Finance Research Letters 49 (2022) 103131

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Is geopolitical risk priced in the cross-section of cryptocurrency returns?

Huaigang Long [a,*], Ender Demir [b,f], Barbara Będowska-Sójka [c], Adam Zaremba [d,e], Syed Jawad Hussain Shahzad [d]

[a] School of Finance, Zhejiang University of Finance and Economics, 18 Xueyuan Street, Hangzhou, Zhejiang 310018, China
[b] Department of Business Administration, School of Social Sciences, Reykjavik University, Menntavegur 1, 102, 101, Reykjavík, Iceland
[c] Department of Econometrics, Institute of Informatics and Quantitative Economics, Poznan University of Economics and Business, al. Niepodległości 10, Poznań 61-875, Poland
[d] Montpellier Business School, 2300 Avenue des Moulins, Montpellier 34185 Cedex 4, France
[e] Department of Investment and Financial Markets, Institute of Finance, Poznan University of Economics and Business, al. Niepodległości 10, Poznań 61-875, Poland
[f] Tomas Bata University in Zlin, Zlin, Czech Republic

ARTICLE INFO

JEL codes:
F51
G11
G12
H56

Keywords:
Cryptocurrencies
The cross-section of returns
Asset pricing
Geopolitical risk
Return predictability

ABSTRACT

We examine the role of geopolitical risk in the cross-sectional pricing of cryptocurrencies. We calculate cryptocurrency exposure to changes in the geopolitical risk index and document that coins with the lowest geopolitical beta outperform those with high geopolitical beta. Our findings suggest that risk-averse investors require additional compensation as motivation to hold cryptocurrencies with low and negative geopolitical betas, and they are willing to pay a premium for assets with high and positive geopolitical betas. The effect cannot be explained by known return predictors and is robust to many considerations.

1. Introduction

The Russia-Ukraine war has shone a light on the role of geopolitical risk in cryptocurrency markets. Not all coins were equally affected, with some assets benefitting from the tensions and thus serving as a hedge against geopolitical risk. Others proved highly sensitive, and their prices fell. Knowing this, do investors use this information while making pricing decisions on cryptocurrencies?

This paper examines whether the exposure to geopolitical risk is priced in cryptocurrency markets. We proxy geopolitical risk with the geopolitical risk (GPR) index by Caldara and Iacoviello (2022) and introduce a novel measure of exposure: the *geopolitical beta* (β^{GPR}). Assets with high and positive betas act as risk hedges—spikes in GPR coincide with a positive payoff. Hence, risk-averse investors should be willing to pay a premium to hold these assets. Conversely, assets with low and negative betas fall when GPR increases. Consequently, investors should demand extra compensation for exposure to this additional risk. In short: cryptocurrencies

* Corresponding author at: School of Finance, Zhejiang University of Finance and Economics, 18 Xueyuan Street, Hangzhou City, Zhejiang Prov, China 310018.

E-mail address: longhuaigang@zufe.edu.cn (H. Long).

https://doi.org/10.1016/j.frl.2022.103131
Received 20 May 2022; Received in revised form 21 June 2022; Accepted 5 July 2022
Available online 6 July 2022

with low (high) β^{GPR} should produce high (low) returns.[1] This study tests these conjectures explicitly using a comprehensive sample of nearly 2000 cryptocurrencies.

We begin with univariate portfolio sorts and find that low β^{GPR} coins markedly outperform their high β^{GPR} counterparts. The associated long-short strategy produces an annualized Sharpe ratio of 0.75. Popular factor pricing models fail to explain these abnormal returns, and the results hold for both equal- and value-weighted portfolios. The most impressive returns derive mainly from the superior performance of coins with the lowest β^{GPR}.

We continue with bivariate sorts and cross-sectional regressions. These tests demonstrate that β^{GPR} contains unique and independent information about future returns. Its effect cannot be subsumed by other known effects such as cryptocurrency size, momentum, market beta, idiosyncratic risk, liquidity, downside risk, lottery preference, co-skewness, and co-kurtosis. Our results also are robust to many considerations, surviving various modifications to the baseline methodology.

Our study adds to three strands of research. First, we extend the discussion on how geopolitical risk affects asset pricing. Earlier studies focused on currencies (Hui, 2021; Salisu et al., 2022), stocks (Salisu et al., 2021; Zaremba et al., 2022), bonds (Lee et al., 2021), and commodities (Baur and Smales, 2020; Chatziantoniou et al., 2021). To our knowledge, no one has explored the role of geopolitical risk in the cross-sectional pricing of cryptocurrencies.

Second, we contribute to the growing evidence that geopolitical risk affects crypto assets. The extant literature on this topic is relatively scarce. Earlier research is composed of time-series investigations of returns, volatility, or jumps (e.g., Aysan et al., 2019; Al Mamun et al., 2020; Aloui et al., 2021; Bouri et al., 2022a; Jiang et al., 2020; Su et al., 2020; Colon et al., 2021; Liang et al., 2022; Selmi et al., 2022). Furthermore, Patel and Pereira (2021) analyze the influence of terrorist attacks on the cryptocurrency markets. Finally, several papers explored the cryptocurrencies' behavior in the wake of the Ukraine-Russia conflict (Będowska-Sójka et al., 2022; Wang et al., 2022; Umar et al., 2022). No study has tested cross-sectional variation in cryptocurrency risk exposure.

