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Pay Attention! A Country-Level Analysis of Investor Attention & Policy Uncertainty on Bitcoin

by

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Abstract

This paper investigates the relationship between measures of policy uncertainty, investor attention, and Bitcoin markets at a national level. To date, there are limited studies on the region-specific impact of policy uncertainty and investor attention on Bitcoin, despite evidence showing significant heterogeneities in the use, purpose, and acceptance of Bitcoin across different countries. These heterogeneities may also lead to regional Bitcoin 'premia', which we define as the price differences of Bitcoin between local markets and the US market. Using multivariate regression in conjunction with panel and Quantile-on-Quantile (QQ) regression analysis, we explore how Bitcoin is treated across different countries and under varying market conditions. Our analysis reveals that regional Bitcoin markets exhibit high levels of speculation driven by investor attention, which we measure using Google Search Volume (GSV), and that these markets also demonstrate significant inefficiencies evidenced by pronounced momentum effects. Interestingly, we observe a negligible contemporaneous relationship between policy uncertainty and Bitcoin markets. Moreover, we find that Bitcoin premia are unaffected by local investor sentiment but are best accounted for by the appreciation of local foreign exchange rates against the US dollar (USD). Our findings challenge conventional financial theories and provide practical tools for investors and regulators aiming to navigate or govern speculative Bitcoin markets.

Keywords: Policy Uncertainty, Investor Attention, Bitcoin Markets, Country Analysis, Bitcoin Premia

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Finally, and perhaps most importantly, this thesis could not have been completed without the help of countless caffeinated drinks!

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Abbreviations

BTC Bitcoin
EPU Economic Policy Uncertainty
FX Foreign Exchange
GPR Geopolitical Risk
GSV Google Search Volume
UCRY Cryptocurrency Uncertainty
VIX Volatility Index

1. Introduction

In a world where economic landscapes are rapidly shifting, traditional financial systems frequently come under strain. Economic recklessness culminated in the Global Financial Crisis (GFC) from 2007-2009 that resulted in the worst recessions faced by major advanced economies since the Great Depression in 1930. Within this context of financial instability and growing distrust in traditional financial institutions, the Bitcoin White Paper (Nakamoto, 2008) was released. Since its release, Bitcoin's role in global finance has sparked intense debate. There is a growing body of literature with varied conclusions, portraying Bitcoin both as a promising investment (e.g. Liu & Tsyvinski, 2021; Craig & Kachovec, 2019; Dyhrberg, 2016) and a high-risk speculative venture (e.g. Gandal et al., 2018; Baur & Dimpfl, 2021). Notwithstanding, the recent Securities Exchange Commission (SEC) approval of spot Bitcoin ETFs in the US represents a pivotal advancement towards Bitcoin's mainstream financial adoption.[1]

The increasing adoption of Bitcoin, coupled with the lack of region-specific studies on Bitcoin markets, despite significant heterogeneities in Bitcoin's use, purpose, and acceptance in various countries (Kliber et al., 2019; Wüstenfeld & Geldner, 2022), motivates our study. We focus on Bitcoin markets in Australia, Canada, Germany, Japan, South Korea, the United Kingdom (UK), and the United States (US) from January 2015 to February 2024.[2] By applying multivariate, panel, and Quantile on Quantile (QQ) regression analysis, we examine the influence of two key determinants of regional Bitcoin market behaviour: (i) regional policy uncertainty—as regulatory uncertainties pose significant challenges to Bitcoin's adoption and utilisation as an asset, and (ii) regional investor attention—which reveals investor sentiment and Bitcoin's perception as a speculative investment. Further, regional differences in the treatment of Bitcoin may create Bitcoin 'premia,' defined as Bitcoin's price disparity between local markets and the US market, indicating local investor sentiment (Choi et al., 2022). Guided by these motivations, we propose the following research questions: Do regional Bitcoin markets respond to changes in policy uncertainty and investor attention? Furthermore, is there a corresponding relationship for regional Bitcoin premia?

In the modern digital age, the investing landscape has undergone a profound transformation, driven by the ubiquity of information and the ease with which it can be accessed. This shift has notably altered how investors interact with financial markets, with investor attention

[1] Browne (2024).

[2] Due to data availability, the period of analysis for Canada is 1 July 2015 to 1 February 2024.

emerging as a critical factor influencing asset performance (Da et al., 2011a, 2011b, 2015; Ding & Hou, 2015; Dzielinski, 2012; Joseph et al., 2011; Mondria et al., 2010; Vlastakis & Markellos, 2012). The surge in real-time data and news, along with the proliferation of financial analysis tools, has empowered retail investors to engage with markets more dynamically than ever before. Internet-based measures of attention have emerged as the most important factor influencing Bitcoin price movements (Smales, 2022). We use investor attention as a proxy for speculative behaviour because, in periods of heightened attention, assets often experience rapid price adjustments as many investors enter the market with expectations of short-term gains, rather than long-term investment based on fundamentals. These speculative actions can significantly impact the volatility and trading volume of various asset classes (Smith & Jones, 2020; Lee et al., 2021). This phenomenon is exacerbated in nascent or highly volatile markets, such as Bitcoin markets where news and public sentiment can trigger swift price movements (Bukovina & Martiček, 2016).

To measure investor attention we use the Google Search Volume (GSV) index from Google Trends, which we define as the number of search queries for the keyword "Bitcoin" within a given location. GSV is shown to be a significant predictor of Bitcoin price, trading volume, and market behaviour (Kristoufek, 2013; Matta et al., 2015; Urquhart, 2018), but to the best of our knowledge, there are no studies on the impact of regional GSV on Bitcoin markets. Furthermore, Lucey et al. (2022) suggests that the speculative nature of cryptocurrencies makes them appealing to retail investors who interpret public information differently from institutional investors. The presence of such "noise" traders may provide one explanation as to why cryptocurrency prices diverge significantly from fundamental value (De Long et al., 1990). In our analysis, we examine these price divergences (or Premia) at a country level, which to the best of our knowledge, has also not been studied with regional investor attention, despite evidence suggesting that Bitcoin premia reflect local investor sentiment (Choi et al., 2022).

In addition, while Bitcoin operates independently from traditional financial systems, and by design eludes the direct manipulation of any single government, it remains susceptible to the effects of policy decisions in different countries. For example, China's ban on Bitcoin mining in May 2021 precipitated a 50% fall in the network's hash rate, exacerbating price volatility (Sigalos, 2021).[3] Such regulatory actions underscore how policies and therefore policy uncertainty can substantially disrupt Bitcoin markets. Our primary measure of policy

[3]The Bitcoin hash rate is the measure of the computational power used by miners to process transactions and secure the Bitcoin network. It represents the number of hash calculations performed per second, typically expressed in terahashes per second (TH/s). Higher hash rates indicate a more secure and robust network.

uncertainty is the Economic Policy Uncertainty (EPU) index of Baker et al. (2016), regarding the frequency of discussions on economic policy and uncertainty in the media. To date, EPU has been linked to a range of economic fundamentals (e.g. Caggiano et al., 2017; Scheffel, 2016; Aastveit et al. (2013)), traditional assets like stocks and bonds (Liu & Zhang, 2015), in addition to BTC returns (Umar et al., 2023), and BTC volatility (Demir et al., 2018; Smales, 2022). Nevertheless, research on Bitcoin markets from a localised perspective remains sparse.

Within existing literature, nuanced market responses are often overlooked with aggregate or global data since Bitcoin is predominantly traded in US Dollars (USD).[4] This is despite discrepancies in the treatment of Bitcoin in different countries, attributed to contrasting economic situations and local regulatory frameworks (Kliber et al., 2019). To the best of our knowledge, to date, only four publications have attempted to estimate the country level impact of EPU on Bitcoin markets (Kliber et al., 2019; Yen & Cheng, 2021; Wang et al., 2020; Wüstenfeld & Geldner, 2022). These studies show mixed results; Wüstenfeld & Geldner (2022) show the speculative nature of BTC in Canada, but propose Australian markets treat BTC as a safe haven under EPU shocks; Wang et al. (2020) indicate that Bitcoin can potentially act as a safe haven during local EPU shocks; Yen & Cheng (2021) show changes in the EPU of China predict volatility, while there exists no such relationship with the U.S., Japan, or South Korea; Kliber et al. (2019) demonstrate that Bitcoin is treated differently in Japan, Venezuela, China, Estonia, and Sweden, in face of EPU shocks.

These mixed results and limited previous studies motivate our analysis of Bitcoin markets at a country level. Driven by our motivations, we have formulated the following expectations based on prior literature. Finally, we also provide a summary of our findings.

Speculation drives regional Bitcoin markets. Therefore, there are disconnects between traditional asset pricing models and Bitcoin returns: The speculative nature of Bitcoin markets attracts retail investors (Lucey et al., 2022). Retail investors often engage in speculative behaviour driven by factors such as fear of missing out (FOMO), herd behaviour and psychological biases commonly referred to as "animal spirits" (Akerlof & Shiller, 2009). Further, momentum trading strategies can create self-reinforcing price trends (Bouri et al., 2017). Also, despite Bitcoin's increased correlation with traditional assets (Ghorbel & Jeribi, 2021), Bitcoin's adoption and price are driven by alternate factors including uncertainty and attention (Dastgir et al., 2019), thereby conventional asset pricing models fail to account for Bitcoin-specific risk factors.

[4] Investopedia.com

The impact of Local EPU on regional Bitcoin markets varies depending on the country: Investors typically react to increased uncertainty, consistent with requiring a higher risk premium to compensate for greater uncertainty (Andrei & Hasler, 2015). In addition, different economic and regulatory frameworks lead investors to treat Bitcoin differently across countries (Kliber et al., 2019). Despite this, previous literature finds mixed results regarding the influence and significance of EPU on local BTC markets.

Bitcoin Premia exists across markets and can be explained by uncertainty and attention: Bitcoin markets operate globally, but trading behaviours, regulations, and market sentiment vary significantly across regions. This variation leads to persistent price premiums or discounts between exchanges that persist due to market inefficiencies (Wüstenfeld & Geldner, 2022). Perhaps the most well-known and studied Bitcoin premium exists in South Korea and is better known as the 'Kimchi Premium' (see e.g. Choi et al., 2018; Eom, 2021). The Kimchi Premium reached a two-year high of 10.32% in March 2024.[5][6] Further, Choi et al. (2022) find that local Bitcoin premia reflect local investor sentiment.

Our findings show that heightened investor attention, a measure of speculation and investor sentiment, is the largest driver of Bitcoin returns and volatility. Heightened attention, often driven by speculative behaviour and common psychological trading biases, underscores Bitcoin's sensitivity to shifts in market sentiment rather than economic fundamentals. Furthermore, momentum effects, which have been defined as the source of a premium, where assets with high cumulative returns over the past continue to perform well (Jegadeesh & Titman, 1993), are particularly salient in explaining Bitcoin's price movements (Cheng et al., 2019; Liu et al., 2022). Historical price trends significantly influence current and future market behaviour, suggesting that past gains often predict future increases. This momentum effect, reinforced by the rapid dissemination of market information through digital channels, catalyzes ongoing investment as traders and investors anticipate continued upward movements based on recent trends. Our findings suggest that Bitcoin markets are inefficient.[7]

Interestingly, we find little relationship between local EPU and BTC markets, which is surprising given local EPU has been linked to BTC across multiple countries. However, we propose that EPU has a diminishing effect on BTC markets as Bitcoin has matured as an asset. Our findings also imply that Bitcoin markets are evolving, and as a result, the factors

[5] Park (2024).

