
-1.25
4/30/2013
10/31/2013
4/30/2014
10/31/2014
4/30/2015
10/31/2015
4/30/2016
10/31/2016
4/30/2017
10/31/2017
4/30/2018
10/31/2018
4/30/2019
10/31/2019


Rippler
Jumps
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
4/30/2013
10/31/2013
4/30/2014
10/31/2014
4/30/2015
10/31/2015
4/30/2016
10/31/2016
4/30/2017
10/31/2017
4/30/2018
10/31/2018
4/30/2019
10/31/2019


Litecoinr
Jumps
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
4/30/2013
10/31/2013
4/30/2014
10/31/2014
4/30/2015
10/31/2015
4/30/2016
10/31/2016
4/30/2017
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10/31/2018
4/30/2019
10/31/2019

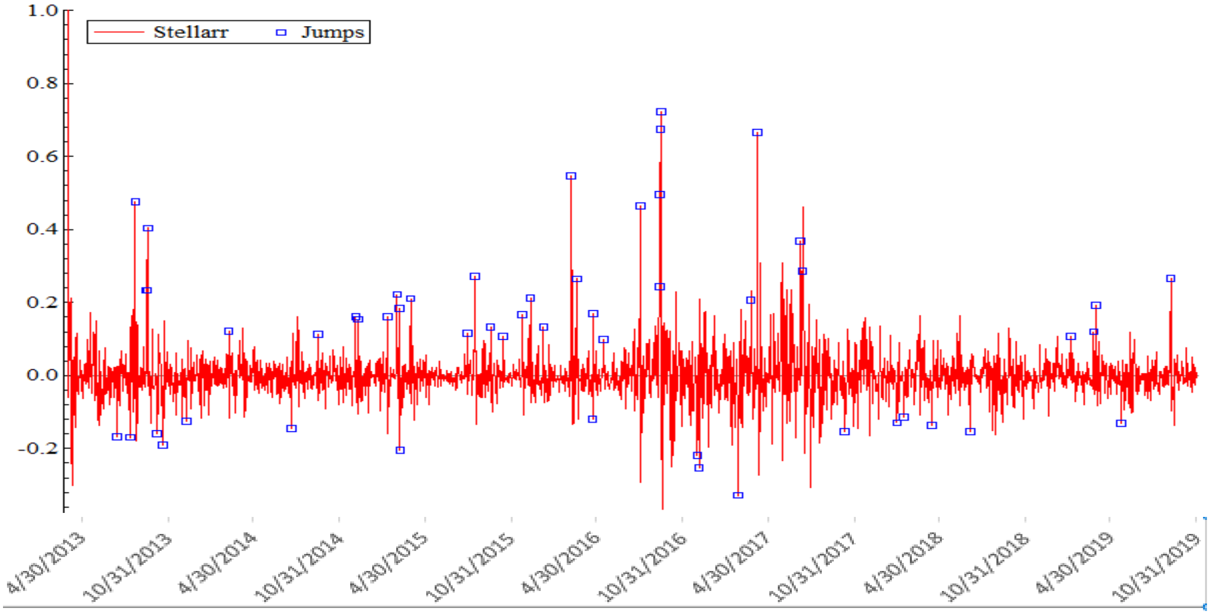

Figure A2. Plots of jumps in the GPR-threat