Third, we broaden the research on the cross-sectional predictability of cryptocurrency returns. Earlier papers documented the effect of size (Shen et al., 2020; Liu et al., 2022), past returns (Tzouvanas et al., 2020; Jia et al., 2022; Liu et al., 2022), liquidity (Zhang and Li, 2021a), downside risk (Zhang et al., 2021b), idiosyncratic volatility (Bouri et al., 2022b; Zhang and Li, 2020), and lottery preferences (Li et al., 2021; Ozdamar et al., 2021). We now add a new return predicting variable to this list: the geopolitical beta.

The remainder of the paper proceeds as follows. Section 2 discusses the data and variables. Section 3 presents the findings. Finally, Section 4 concludes.

2. Data and variables

2.1. Research sample

We use daily cryptocurrency data from https://coinmarketcap.com/. The study period runs from 02/03/2014 to 12/12/2021, but we also use earlier data when necessary to calculate certain variables. To avoid selection or survivorship bias, we use all available cryptocurrencies—both active and dead. We apply several filters from Liu and Tsyvinski (2021) to eliminate potential data errors. We require the coins to have price, volume, and capitalization data available, and we exclude assets with market capitalizations of less than \$1 million or a trading history of fewer than 60 days.

Our final cryptocurrency selection covers 1980 different coins. The sample size increases gradually from 16 at the beginning of the study period to 1316 at the end. The average number of cryptocurrencies is 408. Fig. A1 in the Online Appendix illustrates the evolution of sample size through time. We proxy the risk-free rate with the U.S. T-bill returns from French (2022).

2.2. Geopolitical beta

Geopolitical risk can be defined as "the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations" (Caldara and Iacoviello, 2022, p. 2). We account for this by using the daily GPR index by Caldara and Iacoviello (2022) obtained from Iacoviello (2022). The index construction builds on Baker et al. (2016) and counts the frequency of articles mentioning adverse geopolitical events in leading newspapers.[2]

Our primary predicting variable is exposure to geopolitical risk, β^{GPR}, estimated similarly to Bali et al. (2017). We calculate β^{GPR} using a rolling time-series regression of excess daily returns on daily changes in GPR and control factors from Liu et al. (2020, 2022) and Jia et al. (2022) as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{GPR}\Delta GPR_t + \beta_{i,t}^{MKT}MKT_t^F + \beta_{i,t}^{SIZE}SIZE_t^F + \beta_{i,t}^{MOM}MOM_t^F + \varepsilon_{i,t}, \tag{1}$$

where ΔGPR_tdenotes the daily percentage change in the GPR index; $R_{i,t}$ is the daily excess return on cryptocurrency i; MKT_t^F, $SIZE_t^F$, MOM_t^F are the excess returns on the market, size, and momentum factors, respectively (for details, see Table A1 in the Online Appendix); $\varepsilon_{i,t}$ is the error term; and $\alpha_{i,t}$, $\beta_{i,t}^{GPR}$, $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SIZE}$, $\beta_{i,t}^{MOM}$ are the model's coefficients.

[1] Our economic interpretation of the geopolitical beta is fully consistent with the interpration of the uncertainty beta of Bali et al. (2017).

[2] In its baseline form, the index is derived from a selection of U.S. newspapers. Viewed through the lens of a U.S. investor, GPR represents the perception of global geopolitical risk.

Asset pricing literature typically derives variables reflecting investor perceptions of return distribution from relatively short periods that do not exceed a month of daily data (Ang et al., 2006; Bali et al., 2011; Cosemans and Frehen, 2021; Mohrschladt, 2021). Similarly, our study aims to capture dynamic changes in investor perception of cryptocurrency's hedging abilities. Hence, in the default approach, we use a 21-day estimation period. Nevertheless, our results do not hang on this choice, and we also run robustness checks for longer estimation periods.

A high and positive β^{GPR} indicates risk-hedging properties (i.e., higher returns during GPR spikes). On the other hand, low or negative β^{GPR} suggests that surges in GPR negatively affect the cryptocurrency price. Investors should be compensated with an additional premium to hold low- β^{GPR} assets relative to high- β^{GPR} assets. Thus, we expect β^{GPR} to be negatively associated with future cryptocurrency returns in the cross-section.

2.3. Control variables

In addition to β^{GPR}, we consider a set of control variables from cryptocurrency literature (Bouri et al., 2022b; Buggraf and Rudolf, 2021; Jia et al., 2021, 2022; Li et al., 2021; Liu et al., 2020, 2022; Long et al., 2020; Ozdamar et al., 2021; Tzouvanas et al., 2020; Zhang et al., 2020, 2021a, 2021b). Size effect (*SIZE*) is the logarithm of market value at *t*-1. Momentum (*MOM*) is the trailing total return from *t*-21 to *t*-2. Market beta (*BETA*) is proxied by the slope coefficient from the regression of daily cryptocurrency excess return on the MKT^F factor. Idiosyncratic volatility (IVOL) is estimated from daily regressions of excess returns on the MKT^F, $SIZE^F$, and MOM^F factors. Systematic skewness (*SKEW*) and kurtosis (*KURT*) are calculated as the third and fourth cross-central moment between the individual coins' excess return and MKT^F. Illiquidity (*ILLIQ*) is measured using the Amihud (2002) ratio (i.e., the average of absolute daily returns divided by the daily dollar trading volume.) Downside risk is captured as value at risk (*VAR*), which is computed as the 5th percentile of daily returns multiplied by −1. Moreover, we also control for the lottery preference, including a maximum daily return (*MAX*) among the control variables. Finally, we calculate the cross-sectional seasonality effect (*SEAS*) following Long et al. (2020) as the average same-weekday return over the last 20 weeks. To assure an apples-to-apples comparison, all control variables (except for *SIZE* and *SEAS*) are estimated from an identical period as β^{GPR}. Nonetheless, our results do not depend on this and hold for other estimation periods.[3] Finally, to alleviate concern about outliers, we winsorize all non-return variables by the 1st and 99th percentiles each week.