[6] The Kimchi premium reached an all time high of roughly 60% in 2017/2018 at lower trading time frames.

[7] Refer to the efficient market hypothesis (EMH) of Fama (1970).

that influence Bitcoin performance are also evolving. For these same reasons, traditional asset pricing models such as the Fama French 5-Factor (FF5) model fail to adequately account for the risk factors that influence Bitcoin price.

Finally, we identify the existence of large local Bitcoin premiums in South Korea and Australia. However, investor attention and uncertainty do not explain premia, despite evidence investor sentiment leads to local premia. Instead, we find that local currency appreciation against the USD best explains positive movements in premia across all countries, a relationship reflective of purchasing power parity. Nevertheless, these premia tend to persist due to market inefficiencies and frictions.

Our findings provide useful insights for policymakers and investors: Investment in Bitcoin should be regarded as speculative, and policymakers should acknowledge that Bitcoin markets are inefficient and heavily influenced by irrational investors. A deeper understanding of market sentiment and momentum is essential when interacting with Bitcoin markets.

2. Data

2.1 Bitcoin Data

Our empirical analysis focuses on Bitcoin markets in Australia, Canada, Germany, Japan, South Korea, the UK and the US. For each country, the exchange with the highest liquidity and longest historical price data was chosen from `www.bitcoinity.org`.[8] The corresponding country, currency and exchange are shown in Table 2.1. We extracted monthly price data in the local currency from 1 January 2015 to 1 February 2024. Due to data availability, the sample period for Canada is 1 June 2015, to 1 February 2024. The decision to use monthly data is primarily influenced by data availability, and to mitigate the noise inherent in more granular data points, thereby providing clearer insights into long-term trends.

Figure 2.1 displays the BTC price and realised volatility (6-month rolling volatility) from 2010 to 2024. There has been significant price growth and a corresponding fall in volatility since 2015, as the market has become more liquid and mature (Liu & Tsyvinski, 2021). Our sample period is chosen because it captures the increased maturity of Bitcoin markets post-2015 (Drożdż et al., 2018), marked by higher liquidity, the introduction of competing protocols, and a broader acceptance of Bitcoin for real economic transactions. Before 2015, Bitcoin trading was limited to a few exchanges, resulting in less reliable data due to lower market liquidity and higher susceptibility to price manipulation.

Since the most-traded national currency for Bitcoin is the USD, we use an aggregate US market price for our 'Global' measure.[9] Although our data does not perfectly represent Bitcoin trading activity in each country, it provides a useful snapshot of Bitcoin trading in each region.

For each market, we calculate a time series of measures of return and volatility as follows:

$$Return : R_t = \ln(P_t) - \ln(P_{t-1}) \tag{2.1}$$

$$Volatility : Vol_t = |R_t| \tag{2.2}$$

[8] Bitcoinity.org uses Application Programming Interfaces (APIs) to extract Bitcoin price data from each local exchange.

[9] Aggregate US market price refers to the volume weighted average BTC/USD price across multiple price feeds of Bitcoin exchanges in the US.

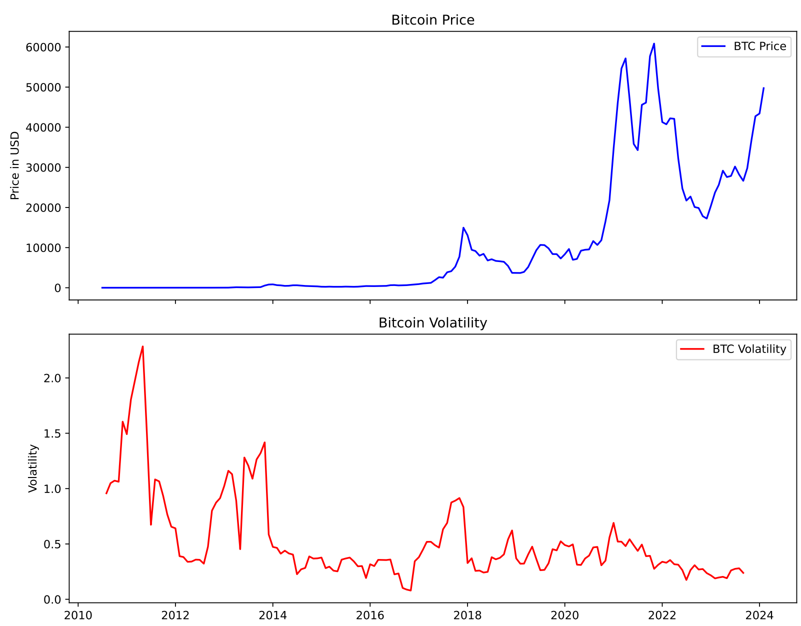
Where P_t is the price of Bitcoin at the end of each month, and Vol_t is the absolute one-month return.[10]

Table 2.1: BTC Markets per Country

Country	Currency	Exchange
Global	USD	Total Market
Australia	AUD	BTC Markets
Canada	CAD	Kraken
Germany	EUR	Kraken
Japan	JPY	Kraken
Korea	KRW	Korbit
US	USD	Coinbase
UK	GBP	Kraken

Note: This table shows the corresponding country of analysis (Country), the local currency that Bitcoin is traded in (Currency), and the Bitcoin exchange the price data is based on (Exchange). All local Bitcoin prices are extracted as BTC/"Currency". The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Figure 2.1: Bitcoin Price & Volatility



Note: This figure displays the BTC price and realised volatility (6-month rolling volatility) derived from 'US total market' data obtained from `www.bitcoinity.org`. The US total market refers to a volume-weighted average BTC/USD price from multiple US Bitcoin exchanges. The sample period of our analysis is 1 Jan 2015 - 1 Feb 2024.

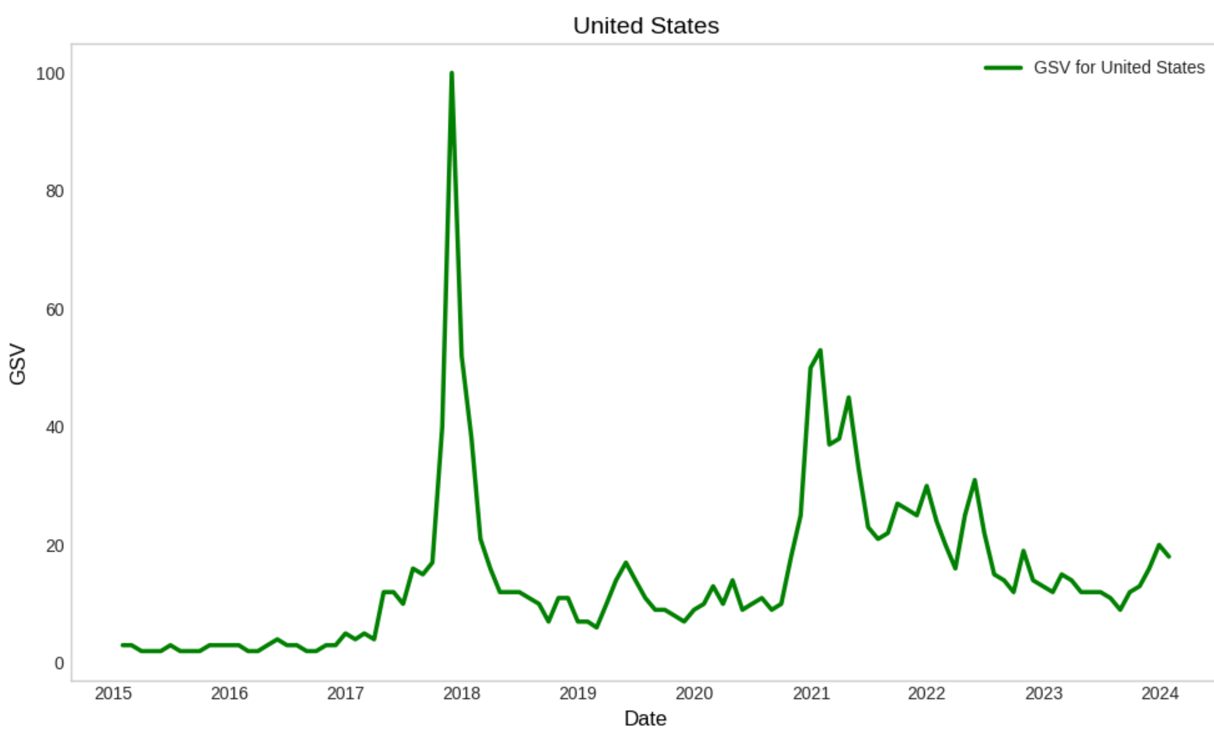
[10]Following the approach of Smales (2022)

2.2 Google Search Volume (GSV) Data

To measure investor attention we use the Google Search Volume (GSV) index from Google Trends. We gather data specifically for the search term "Bitcoin." GSV normalises search query data, scaling it between zero and 100 based on the term's proportion of all searches in a given region. A value of 100 indicates that the search term is highly active within the selected time frame and location. Google Trends also applies filters to exclude duplicate searches, searches containing special characters, and those made by an insignificant number of users.

Figure 2.2 contains the GSV for the search term "Bitcoin" for the US. The remaining markets are shown in Appendix C. For all markets, the GSV index spiked to 100 in late 2017, coinciding with the 2017 BTC bull market, except for Germany which spiked in 2021. Similar to BTC volatility and return charts, there exist spikes in investor attention in 2017-2018 and 2021-2022, coinciding with Bitcoin "bull runs".

Figure 2.2: Google Search Volume (GSV) for Search Term "Bitcoin"



Note: This figure illustrates the Google Search Volume (GSV) for the United States (US)—from 1 January 2015 to 1 February 2024. GSV refers to the search for the word "Bitcoin" in the US. The GSV index is scaled between 0 and 100, with 100 representing the peak search interest for Bitcoin within the specified time frame and location. This graph shows the trend and variability in search volume, highlighting periods of significant spikes that correspond to increased public and market interest.

2.3 Uncertainty Data

Our empirical analysis incorporates several measures of uncertainty:

First, we include the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016). This measure is based on the frequency of newspaper articles containing terms relating to a) uncertainty, b) economy, and c) policy. The index of Baker et al. (2016) covers Australia, Canada, Germany, South Korea, the UK and the US. Using a similar methodology, the EPU index of Japan is constructed by Arbatli, Davis, Ito and Miake (2019) and the Global index by Davis (2016).[11] Appendix A shows the local EPU plotted against the BTC return of the corresponding local BTC market. There appears no relationship between EPU and BTC returns, although further analysis is warranted.