Table 1 presents the variables' statistical properties. Panels A focuses on descriptive statistics, and Panel B shows correlation coefficients. Notably, β^{GPR} exhibits no substantial correlation with any of the control variables.

3. Empirical findings

3.1. Univariate sorts

We begin our investigation with tests of univariate portfolios. Each week, we sort all cryptocurrencies on β^{GPR} into quintiles and form equal- and value-weighted portfolios.[4] We also build a long-short strategy that buys (sells) the bottom (top) β^{GPR} quintile. We evaluate the portfolio returns using two models: (i) a single-factor market model and ii) a three-factor model including three factors advocated by Liu et al. (2020, 2022) and Jia et al. (2022)—value, size, and momentum.

$$R_{p,t} = \alpha_{MKT,p,t} + \beta_{p,t}^{MKT} MKT_t^F + \varepsilon_{p,t}, \tag{2}$$

$$R_{p,t} = \alpha_{F3,\ p,t} + \beta_{p,t}^{MKT} MKT_t^F + \beta_{p,t}^{SIZE} SIZE_t^F + \beta_{p,t}^{MOM} MOM_t^F + \varepsilon_{p,t}. \tag{3}$$

$R_{p,t}$ in Eqs. (2) and (3) is the weekly excess return on portfolio *p*; MKT_t^F, $SIZE_t^F$, MOM_t^F are the market, size, and momentum factor returns (as defined in Table 1 in the Online Appendix); $\beta_{p,t}^{MKT}$, $\beta_{p,t}^{SIZE}$, $\beta_{p,t}^{MOM}$ are the partial slope coefficients; and $\varepsilon_{p,t}$ is the error term. Finally, $\alpha_{MKT,p,\ t}$ and $\alpha_{F3,p,\ t}$ denote the models' alphas.[5]

Table 2 summarizes the one-way sorts. A quick overview of the results reveals that low β^{GPR} cryptocurrencies visibly outperform those with a high β^{GPR}. The average weekly return differential between the bottom and top equal-weighted (value-weighted) quantiles equals 5.72% (5.95%) with a Sharpe ratio of 0.75 (0.77). Both values significantly depart from zero and cannot be explained by the factor models (2) and (3). The three-factor model alpha for the equal-weighted (value-weighted) portfolios is 4.40% (4.41%). To sum up, the results of univariate sorts comply with our initial intuition that geopolitical risk is priced in cryptocurrency markets.

Interestingly, the alphas on quintile portfolios exhibit certain asymmetry. In absolute terms, the positive alphas on low β^{GPR} portfolios are noticeably higher than the negative alphas on high β^{GPR} cryptocurrencies. This indicates the abnormal returns derive mainly from investors requiring higher returns to hold assets with excessive sensitivity to geopolitical risk. The premium paid for cryptocurrencies with hedging properties plays a minor role.

[3] Additional robustness checks are available upon request.

[4] The size distribution of cryptocurrencies is highly skewed, with Bitcoin representing more than 30% of the aggregate market capitalization (as of 12/12/2021). Hence, we follow Jensen et al. (2021) and trim the weights at 20% and 80% percentile to obtain balanced yet investible portfolios.

[5] All *t*-statistics on regression coefficients in this paper are calculated using the Newey-West (1987) method. The number of lags equals five is determined by the formula $4(T/100)^a$ by Newey and West (1994), where *T* is the sample length and the constant *a* depends on the kernel type.

Table 1
Summary Statistics for the Variables of Interest
The table presents the summary statistics for the variables used in the study: geopolitical risk beta (β^{GPR}), size (*SIZE*), momentum (*MOM*), market beta (*BETA*), idiosyncratic risk (*IVOL*), co-skewness (*SKEW*), co-kurtosis (*KURT*), Amihud's (2002) illiquidity ratio (*ILLIQ*), value at risk (*VAR*), and maximum daily return (*MAX*), and cross-sectional seasonality (*SEAS*). Panel A presents the descriptive statistics: the mean, standard deviation, the 1st quartile, median, and the 3rd quartile. Panel B reports Pearson's pairwise correlation coefficients. The values above the diagonal are Pearson's product-momentum coefficients, and the values below the diagonal are Spearman's rank-based coefficients. The sample contains 1980 cryptocurrencies and the study period is from 02/03/2014 to 12/12/2021.

	β^{GPR}	SIZE	MOM	BETA	IVOL	SKEW	KURT	ILLIQ	VAR	*MAX*	*SEAS*
Panel A: Descriptive statistics											
Mean	−0.001	3.149	0.137	0.931	0.077	−0.032	0.089	93.441	0.107	0.254	0.008
Standard deviation	0.038	1.830	1.545	0.887	0.089	0.128	0.087	1 610.770	0.068	0.370	0.120
1st quartile	−0.013	1.785	−0.193	0.520	0.033	−0.098	0.036	0.015	0.063	0.096	−0.010
Median	−0.001	2.731	−0.009	0.956	0.053	−0.031	0.078	0.109	0.094	0.157	0.001
3rd quartile	0.010	4.092	0.222	1.334	0.087	0.038	0.127	1.010	0.134	0.273	0.013
Panel B: Correlation coefficients											
β^{GPR}		−0.009	−0.012	0.000	−0.027	0.019	0.011	0.000	−0.011	−0.020	−0.057
SIZE	0.001		0.019	0.040	−0.271	−0.055	0.233	−0.209	−0.287	−0.184	−0.014
MOM	−0.016	0.073		0.053	0.412	0.044	−0.155	0.130	0.040	0.473	0.145
BETA	−0.008	0.050	0.052		0.034	0.026	0.548	0.000	0.149	0.132	0.020
IVOL	−0.037	−0.342	0.214	0.048		0.070	−0.463	0.423	0.742	0.923	0.192
COSKEW	0.018	−0.059	0.036	0.049	0.075		−0.081	0.046	0.020	0.113	0.026
COKURT	0.018	0.235	−0.099	0.550	−0.557	−0.059		−0.171	−0.310	−0.337	−0.046
ILLIQ	0.002	−0.698	0.007	−0.013	0.497	0.106	−0.297		0.383	0.360	0.164
VAR	−0.019	−0.307	−0.116	0.217	0.730	0.003	−0.300	0.424		0.609	0.200
MAX	−0.026	−0.225	0.337	0.221	0.852	0.156	−0.371	0.372	0.603		0.183
SEAS	−0.059	0.020	0.167	0.057	0.076	0.028	−0.008	0.008	0.075	0.088	

Table 2
Univariate portfolio sorts
The table reports the weekly excess returns on quintile portfolios based on the geopolitical risk beta (β^{GPR}). *High* β^{GPR} (*Low* β^{GPR}) are the quintiles with the highest (lowest) β^{GPR}, and *Low-High* is the long-short portfolios that buy (sell) the *Low* β^{GPR} (*High* β^{GPR}) coins. The strategies are equal-weighted (*Panel A*) or value-weighted (*Panel B*) and rebalanced weekly. *RET* is the mean return, *SD* is the standard deviation, and *SR* is the annualized Sharpe ratio, and *Turn* is the portfolio turnover rate. α_{MKT} and α_{F3} are alphas from the factor models (2) and (3). The returns, standard deviations, and alphas are expressed as percentages. The numbers in parentheses are *t*-statistics adjusted using bootstrap and Newey and West's (1987) method for mean returns and alphas, respectively. The sample contains 1980 cryptocurrencies and the study period is from 02/03/2014 to 12/12/2021.

	Low β^{GPR}	2	3	4	High β^{GPR}	Low-High
Panel A: Equal-weighted portfolios						
RET	7.06	2.14	2.44	1.84	1.34	5.72
	(2.45)	*(2.46)*	*(2.65)*	*(2.17)*	*(1.35)*	*(2.15)*
SD	57.09	14.33	15.58	13.76	15.42	55.12
SR	0.90	1.08	1.12	0.96	0.62	0.75
Turn	49.50	67.66	66.52	67.17	49.71	99.21
α_{MKT}	4.45	0.38	0.72	0.10	−0.45	−4.90
	(1.81)	*(0.71)*	*(1.19)*	*(0.22)*	*(−0.78)*	*(2.02)*
α_{F3}	3.77	0.14	0.38	0.11	−0.63	4.40
	(1.61)	*(0.30)*	*(0.79)*	*(0.24)*	*(−1.19)*	*(1.98)*
Panel B: Value-weighted portfolios						
RET	7.27	1.87	2.21	1.57	1.32	5.95
	(2.53)	*(2.15)*	*(2.38)*	*(1.78)*	*(1.37)*	*(2.27)*
SD	57.32	14.38	15.64	13.98	15.54	55.19
SR	0.92	0.94	1.02	0.81	0.60	0.77
Turn	54.41	67.63	65.42	66.96	54.71	109.12
α_{MKT}	4.50	0.08	0.38	−0.19	−0.52	5.02
	(1.92)	*(0.15)*	*(0.71)*	*(−0.40)*	*(−1.04)*	*(2.17)*
α_{F3}	3.73	−0.09	0.25	−0.17	−0.67	4.41
	(1.67)	*(−0.20)*	*(0.52)*	*(−0.37)*	*(−1.47)*	*(2.02)*

Besides the pure performance statistics, Table 2 also displays the portfolio turnover. We calculate it as the average portfolio share that is replaced each week. The portfolio turnover on the examined strategies is relatively high, amounting to 99% (109%) for the equal-weighted (value-weighted) strategies. From a practical perspective, elevated turnover ratios may imply potentially high trading costs for cryptocurrency investors.

3.2. Bivariate sorts

Though the cross-sectional pattern in Table 2 is evident, it may be equally driven by some other effect on cryptocurrency returns. To ensure the impact of β^{GPR} is not just another anomaly in disguise, we now turn to bivariate sorts.