Next, for robustness, we include the following measures of uncertainty:

This includes the CBOE S&P 500 Implied Volatility Index (VIX), which serves as a gauge of financial market uncertainty. Historically, the VIX has demonstrated a negative correlation with stock market returns and positive correlation with volatility (Jubinski & Lipton, 2012), with a similar relationship being observed with Bitcoin suggesting Bitcoin's behaviour is influenced by broader financial market conditions (Akyıldırım et al., 2020; Smales, 2022; Zhao & Zhang, 2023; López-Cabarcos et al., 2019; Bouri et al., 2017). For a more localized perspective, we took the VIX of the largest stock market of each nation, including the S&P/ASX 200 VIX Index (AXVI) in Australia, the S&P/TSX 60 VIX Index (VIXI) in Canada, the DAX New Volatility Index (V1XI) in Germany, the Nikkei Volatility Index (JNIV) in Japan, and the KOSPI Volatility Index (KSE KOSPI) in South Korea.[12] In the US, we refer to the CBOE Volatility Index (ˆVIX). The discontinuation of the UK's VIX (VFTSE) has necessitated the use of the US VIX for analysing the UK market.

We also utilize the cryptocurrency uncertainty index (UCRY) of Lucey et al. (2022), which is measured at the global level.[13] This index is constructed similarly to that of Baker et al. (2016) with two important differences. First, the focus is on news specifically related to uncertainty in the cryptocurrency market. Second, the index is constructed using the LexisNexis Business database, rather than relying solely on major newspapers. This approach

[11] All Economic Policy Uncertainty (EPU) data was retrieved from the official website https://www.policyuncertainty.com/

[12] Volatility Index (VIX) data for all countries was obtained from www.investing.com

[13] UCRY Policy data retrieved from https://sites.google.com/view/cryptocurrency-indices/the-indices/crypto-uncertainty?authuser=0)

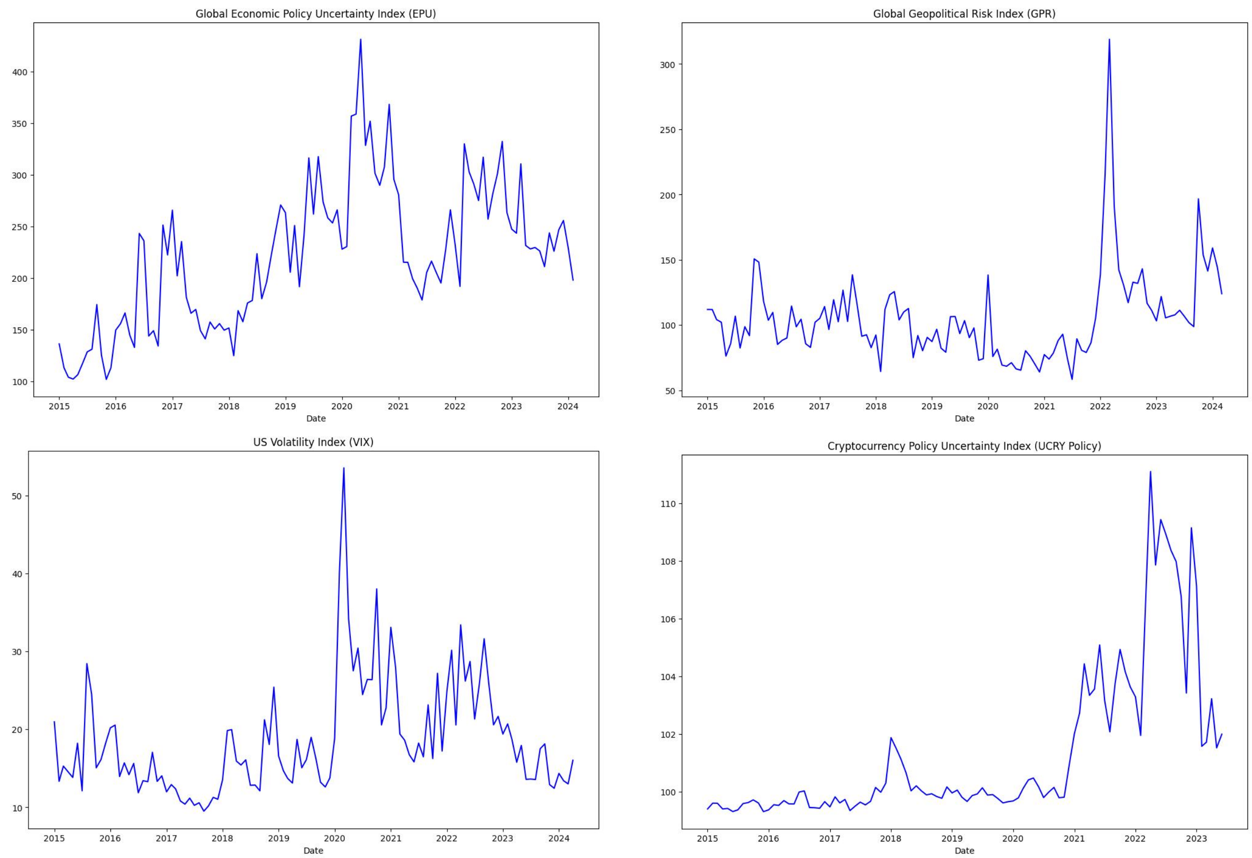
allows for a broader array of news sources, better reflecting the diverse range of information considered by cryptocurrency investors. We take the UCRY Policy measure that addresses uncertainties related to regulatory and policy shifts affecting cryptocurrencies, capturing sector uncertainty beyond just Bitcoin. Hasan et al. (2021) find that during periods marked by high UCRY Policy, traditional safe havens like gold tend to perform well, while cryptocurrencies like Bitcoin do not consistently act as hedges or safe havens. Smales (2022) also contends that while cryptocurrencies generally respond poorly to UCRY spikes, US Bitcoin markets themselves are unaffected.

Additionally, we include the Geopolitical Risk Index (GPR) of Caldara & Iacoviello (2022).[14] The GPR index reflects automated text-search results of the electronic archives of 10 newspapers and calculates the index by counting the number of articles related to geopolitical events in each newspaper for each month (as a share of the total number of news articles). To provide a more localised perspective, we took the country-specific GPR, which collects data from the same 10 newspapers, but also controls for search terms related to each country. Aysan et al. (2019) found global GPR to have predictive power on returns and price volatility of Bitcoin. Ben Nouir & Ben Haj Hamida (2023) highlight the significant influence of economic policy uncertainty and geopolitical risks on Bitcoin volatility, finding that geopolitical events have a pronounced effect on Bitcoin. Kyriazis (2020) suggests cryptocurrencies exhibit distinct reactions to geopolitical risks, likely due to their decentralized nature and the global span of their investor base, setting them apart from more traditional assets. Aysan et al. (2019) reveal that Bitcoin often experiences increased volatility during periods with more geopolitical risks, serving both as a speculative tool and a potential safe haven.

Figure 2.3 plots the EPU, VIX, GPR and UCRY Policy index. Significant movements in EPU tend to occur during periods of economic stress such as the GFC and Eurozone Crisis and large spikes in the GPR index occur after 9/11 and during COVID-19. For simplification, we plot the US VIX, which exhibited periods of significant volatility from 2015 to 2024, notably peaking during the COVID-19 pandemic in early 2020 and stabilising to pre-pandemic levels in subsequent years. Moreover, the UCRY Policy index has been elevated in recent years, coinciding with significant developments since 2020 relating to cryptocurrencies within the Securities Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC), along with increased political interest in the sector.

[14] Geopolitical Risk (GPR) index data was obtained from https://www.matteoiacoviello.com/gpr.html

Figure 2.3: Uncertainty Indices EPU, GPR, VIX, & UCRY



Note: This figure plots the global Economic Policy Uncertainty Index (EPU), global Geopolitical Risk Index (GPR), US Volatility Index (VIX) and the Cryptocurrency Policy Uncertainty Index (UCRY). All figures refer to the nominal level of the respective index. The sample period of our analysis is 1 January 2015 to 1 February 2024 for EPU, GPR and VIX, and 1 January 2015 to 1 June 2023 for UCRY.

2.4 Descriptive Statistics

For each predictor variable in our analysis, we take the log change relative to the previous period (Equation 2.3), allowing us to test the change in BTC for a change in the independent variable, otherwise known as the elasticity. Our analysis focuses on this relationship rather than absolute levels of uncertainty and attention. This methodology follows the work of Smales (2022). Table 2.2 shows the descriptive statistics for the dependent variable BTC returns, and predictors ΔEPU, ΔGPR, ΔVIX and ΔGSV.

$$\Delta\text{Variable} = \ln(\text{Variable}_t) - \ln(\text{Variable}_{t-1}) \tag{2.3}$$

Table 2.2: Descriptive Statistics for Bitcoin Return, Uncertainty & Investor Attention

	BTC Return				**ΔEPU**				**ΔVIX**			
Country	Mean	Std Dev	Skewness	Kurtosis	Mean	Std Dev	Skewness	Kurtosis	Mean	Std Dev	Skewness	Kurtosis
Australia	0.047	0.184	0.403	0.814	0.003	0.414	-0.296	1.928	-0.003	0.193	0.479	1.157
Canada	0.051	0.180	0.378	0.390	0.001	0.307	0.226	-0.376	0.001	0.185	-0.003	0.667
Germany	0.046	0.181	0.284	0.391	0.012	0.327	0.616	1.024	-0.005	0.207	0.434	1.550
Japan	0.047	0.187	0.223	0.669	-0.001	0.171	0.185	1.457	-0.003	0.213	0.713	1.827
South Korea	0.047	0.192	0.356	1.474	0.006	0.300	0.623	1.864	0.002	0.204	0.320	0.486
UK	0.047	0.176	0.298	0.287	0.002	0.297	0.186	1.142	-0.003	0.255	0.448	0.862
US	0.045	0.185	0.239	0.694	0.003	0.294	0.212	0.500	-0.003	0.255	0.448	0.862

	ΔGPR				**ΔGSV**			
Country	Mean	Std Dev	Skewness	Kurtosis	Mean	Std Dev	Skewness	Kurtosis
Australia	0.001	0.676	0.189	0.232	0.020	0.319	0.772	1.282
Canada	0.004	0.462	0.520	0.575	0.024	0.305	0.840	1.244
Germany	0.009	0.437	0.348	-0.412	0.029	0.312	0.456	0.127
Japan	0.004	0.523	0.272	-0.339	0.014	0.242	0.343	0.171
South Korea	0.003	0.466	0.173	0.363	0.017	0.291	0.416	1.318
UK	0.006	0.288	-0.042	0.689	0.019	0.298	0.688	1.138
US	0.006	0.244	0.068	1.431	0.016	0.309	0.773	1.079

Note: This table presents the descriptive statistics for Bitcoin returns, measures of uncertainty and investor attention, which include BTC (Bitcoin returns in local currency), EPU (Economic Policy Uncertainty), GPR (Geopolitical Risk), VIX (Volatility Index), and GSV (Google Search Volume) across our selected countries: Australia, Canada, Germany, Japan, South Korea, the UK, and the US. The statistics reported for each measure include the mean, standard deviation (Std Dev), skewness, and kurtosis. Each predictor variable is taken as the log change from the prior period. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all indices except Canada (1 July 2015 to 1 February 2024).

Table 2.3: Correlation Between Measures of Uncertainty

	ΔVIX	ΔEPU	ΔGPR	ΔUCRY
ΔVIX	1.00			
ΔEPU	0.11	1.00		
ΔGPR	-0.02	0.10	1.00	
ΔUCRY	-0.05	-0.04	-0.06	1.00

Note: This table provides correlation estimates for the measures of uncertainty used in this study which includes global economic policy uncertainty (EPU), global geopolitical risk (GPR), cryptocurrency markets uncertainty policy (UCRY), and general financial markets (VIX). For simplicity, the US VIX is used in this table. The sample period is 1 January 2015 to 1 February 2024.