Each week, we sort cryptocurrencies sequentially. First, we rank them on one of the control variables from Section 2.3 and form terciles. Next, within each of these subsets, we sort assets into terciles based on β^{GPR}. Finally, we calculate average returns on the portfolio with a consistent level of β^{GPR} across the terciles with different levels of control variables. This enables us to obtain the β^{GPR} portfolios purified of the influence of control variables. Last, as in 3.1, we compute long-short portfolios and assess them using factor models.

Table 3 displays the performance of double-sorted portfolios. The results fail to support the view that the β^{GPR} effect is a manifestation of some other anomaly. For all control variables, low β^{GPR} coins continue to outperform high β^{GPR} coins. The alphas on long-short portfolios are positive and significant in all cases, regardless of the factor model applied or the weighing scheme. To be specific, the three-factor alphas range from 2.04 to 3.21%. This indicates that the control variables explain no more than 27% to 54% of the abnormal returns depending on a particular specification. Therefore, β^{GPR} contains unique and independent information about future returns.

3.3. Cross-Sectional regressions

Although bivariate sorts are a powerful tool to disentangle the impact of other return predictors, they are not free of all shortcomings. First, they do not allow jointly accounting for more than one or two control variables. Second, aggregating stocks into portfolios may lead to information loss. To cope with these issues, we supplement our analyses with cross-sectional regressions in the style of Fama and MacBeth (1973).

Each week we run the following regression:

$$R_{i,t} = \gamma_0 + \gamma_{\beta^{GPR}} \beta^{GPR}_{i,t-1} + \sum_{j=1}^{n} \gamma_{K,j} K_{j,i,t-1} + \varepsilon_{i,t}, \quad (4)$$

where $R_{i,t}$ is the return on cryptocurrency i in week t, $\beta^{GPR}_{i,t-1}$ is the lagged geopolitical beta estimated with daily data using Eq. (1), and K_j,

Table 3
Bivariate Portfolio Sorts
The table reports the returns on portfolios from bivariate sorts on control variables and the geopolitical risk beta (β^{GPR}). In the first step, we sort the cryptocurrencies into tertiles based on one of the control variables: size (*SIZE*), momentum (*MOM*), market beta (*BETA*), idiosyncratic risk (*IVOL*), co-skewness (*SKEW*), co-kurtosis (*KURT*), Amihud's (2002) illiquidity ratio (*ILLIQ*), value at risk (*VAR*), and maximum daily return (*MAX*), and cross-sectional seasonality (SEAS). Next, within each of the three quantiles, we sort cryptocurrencies into tertiles based on β^{GPR}, producing nine double-sorted portfolios. The table presents the average weekly returns of portfolios with a consistent level of β^{GPR} across different tertiles of the control variables. *Low, Medium*, and *High* indicate portfolios with low, medium, and high β^{GPR}, and *L-H* is the long-short portfolio buying (selling) position in the cryptocurrencies with the lowest (highest) β^{GPR}. *R* is the mean return. α_{MKT} and α_{F3} are alphas from the factor models (2) and (3). The returns and alphas are expressed as percentages. The numbers in parentheses are *t*-statistics adjusted using bootstrap and Newey and West's (1987) method for mean returns and alphas, respectively. The sample contains 1980 cryptocurrencies and the study period is from 02/03/2014 to 12/12/2021.

	Panel A: Equal-weighted Portfolios						Panel B: Value-weighted Portfolios					
	By GPR Beta											
By Controls	Low	Medium	High	L-H R	L-H α_{MKT}	L-H α_{F3}	Low	Medium	High	L-H R	L-H α_{MKT}	L-H α_{F3}
SIZE	5.19	2.28	1.54	3.66	3.12	2.72	5.41	2.24	1.45	3.96	3.37	2.93
	(2.73)	*(2.71)*	*(1.68)*	*(2.27)*	*(2.12)*	*(1.93)*	*(2.58)*	*(2.69)*	*(1.62)*	*(2.20)*	*(2.09)*	*(1.92)*
MOM	4.89	2.61	1.55	3.34	2.83	2.56	4.05	2.38	1.16	2.89	2.34	2.04
	(2.58)	*(2.90)*	*(1.71)*	*(2.09)*	*(1.93)*	*(1.82)*	*(2.62)*	*(2.67)*	*(1.32)*	*(2.36)*	*(2.25)*	*(2.09)*
BETA	5.02	2.34	1.58	3.44	2.92	2.56	4.79	2.09	1.41	3.37	2.81	2.42
	(2.66)	*(2.62)*	*(1.74)*	*(2.15)*	*(1.98)*	*(1.82)*	*(2.66)*	*(2.34)*	*(1.58)*	*(2.25)*	*(2.14)*	*(1.95)*
IVOL	4.97	2.41	1.65	3.32	2.76	2.43	5.47	2.13	1.50	3.97	3.21	2.78
	(2.60)	*(2.53)*	*(1.94)*	*(2.06)*	*(1.87)*	*(1.72)*	*(2.55)*	*(2.21)*	*(1.73)*	*(2.10)*	*(2.01)*	*(1.85)*
SKEW	5.19	2.33	1.46	3.73	3.20	2.84	5.12	2.08	1.42	3.70	3.18	2.82
	(2.73)	*(2.64)*	*(1.62)*	*(2.32)*	*(2.17)*	*(2.02)*	*(2.59)*	*(2.40)*	*(1.55)*	*(2.21)*	*(2.08)*	*(1.93)*
KURT	5.13	2.52	1.43	3.70	3.19	2.80	5.58	2.16	1.20	4.38	3.67	3.21
	(2.71)	*(2.86)*	*(1.58)*	*(2.31)*	*(2.17)*	*(2.00)*	*(2.60)*	*(2.49)*	*(1.29)*	*(2.31)*	*(2.24)*	*(2.07)*
ILLIQ	5.07	2.24	1.64	3.43	2.89	2.44	5.68	2.16	1.54	4.14	3.32	2.61
	(2.65)	*(2.56)*	*(1.84)*	*(2.11)*	*(1.94)*	*(1.71)*	*(2.56)*	*(2.59)*	*(1.74)*	*(2.08)*	*(2.00)*	*(1.70)*
VAR	5.36	1.95	1.61	3.76	3.23	2.78	5.66	1.60	1.26	4.40	3.58	2.97
	(2.83)	*(2.19)*	*(1.81)*	*(2.35)*	*(2.20)*	*(1.98)*	*(2.81)*	*(1.85)*	*(1.45)*	*(2.50)*	*(2.55)*	*(2.30)*
MAX	5.09	2.43	1.54	3.55	2.98	2.66	5.30	2.34	1.46	3.84	3.16	2.76
	(2.68)	*(2.64)*	*(1.76)*	*(2.21)*	*(2.03)*	*(1.89)*	*(2.62)*	*(2.53)*	*(1.65)*	*(2.19)*	*(2.13)*	*(1.99)*
SEAS	5.10	2.46	1.89	3.21	2.78	2.36	4.20	2.15	1.87	2.32	2.09	2.00
	(2.47)	*(2.72)*	*(2.09)*	*(2.04)*	*(2.07)*	*(1.97)*	*(2.47)*	*(2.40)*	*(2.06)*	*(1.78)*	*(1.99)*	*(1.96)*

Table 4
Cross-sectional regressions
The table reports the average slope coefficients (multiplied by 100) from weekly cross-sectional regressions of cryptocurrency returns on geopolitical risk beta and control variables as follows:
$R_{i,t} = \gamma_0 + \gamma_{\beta^{GPR}}\beta^{GPR}_{i,t-1} + \sum_{j=1}^{n}\gamma_{K,j}K_{j,i,t-1} + \varepsilon_{i,t}$,
where $R_{i,t}$ is the return on cryptocurrency i in week t, $\beta^{GPR}_{i,t-1}$ is the lagged geopolitical beta, and $K_{j,i,\,t-1}$ represents the vector of possible lagged control variables: size (*SIZE*), momentum (*MOM*), market beta (*BETA*), idiosyncratic risk (*IVOL*), co-skewness (*SKEW*), co-kurtosis (*KURT*), Amihud's (2002) illiquidity ratio (*ILLIQ*), value at risk (*VAR*), and maximum daily return (*MAX*), and cross-sectional seasonality (SEAS). γ_0, $\gamma_{\beta^{GPR}}$, and $\gamma_{K,j}$ are the estimated regression coefficients, and $\varepsilon_{i,t}$ denotes the error term. The numbers in parentheses are *t*-statistics adjusted using Newey and West's (1987) method. The table also presents the average cross-sectional R^2 coefficient ($\overline{R^2}$) and the total number of weekly observations in each specification (*#Obs*). The sample contains 1980 cryptocurrencies and the study period is from 02/03/2014 to 12/12/2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β^{GPR}	−0.659	−0.660	−0.650	−0.626	−0.836	−0.655	−0.754	−0.762	−0.784	−0.822	−0.635	−0.779
	(−2.18)	*(−2.18)*	*(−2.16)*	*(−2.14)*	*(−2.15)*	*(−2.18)*	*(−2.15)*	*(−2.14)*	*(−2.06)*	*(−2.25)*	*(−1.99)*	*(−2.02)*
SIZE		0.003										0.003
		(1.02)										*(0.49)*
MOM			0.028									0.015
			(2.72)									*(0.89)*
BETA				0.001								−0.018
				(0.07)								*(−0.92)*
IVOL					0.410							0.664
					(1.41)							*(1.22)*
SKEW						0.218						0.113
						(1.34)						*(0.94)*
KURT							−0.559					−0.026
							(−1.74)					*(−0.10)*
ILLIQ								0.000				0.000
								(0.22)				*(0.50)*
VAR									0.263			−0.178
									(1.20)			*(−0.73)*
MAX										0.124		−0.079
										(1.49)		*(−0.64)*
SEAS											0.335	0.185
											(1.79)	*(1.07)*
$\overline{R^2}$	0.029	0.055	0.071	0.067	0.068	0.057	0.059	0.071	0.064	0.070	8.38	32.87
#Obs	165,994	165,994	165,994	165,994	165,994	165,892	165,892	165,994	165,994	165,994	145,028	141,552

$_{i,\,t-1}$ represents the vector of possible lagged control variables from Section 2.3. Finally, γ_0, $\gamma_{\beta^{GPR}}$, and $\gamma_{K,j}$ are the estimated regression coefficients, and $\varepsilon_{i,t}$ denotes the error term.

Table 4 presents the average slope coefficients from the cross-sectional regression. The results confirm the critical role of geopolitical risk exposure in all specifications. The β^{GPR} is significant in univariate regression (specification [1]), explaining on average 2.3% of the cross-sectional variation in returns. A similar relationship is present in bivariate tests (specifications [2] to [10]) that control for one variable at a time. Specification (11) employs a 'kitchen-sink' approach, incorporating all the predictors from Section 2.3. simultaneously. The β^{GPR} remains priced, indicating that even all control variables jointly cannot subsume the effect of geopolitical risk exposure.