Table 2.3 shows the correlation matrix between different measures of uncertainty. Across all measures of uncertainty, there are near-zero levels of correlation. ΔEPU with both the ΔVIX (0.11) and ΔGPR (0.10) are the only positive correlations. The ΔUCRY has a weak negative correlation with all other measures of uncertainty. Based on these results, we anticipate minimal issues of multicollinearity across our regression analysis.[15]

2.5 Other Data

Furthermore, we collect a set of macroeconomic data to use as control variables in our analysis, including a measure of US business conditions that integrates various economic indicators such as employment, output, and sales (the Aruoba-Diebold-Scotti Business Conditions Index (ADS))[16], a term premium (10-2YTERM)[17] calculated as the difference between the 10-year and 2-year US Treasury securities, and Credit Spread[18], a measure of the difference between the yields of corporate bonds and risk-free government bonds. These macroeconomic variables are US-centric, informed by the size of the US Bitcoin market and the influence of the US economy on the global economy.

We collected foreign exchange rate data for the currency pairs AUD/USD, CAD/USD, EUR/USD, GBP/USD, JPY/USD, and KRW/USD.[19] Importantly, all pairs are quoted with the local currency as the base currency and USD as the quote currency. Furthermore, we include the Dollar Index (DXY), which provides a measure of the USD's overall strength, to represent the US foreign exchange rate in our regression analysis.

Finally, we also include the Fama and French Five-Factor Model data including a market risk premium (`Mkt-RF`), size premium (`SMB`), value premium (`HML`), profitability (`RMW`), and investment (`CMA`) factors.[20]

[15] Correlations between the unadjusted uncertainty indices were high, potentially resulting in multicollinearity issues.
[16] ADS data retrieved from https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads
[17] 10-2YTERM data retrieved from https://www.cnbc.com/quotes/10Y2YS
[18] Credit spread data retrieved from https://fred.stlouisfed.org/series/BAMLH0A0HYM2
[19] Foreign exchange rate data was retrieved from www.finance.yahoo.com
[20] Fama-French data was obtained from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3. Methodology

3.1 Multivariate OLS Regression Analysis

We begin our analysis with a multivariate regression to analyse the collective influence of various uncertainty and investor attention predictor variables that have been shown to impact Bitcoin markets. For this reason, we do not perform any major feature selection at this stage.[21]

We use the following model for the multivariate regression, running the regression for both BTC return and for BTC volatility, for each country:

$$\begin{aligned} BTC_{it} = \beta_0 &+ \beta_1 \text{ADS}_t + \beta_2 \text{CreditSpread}_t + \beta_3 \text{10Y2YTERM}_t \\ &+ \beta_4 \text{EPU}_{it} + \beta_5 \text{GPR}_t + \beta_6 \text{VIX}_t + \beta_7 \text{GSV}_{it} + \beta_8 \text{BTC lag}_{it} + \epsilon_i \end{aligned} \tag{3.1}$$

Where:

Variable	**Description**
BTC_{it}	Bitcoin returns in country i at month t; Bitcoin volatility in country i at month t
ADS_t	ADS Index representing overall business conditions at month t
CreditSpread_t	Spread between corporate bonds and Treasury securities at month t
10Y2YTERM_t	10-year minus 2-year Treasury yield spread at month t
EPU_{it}	Economic Policy Uncertainty Index at country i in month t
GPR_{it}	Geopolitical Risk Index at country i in month t
VIX_{it}	Market Volatility Index at country i in month t
GSV_{it}	Google Search Volume for Bitcoin at country i in month t
BTC lag_{it}	Lagged Bitcoin returns at country i in month t

[21] See also Appendix C, Appendix D, Appendix E for univariate regression analysis methodology and results.

3.2 Fama French Five-Factor (FF5) Model

Next in our analysis, we evaluate the effectiveness of traditional asset pricing models in explaining BTC return. By using the Fama and French 5 Factor Model (Fama & French, 2015), which has been demonstrated to be a significant predictor of stock market returns (Fama & French, 2017), we aim to discern whether traditional asset pricing factors can account for Bitcoin's performance. This is a crucial step in our analysis to identify any potential explanatory power traditional asset pricing factors may have over BTC returns. Depending on our multivariate results, we can attempt to uncover why or why not this may be the case and the possible reasoning for our findings. In addition, we can infer the efficiency of Bitcoin markets, and attempt to determine the relevant risk factors that influence Bitcoin price. Finally, this analysis may identify potential arbitrage opportunities.

The FF5 model incorporates factors for market excess return (Mkt-RF), size (SMB: Small Minus Big) referring to the historical outperformance of small-cap stocks, value (HML: High Minus Low) capturing the superior returns of high book-to-market firms, profitability (RMW: Robust Minus Weak) distinguishing between high and low profitability companies and investment (CMA: Conservative Minus Aggressive) contrasting the returns of firms with conservative versus aggressive investments.

We propose the following model:

$$\begin{aligned} ER(BTC)_t = R_f + \beta_{MKT}(R_M - R_F) + \beta_{SMB} \cdot SMB + \beta_{HML} \cdot HML \\ + \beta_{RMW} \cdot RMW + \beta_{CMA} \cdot CMA + \epsilon_t \end{aligned} \tag{3.2}$$

3.3 Estimating Bitcoin Premia

Following the assessment of Bitcoin returns and volatility, we investigate whether we can observe a similar relationship in regional Bitcoin premia and its response to changes in policy uncertainty and investor attention. We analyse market-specific price discrepancies to identify inherent inefficiencies or distinct behaviours within each country, and whether factors like uncertainty and attention contribute to Bitcoin premia.

We begin by calculating implied foreign exchange (FX) rates for converting the local currency to USD based on Bitcoin prices. This represents the effective exchange rate if one were to buy Bitcoin in the local currency, and simultaneously sell the Bitcoin for USD. It tells us how much of the local currency is equivalent to one US dollar, based on Bitcoin prices in both currencies. This implied foreign exchange rate should be equal to the prevailing market foreign exchange rate, similar to the concept of purchasing power parity (PPP) (see e.g. Dornbusch, 1985) where the price of a good should be the same in different markets when adjusted for exchange rates. This equality is represented in Eq. 3.3 below:

$$\text{Implied FX rate}\left(\frac{\text{Currency}_{it}}{\text{USD}_t}\right) = \frac{\text{BTC Price }(\text{USD}_t)}{\text{BTC Price }(\text{LOCAL}_{it})} \tag{3.3}$$

which by the Law of One Price should equal:

$$\text{Market FX Rate} = \frac{\text{Currency}_{it}}{\text{USD}_t} \tag{3.4}$$

Where LOCAL_{it} is the price of Bitcoin on the local exchange denominated in the local currency i for each month t. And, Currency_{it} is the relative strength of the local currency i against the USD for each month t.

The theoretical basis for this approach is grounded in several key financial principles. Firstly, the Law of One Price states that in an efficient market, identical goods should have the same price when expressed in a common currency. Applied to Bitcoin, this principle implies that the price of Bitcoin in different currencies should reflect the prevailing exchange rates between those currencies. Secondly, Arbitrage Theory suggests that arbitrage involves the simultaneous purchase and sale of an asset to profit from price differences across markets. If the implied FX rate differs from the market FX rate, arbitrageurs can exploit this discrepancy by buying Bitcoin in the cheaper currency and selling it in the more expensive currency, thereby driving the prices toward equilibrium. Lastly, the concept of market efficiency posits that in efficient markets all available information is reflected in asset prices, minimising arbitrage opportunities. Any disparities between implied and market FX rates can highlight areas where the market is not fully efficient.

Next, in Eq. 3.5 we calculate the percentage difference ("Premia") between the implied FX rate from Bitcoin prices (Eq. 3.3) and the actual market FX rate, taken from `yahoo.finance`. A positive spread implies a Bitcoin price premium in the local market relative to the US market. Similarly, a negative spread implies a discount in the local Bitcoin market relative to the US market.[22]

$$\text{Local BTC Premia} = \left(\frac{\text{Implied FX Rate} - \text{Market FX Rate}}{\text{Market FX Rate}}\right) \times 100 \times (-1) \tag{3.5}$$

The importance of the premia lies in its ability to reveal market inefficiencies and potential arbitrage opportunities. It also provides insights into local market sentiment and demand for Bitcoin relative to the US market. Understanding these premia can help investors make informed decisions and develop strategies to potentially capitalise on price differentials across different regions.

3.4 Robustness Tests

3.4.1 Panel Data Analysis

To ensure the robustness of our findings, we employ additional methodologies. Firstly, we use a panel data approach. The benefit of a panel data approach is that it combines cross-sectional data—data collected from multiple entities at a single point in time—with time series data—data collected from a single entity over multiple periods—resulting in a dataset where each entity has multiple observations across periods. Due to our sample size, by observing multiple cross sections we can increase the total amount of data points in our analysis and improve the statistical power and reliability of our analysis.

We can also use fixed effects to control for unobserved heterogeneity across different regions. We extend Eq. 3.1 to include unobserved exchange fixed effects (μ_i), running the regression for BTC return, BTC volatility, and Bitcoin premia for each country:

$$\begin{aligned} BTC_{it} = \beta_0 &+ \beta_1 \text{ADS}_t + \beta_2 \text{CreditSpread}_t + \beta_3 \text{10Y2YTERM}_t + \beta_4 \text{EPU}_{it} \\ &+ \beta_5 \text{GPR}_t + \beta_6 \text{VIX}_t + \beta_7 \text{GSV}_{it} + \beta_8 \text{BTC lag}_{it} + \mu_i + \epsilon_i \end{aligned} \tag{3.6}$$

Furthermore, we conduct an F-test for poolability. We test the null hypothesis (H_0) that the coefficients are equal across all cross-sections, meaning that there is no significant difference between the individual countries and can be pooled together. The alternative hypothesis

[22] Note: we only examine the relationship between the local market and US market spread. We acknowledge there may exist larger spreads between local markets.

(H_1) states that there are significant differences between the cross-sections, indicating that the data should not be pooled. Results from the F-Test for poolability tell us whether there are distinct cross-sectional differences that should be modelled separately. In the context of our study, rejecting the null hypothesis would mean acknowledging that there are country-specific factors that significantly affect Bitcoin returns, volatility, or premia. This implies that the intercepts are not the same for all cross-sections, and a fixed effects model is more appropriate.

The F-statistic is calculated using the sum of squared residuals from both models. The formula is:

$$F = \frac{\left(RSS_{\text{pooled}} - RSS_{\text{fixed}}\right)/(N-1)}{RSS_{\text{fixed}}/(NT-N-K)} \tag{3.7}$$

This panel data and fixed effects approach is valuable for capturing intricacies and individual characteristics of the Bitcoin market, which would otherwise be lost in a simple time series or cross-sectional data analysis. Fixed effects modelling is chosen to control for all time-invariant differences in investor attention and uncertainty among the countries that could influence Bitcoin's returns.

3.4.2 Quantile-on-Quantile Regression

Also, to aid the robustness of our analysis, we examine the relationship between uncertainty, investor attention, and BTC markets under different market conditions. Demir et al. (2018) indicate that Economic Policy Uncertainty (EPU) can have predictive power on Bitcoin returns, particularly at higher and lower quantiles of Bitcoin return. Following the approach of Sim and Zhou (2015) and Demir et al. (2018), we apply the QQ regression to Bitcoin returns against the predictor variables ΔEPU and ΔGSV. We apply quantiles ranging from 0.05 to 0.95 in increments of 0.05 for each country.[23]

We propose the following methodology:

$$BTC_{qx} = \alpha_{qx} + \beta_{qy}\text{Predictor}_{qy} + \epsilon_{qx,qy} \tag{3.8}$$

[23] Following the approach of Demir et al. (2018) on EPU and BTC markets.

Where:

- $\mathbf{BTC}_{qx}$: Quantile qx of Bitcoin returns
- $\mathbf{Predictor}_{qy}$: Quantile qy of one of the predictors (either EPU or GSV)

QQ analysis examines the relationship between different quantiles of two distributions. Unlike traditional regression analysis which looks at the relationship between the mean of one variable and the mean of another, QQ analysis provides a more nuanced view by exploring how different quantiles of one distribution relate to different quantiles of another distribution.

In our analysis we evaluate the relationship between EPU and GSV and BTC returns under different market conditions—bull market conditions represented by upper quantiles of BTC return, and during bear markets, represented by lower quantiles of BTC return. Furthermore, we also split the data to look at the effect of EPU and GSV during different Bitcoin halving cycles.[24] We consider two periods running from July 2016 - May 2020 ("Period 1"), representing the period between the second to third Bitcoin halving, and May 2020 - February 2024 ("Period 2"), representing the period post the third Bitcoin halving. This allows us to compare the effect of EPU and GSV on BTC returns across two different market phases, one characterized by relatively lower liquidity and the other by increased adoption and increased market maturity.

[24] The Bitcoin halving is when Bitcoin's mining reward is split in half. It takes the blockchain network about four years to open 210,000 more blocks, a standard set by the blockchain's creators to continuously reduce the rate at which Bitcoin is introduced. The mining reward split in half can be thought of as a 50% reduction in the level of inflation of new Bitcoin being introduced. The Bitcoin halving generally precipitates significant price increases.

4. Results

4.1 Findings from the Multivariate OLS Regression

Table 4.1 contains the multivariate regression results using BTC return as the dependent variable. We find speculation is the strongest driver of BTC returns indicated by positive and statistically significant coefficients for ΔGSV (0.182 to 0.298 with significance at the 0.01 level). These results demonstrate a robust relationship where increased search behaviour, which serves as a proxy for heightened investor interest or speculative demand, correlates with higher Bitcoin returns. The effect is more pronounced in Japan, South Korea and Canada, with a lesser effect observed in Germany and the UK, clarifying a heterogeneous impact of investor attention on local Bitcoin markets. These findings are unsurprising given the strong connection between GSV and BTC in literature; Bouoiyour & Selmi (2015) and Kristoufek (2013) find Google trends are the most important factor that drives Bitcoin price. Panagiotidis et al. (2018) examine the significance of twenty-one potential drivers of Bitcoin returns and find GSV to be one of the most influential. The presence of speculative behaviour in Bitcoin markets is interesting for several reasons; Speculative behaviour can inflate asset prices beyond their intrinsic value, creating market bubbles that may eventually burst, leading to sharp corrections and potential financial losses for traders; Additionally, high levels of speculation can make the market more susceptible to manipulation as large players might influence prices. The primary implication of these findings is that Bitcoin markets are inefficient, Bitcoin price movements tend to be less tied to traditional economic fundamentals and there are heterogeneities in the impact of local attention on Bitcoin return.

The inefficiency of local Bitcoin markets is further exemplified by strong momentum effects, aligning with the findings of Liu et al. (2022) and Cheng et al. (2019). Past returns tend to positively influence future performance, making it possible for traders to profit from buying during upward trends and selling during downward trends. The coefficients for BTC lagged returns show a significant positive relationship in nearly all countries, ranging from 0.226 to 0.305 with statistical significance at the 1% level in all markets except the US. This effect is most pronounced in South Korea. Momentum effects pose several implications for Bitcoin markets; Momentum can lead to overreaction (Jegadeesh & Titman, 1993), where prices move too far in one direction before correcting, which amplifies market volatility; Momentum effects can lead to price predictability due to behavioural biases such as herding (Grinblatt et al., 1995), which reinforce price trends and provide avenues for more advanced traders to exploit.

Interestingly, we find near zero and insignificant ΔEPU coefficients across all countries. Whilst this was expected for the US, Japan and South Korea (Yen & Cheng, 2021), recent evidence from Wüstenfeld & Geldner (2022) found a relationship with markets in Canada and Australia, especially since COVID-19. Nonetheless, our findings are similar to Colon et al. (2021), and Smales (2022) in their study of global EPU and Bitcoin markets. Further, Smales (2022) proposes that "although the correlation between EPU and other uncertainty variables is low, it is possible because some of the information contained in EPU is captured by other variables in our model." Notwithstanding, prior studies have found a strong relationship between global EPU and BTC under different market conditions (Demir et al., 2018; Phan et al., 2018), underscoring the need for this study at a regional level.

In addition, positive and weakly significant constants across all markets except South Korea suggest there is some baseline positive return of approximately 3% per month, that is not explained by the variables in the model. Credit spread, with varying degrees of significance, implies that wider spreads or higher perceived risk tend to decrease Bitcoin returns, highlighting Bitcoin's sensitivity to broader economic conditions and investors' risk perceptions within financial markets. Despite the significance of speculation and momentum, this relationship with credit spread suggests that BTC returns are still somewhat related to overall economic conditions. Other measures of uncertainty (ΔGPR, ΔVIX) and macroeconomic variables (ΔADS and Δ10-2YTERM) have near zero and insignificant relationships, as also documented by Ciaian et al. (2015).

Table 4.1: Bitcoin Return Multivariate Regression Results

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.031**	0.033**	0.028*	0.028*	0.025	0.027*	0.030*
ΔADS	0.000	0.000	0.001	0.001	-0.001	0.000	0.001
ΔCredit spread	-0.233*	-0.153	-0.215	-0.185	-0.279**	-0.232*	-0.240*
Δ10-2Y TERM	0.002	0.002	0.002	0.009	0.000	0.004	0.004
ΔFX	0.613	1.514**	0.176	-0.024	-0.176	-0.860	-0.516
ΔEPU	0.009	-0.000	-0.050	-0.115	0.076	0.035	-0.007
ΔGPR	0.037*	0.038	0.040	0.040	-0.042	0.067	0.066
ΔVIX	-0.173**	-0.006	-0.006	-0.034	-0.103	-0.105	-0.045
ΔGSV	0.252***	0.277***	0.182***	0.298***	0.281***	0.218***	0.241***
BTC lag	0.226***	0.238***	0.288***	0.265***	0.305***	0.257***	0.231**
Adj. R-squared	0.337	0.357	0.203	0.247	0.294	0.249	0.278
F-statistic	7.097	7.291	4.064	4.939	5.993	4.977	5.626
Observations	109	103	109	109	109	109	109

Note: This table presents the results of the multivariate OLS regression analysis with Bitcoin (BTC) return as the dependent variable across seven different markets: Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States. The coefficients for each variable are displayed, with statistical significance indicated as follows: *p<0.1, **p<0.05, ***p<0.01. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table 4.2 shows the multivariate regression results for Bitcoin volatility. There exists a monthly level of volatility of around 14% (significant at the 0.01 level across all markets). Again, we find that speculative behaviour is a strong predictor of Bitcoin volatility. Notably, the coefficients for ΔGSV remain positive and highly significant across all countries (0.209 in Germany to 0.275 in Canada), indicating that higher public interest and speculation consistently lead to greater Bitcoin volatility. Adjusted R-squared values, ranging from 0.176 in South Korea to 0.443 in Canada, indicate a moderate to strong explanatory power in some countries but less in others. These results are supported by the work of Zhu et al. (2021) who find that investor attention impacts the realized volatility of Bitcoin but in contrast to Bukovina and Martiček (2016) who find sentiment to possess minimal explanatory power for Bitcoin volatility. Also, we find that volatility in the previous period is not a strong predictor of current volatility, consistent with findings from Eom et al. (2019).

Table 4.2: Bitcoin Volatility Multivariate Regression Results

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.133***	0.132***	0.135***	0.134***	0.138***	0.120***	0.149***
ΔADS	0.001	0.000	0.001	0.001	0.000	0.001	0.001
ΔCredit spread	0.050	0.075	0.065	0.076	-0.016	0.058	0.155*
Δ10-2Y TERM	-0.004	-0.002	-0.002	0.000	-0.003	-0.002	-0.002
ΔFX	-0.487	-0.764	-0.259	0.352	0.063	-0.790*	-0.021
ΔEPU	-0.029	-0.033	-0.041	0.082	0.037	-0.032	-0.009
ΔGPR	0.008	0.012	0.000	-0.004	-0.030	0.062*	0.051
ΔVIX	-0.035	-0.045	0.066	-0.021	-0.001	-0.014	0.082*
ΔGSV	0.246***	0.275***	0.209***	0.248***	0.219***	0.214***	0.271***
BTC Vol lag	0.023	0.021	0.018	0.072	0.028	0.109	-0.078
Adj. R-squared	0.333	0.443	0.237	0.196	0.176	0.320	0.352
F-statistic	6.999	9.997	4.719	3.926	3.571	6.655	7.527
Observations	109	103	109	109	109	109	109

Note: This table presents the results of the multivariate OLS regression analysis with Bitcoin (BTC) volatility as the dependent variable across seven different markets: Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States. The coefficients for each variable are displayed, with statistical significance indicated as follows: *p<0.1, **p<0.05, ***p<0.01. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

4.2 Results from Fama French Five-Factor Model

Appendix G presents the regression analysis of the Fama French Five-Factor Model as applied to US Bitcoin returns from January 2015 to February 2024. Our analysis reveals that the Fama French 5 Factors, which are shown to be strong predictors of stock returns (Fama & French, 2017), exhibit limited explanatory power on Bitcoin returns. Only the market risk premium (Mkt-RF) is statistically significant, varying based on model specifications. The market risk premium in the 3 and 5 factor models is significant at 10%, and in the 1, 2 and 4-factor models is significant at the 5% level. Coefficients range from 0.793* to 0.844**, indicating Bitcoin movements tend to be less volatile than the S&P 500. Furthermore, a constant of 0.037** to 0.040** suggests there is generally a positive baseline level of monthly BTC return of around 4%.

Our findings raise several important considerations regarding conventional financial theories and their application to Bitcoin returns. Specifically, we are interested in the no-arbitrage assumption inherent in the Fama-French 5 Factor Model, which implies that all systematic risks should be accounted for by the model, ensuring no opportunity for risk-free profits. We contend that although there appears to be a potential arbitrage opportunity present based on the mispricing of Bitcoin in the FF5 model, this is more indicative of market inefficiencies and inadequate risk factors contained in the model:

Bitcoin markets are less efficient than traditional equity markets, possibly due to their relative novelty, lower liquidity, and higher susceptibility to speculative trading (Baur et al., 2018; Urquhart, 2016). The observed significance of speculation and momentum effects in our study further indicates inherent inefficiencies in Bitcoin markets. This is supported by Cheng et al. (2019).