3.4. Robustness checks

To assure the validity of our findings, we apply a series of additional robustness checks. Precisely, we reproduce the long-short β^{GPR} portfolios from Section 3.1 using various methodological modifications. First, we consider two alternative weighting schemes: (i) risk parity (i.e., weighting on the inverse of the 21-day return volatility), and (ii) rank-weighting as in Asness et al. (2013). Second, we replace quintile sorts with quartiles and sextiles. Third, we modify the sample to alleviate the impact of the biggest and smallest cryptocurrencies. We exclude (i) Bitcoin, (ii) the 10% biggest cryptocurrencies, and (iii) the 10% smallest cryptocurrencies. Fourth, we verify that the influence of β^{GPR} holds for different estimation periods. Fifth, we experiment with β^{GPR} computed using GPR subcomponent indices, namely geopolitical acts and threats indices. Sixth, we modify the set of control factors in Eq. (1), estimating the β^{GPR} without any control factors or with $\mathrm{MKT}^{\mathrm{F}}$ only. Seventh, we explore the performance in subperiods of bull and bear markets, as well as having excluded the month of January from the sample.

For brevity, we report the results of these checks in Table A2 of the Online Appendix. None of these robustness checks materially affect the results. Although portfolio returns differ across the specifications, our principal conclusions remain qualitatively unaffected: geopolitical risk negatively affects future stock returns.

4. Conclusions

This paper examines the impact of geopolitical risk on the pricing of cryptocurrency returns. Using data on almost 2000 cryptocurrencies from the years 2014–2021, we explore the cross-sectional return predictability by geopolitical beta. We find that β^{GPR} reliably forecasts the cross-section of cryptocurrency returns. Low- β^{GPR} coins significantly outperform high- β^{GPR} coins. The effect holds thorughout different tests and robustness checks and cannot be subsumed by a battery of control variables. Our results indicate that investors require extra compensation to hold cryptocurrencies with low and negative geopolitical betas, and they are willing to pay a premium for assets with high and positive geopolitical betas.

Our conclusions have direct practical implications. Purchasing low- β^{GPR} cryptocurrencies enables investors to harvest a geopolitical risk premium. This pattern may lay the foundation for a profitable investment strategy. Future studies may further explore practical implementation of these findings. Issues such as return stability over time or trading costs management could be scrutinized.

CRediT authorship contribution statement

Huaigang Long: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization. **Ender Demir:** Conceptualization, Writing – original draft, Writing – review & editing. **Barbara Będowska-Sójka:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition. **Adam Zaremba:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Syed Jawad Hussain Shahzad:** Resources, Data curation, Writing – review & editing.

Data Availability

Data will be made available on request.

Acknowledgments

We thank Andrew Urquhart and John W. Goodell for helpful comments and suggestions. Barbara Będowska-Sójka acknowledges the support of the National Science Center of Poland [grant no. 2021/41/B/HS4/02443].

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.103131.