There are inadequate risk factors in the FF5 model that do not capture the unique risks associated with Bitcoin. This is perhaps the most plausible reason for the inability of the FF5 model to explain Bitcoin returns. Liu et al. (2022). Polasik et al. (2015) argue that Bitcoin's market dynamics are less connected with traditional financial markets. Factors including investor behaviour and market sentiment drive Bitcoin markets (Demir et al., 2019; Shahzad et al., 2019). Ultimately, traditional financial models fail to capture the nuances of Bitcoin-specific risk factors and, therefore, 'potential arbitrage opportunities' highlighted by the model are only reflective of the inadequacy of the FF5 factor model in pricing Bitcoin risk.

Even though we contend the Fama-French model framework does not provide arbitrage opportunities, our findings of market inefficiencies through the strong influence of speculation and momentum imply that there may still exist exploitable arbitrage opportunities across regional Bitcoin markets. This provides a segue into our analysis of Bitcoin premia, its potential causes and whether these are rooted in market inefficiencies.

4.3 Bitcoin Premia Findings

In the sections above, we found that speculation and momentum effects drive Bitcoin markets, implying market inefficiencies within regional Bitcoin markets. In this section, we aim to see whether these same determinants cause market inefficiencies between regional BTC markets, represented by the existence of regional Bitcoin premia.

Figure 4.1 plots the time series of Bitcoin premia per country from 2015 to 2024. Table 4.3 shows the descriptive statistics of these premias (from Eq. 3.5). A local Bitcoin premium is observed in Australia, Japan, South Korea, and Germany. A local Bitcoin discount is observed in Canada and the UK. We can identify significant premia across all markets, at varying stages. An event study reveals that deviations in premia closely align with periods of heightened volatility and/or major fluctuations in BTC prices.

Notably, in 2018 there was a substantial Bitcoin premium in South Korea of 20% coinciding with sharp price movements in Bitcoin. Similarly, in 2019 Japan saw a discount of 27% during a significant decline in Bitcoin prices. In 2017, there was a 26% Bitcoin discount in the UK and a 9% premium in Australia in 2018, both during times of heightened Bitcoin volatility. In 2022, the European Bitcoin price was trading at a 4% discount, a period marked by volatility in both BTC and the foreign exchange market.

Whilst these larger market disconnects are generally explained by Bitcoin volatility, the smaller and more persistent premia are documented as being mainly caused by market inefficiencies and capital frictions. In discussing the regional Bitcoin premia, we acknowledge the identification of all factors that explain these price deviations is a delicate and challenging process.

A high mean Bitcoin premium in South Korea of 1.62% is documented as being caused by stricter regulations and capital controls that limit international arbitrage (Choi et al., 2022). Specifically, trading on South Korean exchanges is limited to Korean nationals or foreigners with resident registration cards who can open full-fledged bank accounts in the country.[25] And, the absence of short selling on local exchanges means arbitrageurs cannot lock in profits and must assume holding risk. Importantly, the absence of short selling eliminates a valuable source of market information, reducing efficiency.[26] The transfer of Bitcoin from a foreign exchange to a South Korean exchange also takes time, during which the Bitcoin price can change dramatically. CNBC revealed that transfers can take anywhere from one hour to one day. There also exist strict regulations on the transfer of the South Korean Won (KRW) out of the country, posing further constraints, particularly on larger institutions which generally have increased market power.

Local Bitcoin exchanges play a significant role in Bitcoin price and volatility due to varying

[25] Jie (2024)
[26] Ferreira (2023)

levels of liquidity, trading volume, and regulatory environments (Brauneis et al., 2021; Auer & Claessens, 2021). Less liquid markets or those with lower trading volumes can exhibit more significant price discrepancies (Liu & Tsyvinski, 2021), and liquidity has been found to have a significant positive effect on the informational efficiency of Bitcoin prices (Sensoy, 2019). South Korea's high mean premia and large standard deviation (3.92%) suggest strong local demand and less liquidity in local exchanges compared to larger US exchanges (Brauneis et al., 2021). Furthermore, the Bitcoin premia in Japan is characterised by high volatility and extreme values, with Bitcoin data from `bitcoinity.org` suggesting BTC/JPY was the least traded currency pair within our sample countries. In addition, Germany, a proxy for trade of the BTC/EUR, was the second highest traded pair behind BTC/USD and exhibited the lowest volatility in premia.

Furthermore, Giudici & Pagnottoni (2019) propose that the connectedness of overall Bitcoin returns fell substantially right before the Bitcoin price hype, whereas it levelled out during the subsequent down market periods. However, our analysis reveals significant premias during extreme down market events such as the 2017 Bitcoin crash (see South Korea, UK, Australia in Figure 4.1).

Given the existence and persistence of Bitcoin Premia, we can now attempt to identify the determinants of regional Premia.

Table 4.3: Descriptive Statistics of Bitcoin Premia Across Countries

Country	mean	std	min	max	skew	kurtosis
Germany	0.049	1.253	-3.178	4.404	0.394	0.830
South Korea	1.616	3.924	-12.570	21.180	1.409	7.507
UK	-0.475	4.776	-26.539	7.451	-3.106	12.513
Japan	0.131	3.424	-27.124	6.449	-4.454	34.767
Australia	0.612	2.161	-4.081	9.505	1.039	2.094
Canada	-0.209	1.800	-4.488	7.156	1.085	3.836

Note: This table presents the descriptive statistics of Bitcoin premia. The Bitcoin premia represents the percentage difference between the implied foreign exchange rate (derived by dividing the price of Bitcoin in the US by the price of Bitcoin in the local currency) and the actual market exchange rate, indicating the relative premium or discount of Bitcoin in the local market compared to the US market. A positive premia indicates a premium in the local market, while a negative premia indicates a discount. The statistics include the mean, standard deviation (Std Dev), minimum (Min), maximum (Max), skewness, and kurtosis for each currency pair. The premia mean, Std Dev, Min, and Max are percentages. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Figure 4.1: Local Bitcoin Premia

Note: This graph contains the local market Bitcoin Premia. The Bitcoin premia represents the percentage difference between the implied foreign exchange rate (derived by dividing the price of Bitcoin in the US by the price of Bitcoin in the local currency) and the actual market exchange rate, indicating the relative premium or discount of Bitcoin in the local market compared to the US market. Here, positive premia imply a local market Bitcoin premium relative to the US, and conversely, negative spreads imply BTC is undervalued or less expensive in the local market relative to the US market, based on the prevailing foreign exchange rate. A positive premia suggests that an investor could potentially profit by buying Bitcoin on a US exchange in USD, selling Bitcoin on the local exchange for the local currency, and then repurchasing USD at a lower market foreign exchange rate, profiting the premia. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table 4.4 shows the results from the Premia multivariate regression. Local currency appreciation relative to the USD is the largest contributor to Premia. This relationship exists across all sample countries (ranging from 36.91%*** in the UK to 59.87%*** in Japan). A similar relationship is documented by Choi et al. (2022). The magnitude of this relationship is large; For example, a 1% increase in the JPY relative to the USD is associated with a 60% increase in the Japanese Bitcoin Premia. Our findings align with Smith (2016) who argues that implied nominal exchange rates are highly cointegrated with conventional market exchange rates. Driven by arbitrage opportunities, relative Bitcoin prices adjust rapidly to restore parity with market exchange rates. This is consistent with the theory of Purchasing Power Parity (PPP)—whereby the increased purchasing power of local investors can drive up local demand for Bitcoin, leading to a local premium.

In addition, most other predictors have near-zero and insignificant coefficients. GSV only has a significant relationship with Premia in the UK market (2.15%**). Overall, the model explains variations in spreads well, with adjusted R-squared values indicating strong explanatory power, particularly in the UK (0.654) and Australia (0.548), highlighting the importance of exchange rate volatility and investor sentiment in shaping FX spreads. In addition, lagged spreads in Australia (0.256***), South Korea (0.462***), and the UK (0.822***) are a good indicator of spreads in the next period, and we observe a mean-reverting trend in Germany (-0.179**).

Table 4.4: Bitcoin Premia Multivariate Regression Results

	Australia	Canada	Germany	Japan	South Korea	UK
const	-0.579***	0.305*	-0.078	-0.228	-0.901***	0.052
ΔADS	0.009	0.042	0.010	-0.049	0.039	0.057
ΔCredit spread	-0.849	-0.975	-0.903	0.409	-1.052	-0.295
Δ10-2Y TERM	0.108*	0.026	0.012	-0.195	0.118	0.162
ΔFX	-54.150***	-41.217***	-37.868***	-59.871***	-52.356***	-36.909***
ΔEPU	-0.096	-0.357	0.062	1.233	0.011	-0.959
ΔGPR	0.054	-0.447	-0.079	-1.056*	0.013	1.253
ΔVIX	-0.761	-0.822	-0.014	0.325	-0.731	2.299
ΔGSV	-0.130	-0.660	-0.048	-1.489	-1.207	-2.250**
ΔSpread lag	0.256***	0.039	-0.179**	0.090	0.462***	0.822***
Adj. R-squared	0.548	0.224	0.430	0.161	0.338	0.654
F-statistic	15.571	4.269	10.035	3.302	7.140	23.657
Observations	109	103	109	109	109	109

Note: This table presents the results of the multivariate OLS regression analysis with Bitcoin (BTC) premia as the dependent variable across seven different markets: Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States. The coefficients for each variable are displayed, with statistical significance indicated as follows: *p<0.1, **p<0.05, ***p<0.01. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

4.4 Robustness Tests

4.4.1 Panel Data Analysis Results

Appendix F provides the panel regression results for BTC return, BTC volatility, and Premia with country fixed effects (from Eq. 3.6).

By observing multiple cross-sections, we significantly increased the amount of data points in our analysis and improved the statistical power and reliability of our analysis. As a result, in addition to the significant coefficients found in our multivariate analysis for Bitcoin return (Credit spread, GSV and BTC lagged return) we also find significant coefficients for GPR and VIX. Nevertheless, these relationships are weak. For the Bitcoin volatility panel regression, we also observe the significance of credit spread (in addition to GSV found in the multivariate analysis), but once again this coefficient is near zero. For premia, we observe no additional significance among other predictor variables.

In addition, Table 4.5 shows the results from the F-Test for poolability from these panel regressions. We find that there are significant country-specific factors that are not constant over time in the Premia regression. In contrast, Bitcoin returns and volatility may be influenced more by global factors rather than country-specific factors, indicating a more homogeneous market behaviour across different countries. That is, whilst speculation and momentum effects possess a positive and strong explanatory power for Bitcoin returns and volatility, these do not significantly deviate from country to country.

Table 4.5: Panel Regression F-Test for Poolability Results Summary

Panel Regression	F-Statistic	P-Value
BTC Return	0.021	1.000
BTC Volatility	0.099	0.997
Premia	2.523	0.028

Note: This table summarises the F-Test for Poolability Results from the Panel regressions (Eq. 3.7) for Bitcoin Return, Bitcoin Volatility, and Premia. The null hypothesis H_0: The coefficients are equal across all cross-sections, implying that the data can be pooled. The alternate hypothesis H_1: The coefficients are not equal across all cross-sections, implying the data should not be pooled. The rejection of the null hypothesis implies we observe country-fixed effects that should be accounted for in our analysis, and a fixed effects model is suitable.

4.4.2 Quantile-on-Quantile (QQ) Regression Results

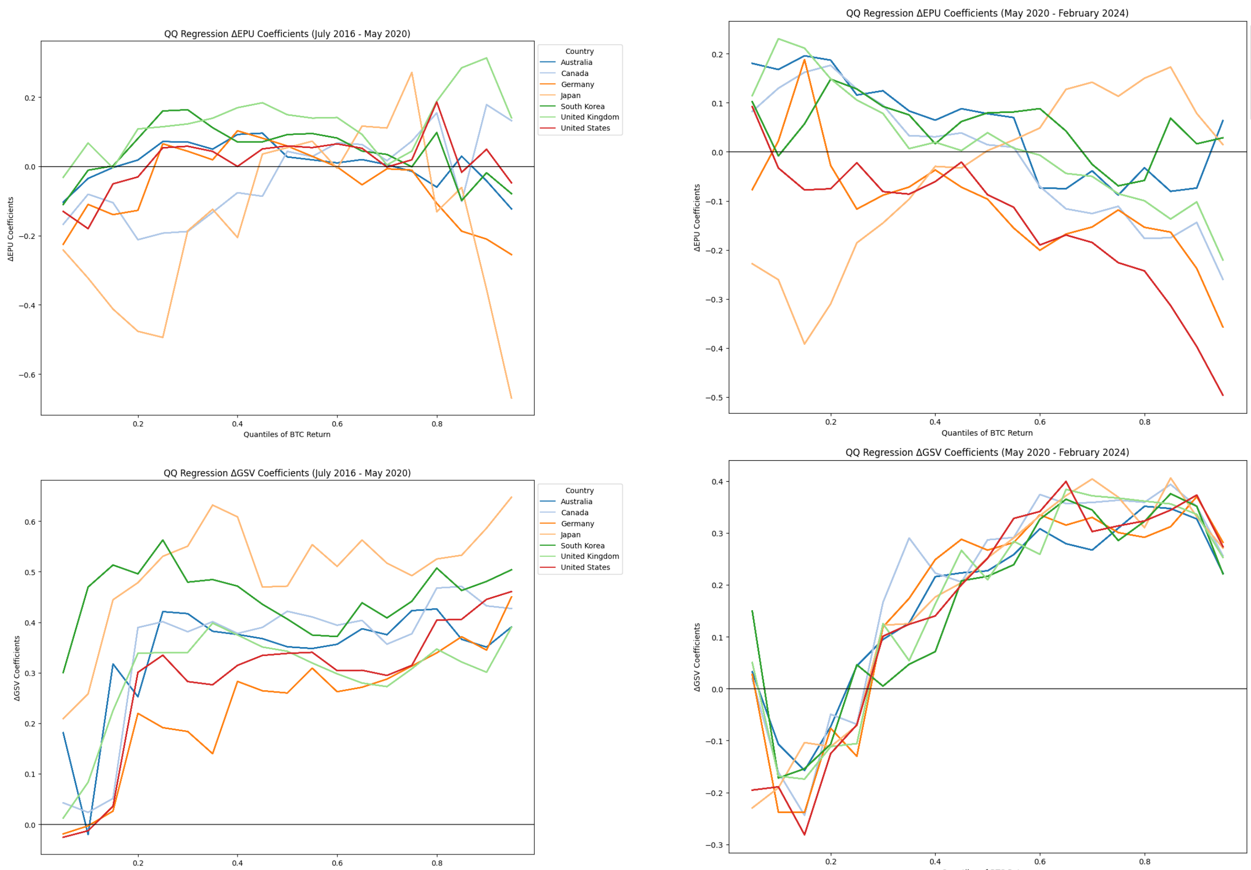
Appendix H shows the QQ regression results for EPU and GSV coefficients for each quantile of BTC return (Eq. 3.8). The coefficients are plotted in Figure 4.2.

In Period 1, EPU coefficients from the quantile regression show a weak and mostly insignificant relationship with BTC returns across all quantiles. EPU coefficients are centred around zero. This is especially the case for middle quantiles of BTC return, which tend to represent normal market conditions. We observe some abnormal behaviour for Japan at high quantiles of BTC return, suggesting that increases in EPU result in larger downside returns for the same period, although this relationship does not hold in the second period. In Period 2, we observe a similar trend of near zero and insignificant coefficients across all quantiles, but this relationship is particularly evident under normal market conditions. In addition, at the high quantiles of Bitcoin return, there is a clear negative relationship between EPU and BTC returns for Germany, Canada and the UK, although these relationships are insignificant. Contrary to findings from Demir et al. (2018) we do not find evidence to support the notion that the relationship between EPU and BTC returns is more pronounced at low and high quantiles of BTC return. We conclude that there are limited predictive abilities of EPU on BTC returns under any market conditions from the period 1 January 2015 to 1 February 2024.

Alternatively, the quantile relationship between BTC return and GSV is far more pronounced in both periods. In Period 1, we observe significant relationships from quantiles 0.15 to 0.90, but not at the extremities. That is, during bear market conditions, and at extreme bull market conditions GSV can not significantly explain BTC returns. However, in the middle and upper quantiles (representing more normal and bull market conditions), GSV has a positive and significant relationship with BTC returns. Furthermore, we observe significant and positive GSV coefficients in Period 2 from quantiles 0.40 - 0.90. This relationship generally exists across all countries. We find evidence to support the increased explanatory power of GSV at higher quantiles across both periods, except for extreme bull market conditions (the 95th quantile). Notably, the relationship between GSV and BTC return is near zero or even weakly negative at lower quantiles. Interestingly, from Period 1 to Period 2 we observe a diminishing effect of the predictive ability of GSV on BTC returns. However, in Period 2 we also observe a convergence in GSV coefficients across markets, indicating that regional attention in each market tends to explain a similar amount of BTC returns per market.

Ultimately, our results for EPU and GSV hold up over different market conditions. For added robustness, we ran the same QQ regression for 0.1 quantile increments of BTC return and found nearly identical results to those displayed in Figure 4.2 and Appendix H.

Figure 4.2: QQ Regression Coefficients for EPU & GSV on BTC Return



Note: These figures illustrate the Quantile-on-Quantile (QQ) regression coefficients for Economic Policy Uncertainty (EPU) and Google Search Volume (GSV) on Bitcoin (BTC) returns across each country. The QQ regression examines the relationship between different quantiles of BTC returns and EPU/GSV, providing insights into how these predictor variables impact BTC returns under varying market conditions. The left panel shows 'Period 1' (from July 2016 to May 2020) representing the time between the second and third Bitcoin halving, and the right panel covers 'Period 2' (from May 2020 to February 2024) which represents the period between the third and fourth Bitcoin halving (up to the end of our sample period).

5. Discussion

Do regional Bitcoin markets respond to changes in local policy uncertainty and investor attention?

We find that investor attention and momentum effects positively impact regional BTC returns. And, investor attention leads to increased regional BTC volatility in all countries. Further, during bull market conditions investor attention has stronger explanatory power on BTC return, suggesting investor attention may catalyse momentum effects. This is likely due to the presence of retail investors in BTC markets, which during periods of high attention assets often experience rapid price adjustments as many investors enter the market with expectations of short-term gains, rather than long-term investment based on fundamentals, leading to inefficient markets. Retail investors often engage in these speculative behaviours driven by factors such as fear of missing out (FOMO), herd behaviour and psychological biases commonly referred to as "animal spirits" (Akerlof & Shiller, 2009). Also, crypto traders are known to herd more quickly in "up-events" (Ballis & Drakos, 2020), making crypto markets more prone to bubbles (Kaiser & Stöckl, 2020). Notwithstanding, it is unclear whether increased investor attention drives BTC price or whether the relationship exists in reverse. This is a possible topic for future study.

Regional Bitcoin markets do not respond to local EPU, implying ΔEPU is not an adequate risk factor for BTC. We propose that the heightened adoption of Bitcoin and its growing significance in the financial system are reasons why ΔEPU may not have a relationship with BTC. Further, our QQ results also contrast Demir et al. (2018) who find asymmetric relationships between EPU and BTC return across different quantiles of BTC return. There are several plausible reasons for these differing results. Prior studies were conducted at a time when there was greater uncertainty about Bitcoin's use and lower liquidity which could have led to more reactive responses to ΔEPU. Secondly, our use of monthly data may aggregate away the effects of ΔEPU on BTC. Finally and interestingly, the relationship between ΔEPU and BTC may have diminished since previous studies (similar to the diminishing explanatory power of GSV from Period 1 to Period 2 that we observe).

Do regional Bitcoin market Premia respond to changes in policy uncertainty and investor attention?

We find that South Korea and Australia have significant local Bitcoin premiums, and at varying points in time, all countries have large movements in premia. However, regional investor attention cannot explain premia, despite its strong relationship with Bitcoin return and volatility. Market frictions, including regulatory barriers, and market liquidity issues are the primary reasons for the persistence of premias. We find that an appreciation of the local currency against the USD is the most significant factor influencing local premia. Smith (2016) contends that Bitcoin prices are highly cointegrated with conventional market exchange rates, mirroring the relationship between physical gold and conventional nominal exchange rates. In contrast, depreciation of the dollar places pressure on investor sentiment, and therefore the observed relationship between Premia and foreign exchange rates may be more indicative of improvements in investor risk appetite. Finally, a stronger local currency means that local investors can buy Bitcoin more cheaply compared to those using a weaker currency. This increased purchasing power can drive up local demand for Bitcoin, leading to a local premium—consistent with the theory of Purchasing Power Parity (PPP).

Whilst there exists Premia, these varied significantly between markets. It is also apparent that markets with less liquidity typically exhibit higher spreads, as market shocks are poorly absorbed and result in price distortion. We believe this is the case in South Korean and Australian Bitcoin markets. Alternatively, BTC/EUR is the second most liquid market behind BTC/USD and has the lowest volatility. Furthermore, arbitrage opportunities are not new in Bitcoin markets, which tend to exist because of market inefficiency (Wüstenfeld & Geldner, 2022). For example, exchanges in Korea and Japan, which for extended periods were often trading more than 10% above other exchanges, have increased capital controls such as the absence of short selling and regulatory constraints. Finally, Choi et al. (2022) find that price risk during the transaction period makes trades less attractive for arbitrageurs, allowing prices to diverge.

6. Conclusion

In this paper, we examined the relationship between Bitcoin markets, uncertainty, and investor attention from a national perspective using multivariate, panel, and QQ regressions. Given the heterogeneous treatment of Bitcoin in use, purpose, and acceptance across different regions worldwide, we aimed to understand the impact of regional uncertainty and regional investor attention on local Bitcoin markets. We examine BTC markets under two primary factors: Economic Policy Uncertainty (EPU) and Google Search Volume (GSV). EPU was chosen due to its relevance to economic outcomes and policy impact on Bitcoin usage, while GSV was chosen as a measure of speculation and a key driver of Bitcoin returns. After we found the prevalence of speculation and momentum effects in Bitcoin markets, we became further interested in the efficiency of Bitcoin markets and whether we could find a relationship with regional Bitcoin premia.