References

Al Mamun, M., Uddin, G.S., Suleman, M.T., Kang, S.H., 2020. Geopolitical risk, uncertainty and Bitcoin investment. Phys. Stat. Mech. Appl. 540, 123107.
Aloui, C., ben Hamida, H., Yarovaya, L., 2021. Are Islamic gold-backed cryptocurrencies different? Financ. Res. Lett. 39, 101615.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5 (1), 31–56.
Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Financ. 61 (1), 259–299.
Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. J. Financ. 68 (3), 929–985.
Aysan, A.F., Demir, E., Gozgor, G., Lau, C.K.M., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. Res. Int. Bus. Financ. 47, 511–518.
Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.
Bali, T.G., Brown, S.J., Tang, Y., 2017. Is economic uncertainty priced in the cross-section of stock returns? J Financ Econ 126 (3), 471–489.
Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J financ econ 99 (2), 427–446.
Baur, D.G., Smales, L.A., 2020. Hedging geopolitical risk with precious metals. J. Bank. Financ. 117, 105823.
Będowska-Sójka, B., Demir, E., & Zaremba, A. (2022). Hedging geopolitical risks with different asset classes: a focus on the Russian invasion of Ukraine. Available at SSRN 4085689.
Bouri, E., Gupta, R., Vo, X.V., 2022a. Jumps in geopolitical risk and the cryptocurrency market: the singularity of Bitcoin. Def. Peace Econ. 33 (2), 150–161.
Bouri, E., Kristoufek, L., Ahmad, T., Shahzad, S.J.H., 2022b. Microstructure noise and idiosyncratic volatility anomalies in cryptocurrencies. Ann Oper Res forthcoming.
Burggraf, T., Rudolf, M., 2021. Cryptocurrencies and the low volatility anomaly. Financ. Res. Lett. 40, 101683.
Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk. Am. Econ. Rev. 112 (4), 1194–1225.
Chatziantoniou, I., Degiannakis, S., Delis, P., Filis, G., 2021. Forecasting oil price volatility using spillover effects from uncertainty indices. Financ. Res. Lett. 42, 101885.
Colon, F., Kim, C., Kim, H., Kim, W., 2021. The effect of political and economic uncertainty on the cryptocurrency market. Financ. Res. Lett. 39, 101621.
Cosemans, M., Frehen, R., 2021. Salience theory and stock prices: empirical evidence. J. Financ. Econ. 140 (2), 460–483.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81 (3), 607–636.
French, K.R. (2022). U.S. research returns data. Data Library. Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed 25/04/2022).
Hui, H.C., 2021. The long-run effects of geopolitical risk on foreign exchange markets: evidence from some ASEAN countries. Int. J. Emerg. Mark. forthcoming.
Iacoviello, M. (2022). Geopolitical risk (GPR) index. Retrieved from https://www.matteoiacoviello.com/gpr.htm (accessed 25/04/2022).
Jensen, T.I., Kelly, B.T., & Pedersen, L.H. (2021). *Is there a replication crisis in finance?* NBER working paper no. w28432. National Bureau of Economic Research. Available at https://www.nber.org/papers/w28432.
Jia, B., Goodell, J.W., Shen, D., 2022. Momentum or reversal: which is the appropriate third factor for cryptocurrencies? Financ. Res. Lett. 45, 102139.
Jia, Y., Liu, Y., Yan, S., 2021. Higher moments, extreme returns, and cross–section of cryptocurrency returns. Financ. Res. Lett. 39, 101536.
Jiang, Y., Wang, G.J., Wen, D.Y., Yang, X.G., 2020. Business conditions, uncertainty shocks and Bitcoin returns. Evol. Instit. Econ. Rev. 17 (2), 415–424.
Lee, C.C., Lee, C.C., Li, Y.Y., 2021. Oil price shocks, geopolitical risks, and green bond market dynamics. N. Am. J. Econ. Financ. 55, 101309.
Li, Y., Urquhart, A., Wang, P., Zhang, W., 2021. MAX momentum in cryptocurrency markets. Int. Rev. Financ. Anal. 77, 101829.
Liang, C., Zhang, Y., Li, X., Ma, F., 2022. Which predictor is more predictive for Bitcoin volatility? And why? Int. J. Financ. Econ. 27 (2), 1947–1961.
Liu, W., Liang, X., Cui, G., 2020. Common risk factors in the returns on cryptocurrencies. Econ. Model. 86, 299–305.
Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. Rev. Financ. Stud 34 (6), 2689–2727.
Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Financ. 77 (2), 1133–1177.
Long, H., Zaremba, A., Demir, E., Szczygielski, J.J., Vasenin, M., 2020. Seasonality in the cross-section of cryptocurrency returns. Financ. Res. Lett. 35, 101566.
Mohrschladt, H., 2021. The ordering of historical returns and the cross-section of subsequent returns. J. Bank. Financ. 125, 106064.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation. Econometrica 55 (3), 703–708.
Newey, W.K., West, K.D., 1994. Automatic lag selection in covariance matrix estimation. Rev. Econ. Stud. 61 (4), 631–653.
Ozdamar, M., Akdeniz, L., Sensoy, A., 2021. Lottery-like preferences and the MAX effect in the cryptocurrency market. Financ. Innov. 7 (1), 1–27.
Patel, P.C., Pereira, I., 2021. The relationship between terrorist attacks and cryptocurrency returns. Appl. Econ. 53 (8), 940–961.
Salisu, A.A., Cunado, J., Gupta, R., 2022. Geopolitical risks and historical exchange rate volatility of the BRICS. Int. Rev. Econ. Financ. 77, 179–190.
Salisu, A.A., Lasisi, L., Tchankam, J.P., 2021. Historical geopolitical risk and the behaviour of stock returns in advanced economies. Eur. J. Financ. 1–18.
Selmi, R., Bouoiyour, J., Wohar, M.E., 2022. Digital Gold" and geopolitics. Res. Int. Bus. Financ. 59, 101512.
Shen, D., Urquhart, A., Wang, P., 2020. A three-factor pricing model for cryptocurrencies. Financ. Res. Lett. 34, 101248.
Su, C.W., Qin, M., Tao, R., Shao, X.F., Albu, L.L., Umar, M., 2020. Can Bitcoin hedge the risks of geopolitical events? Technol. Forecast. Soc. Change 159, 120182.
Tzouvanas, P., Kizys, R., Tsend-Ayush, B., 2020. Momentum trading in cryptocurrencies: short-term returns and diversification benefits. Econ. Lett. 191, 108728.
Umar, Z., Polat, O., Choi, S.Y., Teplova, T., 2022. The impact of the Russia-Ukraine conflict on the connectedness of financial markets. Financ. Res. Lett., 102976
Wang, Y., Bouri, E., Fareed, Z., Dai, Y., 2022. Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. Financ. Res. Lett. forthcoming.
Zaremba, A., Cakici, N., Demir, E., Long, H., 2022. When bad news is good news: geopolitical risk and the cross-section of emerging market stock returns. J. Financ. Stab. 58, 100964.
Zhang, W., Li, Y., 2020. Is idiosyncratic volatility priced in cryptocurrency markets? Res. Int. Bus. Financ. 54, 101252.
Zhang, W., Li, Y., 2021.. Liquidity risk and expected cryptocurrency returns. Int. J. Financ. Econ. forthcoming.
Zhang, W., Li, Y., Xiong, X., 2021.. Downside risk and the cross-section of cryptocurrency returns. J. Bank. Financ. 133, 106246.