Our key findings can be summarised as follows: (i) Heightened investor attention, a measure of speculation and investor sentiment, is the largest driver of Bitcoin returns and volatility, underscoring Bitcoin's sensitivity to shifts in market sentiment rather than economic fundamentals. We suggest investors looking to enter Bitcoin markets avoid periods of high investor attention due to increased volatility. In contrast, momentum trading (trading at times of high investor attention) may be effective in Bitcoin markets due to self-perpetuating market trends. Overall, investment in Bitcoin should be regarded as speculative, and policymakers should acknowledge that Bitcoin markets are inefficient and heavily influenced by irrational investors. (ii) Bitcoin markets are not influenced by regional policy uncertainty. This contrasts with previous findings, which we propose is due to the higher adoption and liquidity of Bitcoin in recent years, making it less susceptible to uncertainty. (iii) Traditional asset pricing models, such as the Fama-French Five-Factor Model, are poor predictors of Bitcoin returns because these models fail to capture Bitcoin-specific risk factors. These include non-traditional measures such as speculative behaviour and momentum effects. Due to the evolving nature of Bitcoin, we anticipate these risk factors will continue to evolve. (iv) Finally, the existence of Bitcoin premia between markets suggests Bitcoin markets are inefficient. These premia are best explained by movements in foreign exchange rates. Appreciation in the local currency against the USD resulted in significant upward movements in local Bitcoin prices, reflecting a strong connection between Bitcoin prices and conventional market exchange rates. Smaller and more persistent premias can be better explained by market inefficiencies and capital frictions. Regional Bitcoin premia can potentially be "arbitraged", especially by dual nationals who can access markets with capital constraints, such as in South Korea. However, due to restrictions such as the absence of short-selling, investors cannot lock in profits. Therefore these trades are not risk-free.

Future research can explore how changes in GSV for different search terms, particularly those associated with major speculative trends (e.g. "Bitcoin halving" or "cryptocurrency regulation"), influence Bitcoin's market dynamics. This could provide insights into the role of investor attention in driving Bitcoin markets during unique periods of investor speculation.

References

Aastveit, K. A., Natvik, G. J. J., & Sola, S. (2013). Economic Uncertainty and the Effectiveness of Monetary Policy, SSRN Scholarly Paper, 2353008.

Andrei, D., & Hasler, M. (2015). Investor Attention and Stock Market Volatility, The Review of Financial Studies, vol. 28, no. 1, pp. 33–72.

Arbatli, E. C., Davis, S. J., Ito, A., & Miake, N. (2017). Policy Uncertainty in Japan, ERN: Other Macroeconomics: Monetary & Fiscal Policies.

Auer, R., & Claessens, S. (2021). Cryptocurrency Market Reactions to Regulatory News, in The Routledge Handbook of FinTech, Routledge.

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, vol. 47, pp. 511–518.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty, The Quarterly Journal of Economics, vol. 131, no. 4, pp. 1593–1636.

Ballis, A., & Drakos, K. (2020). Testing for herding in the cryptocurrency market, Finance Research Letters, 33, 101210.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of Exchange or Speculative Assets?, Journal of International Financial Markets, Institutions and Money, vol. 54, pp. 177–189.

Baur, D. G., & McDermott, T. K. (2010). Is Gold a Safe Haven? International Evidence, Journal of Banking & Finance, vol. 34, no. 8, pp. 1886–1898.

Beckmann, J., Berger, T., & Czudaj, R. (2016). Oil Price and FX-Rates Dependency, Quantitative Finance, vol. 16, no. 3, pp. 477–488.

Ben Nouir, J., & Ben Haj Hamida, H. (2023). How Do Economic Policy Uncertainty and Geopolitical Risk Drive Bitcoin Volatility?, Research in International Business and Finance, vol. 64, 101809.

Bouoiyour, J., & Selmi, R. (2015). What Does Bitcoin Look Like?, Annals of Economics and Finance, vol. 16, pp. 449–492.

Bouri, E., & Gupta, R. (2021). Predicting Bitcoin Returns: Comparing the Roles of Newspaper- and Internet Search-Based Measures of Uncertainty, Finance Research Letters, vol. 38, 101398.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin Hedge Global Uncertainty? Evidence from Wavelet-Based Quantile-in-Quantile Regressions, Finance Research Letters, vol. 23, pp. 87–95.

Brauneis, A., Mestel, R., & Theissen, E. (2021). What Drives the Liquidity of Cryptocurrencies? A Long-Term Analysis, Finance Research Letters, vol. 39, 101537.

Bukovina, J., & Martiček, M. (2016). Sentiment and Bitcoin Volatility, MENDELU Working Papers in Business and Economics, 58/2016. Mendel University in Brno, Faculty of Business and Economics.

Caggiano, G., Castelnuovo, E., & Figueres, J. M. (2017). Economic Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach, Economics Letters, vol. 151, pp. 31–34.

Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk, American Economic Review, vol. 112, no. 4, pp. 1194–1225.

Cheng, Q., Liu, X., & Zhu, X. (2019). Cryptocurrency momentum effect: DFA and MF-DFA analysis.

Cheng, H.-P., & Yen, K.-C. (2020). The Relationship between the Economic Policy Uncertainty and the Cryptocurrency Market, Finance Research Letters, vol. 35, 101308.

Choi, K. J., Lehar, A., & Stauffer, R. (2022). Bitcoin Microstructure and the Kimchi Premium, SSRN Scholarly Paper, 3189051.

Christou, C., Gupta, R., & Hassapis, C. (2017). Does Economic Policy Uncertainty Forecast Real Housing Returns in a Panel of OECD Countries? A Bayesian Approach, The Quarterly Review of Economics and Finance, vol. 65, pp. 50–60.

Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2016). The economics of BitCoin price formation, Applied Economics, 48(19), 1799–1815.

Colon, F., Kim, C., Kim, H., & Kim, W. (2021). The Effect of Political and Economic Uncertainty on the Cryptocurrency Market, Finance Research Letters, vol. 39, 101621.

Conlon, T., Corbet, S., & McGee, R. J. (2020). Are Cryptocurrencies a Safe Haven for Equity Markets? An International Perspective from the COVID-19 Pandemic, Research in International Business and Finance, vol. 54, 101248.

Craig, B. R., & Kachovec, J. (2019). Bitcoin's Decentralized Decision Structure, Economic Commentary, [e-journal] no. 2019–12.

Da, Z., Engelberg, J., & Gao, P. (2011a). In Search of Attention, The Journal of Finance, vol. 66, no. 5, pp. 1461–1499.

Da, Z., Engelberg, J., & Gao, P. (2011b). In Search of Fundamentals, SSRN Scholarly Paper, 1589805.

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of All FEARS Investor Sentiment and Asset Prices, The Review of Financial Studies, vol. 28, no. 1, pp. 1–32.

Dastgir, S., Demir, E., Downing, G., Gozgor, G., & Lau, C. K. M. (2019). The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test, Finance Research Letters, 28, pp.

160-164.

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, vol. 26, pp. 145–149.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets, Journal of Political Economy, 98(4), pp. 703-738.

Ding, R., & Hou, W. (2015). Retail Investor Attention and Stock Liquidity, Journal of International Financial Markets, Institutions and Money, vol. 37, pp. 12–26.

Dzielinski, M. (2012). Measuring Economic Uncertainty and Its Impact on the Stock Market, Finance Research Letters, vol. 9, no. 3, pp. 167–175.

Eom, C., Kaizoji, T., Kang, S. H., & Pichl, L. (2019). Bitcoin and Investor Sentiment: Statistical Characteristics and Predictability, Physica A: Statistical Mechanics and its Applications, vol. 514, pp. 511–521.

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model, Journal of Financial Economics, vol. 116, no. 1, pp. 1–22.

Fama, E. F., & French, K. R. (2017). International Tests of a Five-Factor Asset Pricing Model, Journal of Financial Economics, vol. 123, no. 3, pp. 441–463.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance, 25(2), pp. 383–417.

Ferreira, P. (2023). South Korea's Short Selling Ban: Is it Time for a Blockchain-Based Stock Exchange?, Finance Magnates, Available Online: https://www.financemagnates.com/forex/south-koreas-short-selling-ban-is-it-time-for-a-blockchain-based-stock-exchange/.

Gandal, N., Hamrick, J., Moore, T., & Oberman, T. (2018). Price Manipulation in the Bitcoin Ecosystem, Journal of Monetary Economics, vol. 95, pp. 86–96.

Ghorbel, A., & Jeribi, A. (2021). Investigating the relationship between volatilities of cryptocurrencies and other financial assets, Decisions in Economics and Finance.

Giudici, P., & Pagnottoni, P. (2019). High Frequency Price Change Spillovers in Bitcoin Markets, Risks, vol. 7, no. 4, p. 111.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior.

Hasan, M. B., Mahi, M., Hassan, M. K., & Bhuiyan, A. B. (2021). Higher moment connectedness in cryptocurrency market, Journal of Behavioral and Experimental Finance, 32, 100560.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, The Journal of Finance, vol. 48, no. 1, pp. 65-91.

Jubinski, D., & Lipton, A. F. (2011). Equity volatility, bond yields, and yield spreads.

Kaiser, L., & Stöckl, S. (2020). Cryptocurrencies: Herding and the transfer currency, Finance Research Letters.

Kido, Y. (2016). On the Link between the US Economic Policy Uncertainty and Exchange Rates, Economics Letters, vol. 144, pp. 49–52.

Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). Bitcoin: Safe Haven, Hedge or Diversifier? Perception of Bitcoin in the Context of a Country's Economic Situation — A Stochastic Volatility Approach, Physica A: Statistical Mechanics and its Applications, vol. 524, pp. 246–257.

Kliber, A., & Świerczyńska, K. (2019). Bitcoin as a Panacea for the Venezuelan Crisis, in European Financial Systems 2019: Proceedings of the 16th International Scientific Conference.

Kristoufek, L. (2013). BitCoin Meets Google Trends and Wikipedia: Quantifying the Relationship between Phenomena of the Internet Era, Scientific Reports, vol. 3, no. 1, p. 3415.

Kyriazis, . A. (2020). The Effects of Geopolitical Uncertainty on Cryptocurrencies and Other Financial Assets, SN Business & Economics, vol. 1, no. 1, p. 5.

Li, X.-M., & Peng, L. (2017). US Economic Policy Uncertainty and Co-Movements between Chinese and US Stock Markets, Economic Modelling, vol. 61, pp. 27–39.

Lim, H. J. (2024). In the wake of bitcoin's new highs, South Korea's 'kimchi premium' is in the spotlight again, CNBC, Available Online: https://www.cnbc.com/2024/04/03/south-koreas-kimchi-premium-in-the-spotlight-after-btcs-record-highs.html.

Liu, L., & Zhang, T. (2015). Economic Policy Uncertainty and Stock Market Volatility, Finance Research Letters, vol. 15, pp. 99–105.

Liu, Y., & Tsyvinski, A. (2021). Risks and Returns of Cryptocurrency, The Review of Financial Studies, vol. 34, no. 6, pp. 2689–2727.

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common Risk Factors in Cryptocurrency, The Journal of Finance, vol. 77, no. 2, pp. 1133-1177.

Lucey, B. M., Vigne, S. A., Yarovaya, L., & Wang, Y. (2022). The Cryptocurrency Uncertainty Index, Finance Research

Letters, vol. 45, 102147.

Matta, M., Lunesu, I., & Marchesi, M. (2015). The Predictor Impact of Web Search Media on Bitcoin Trading Volumes, in 2015 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K), November 2015, pp. 620–626.

Mokni, K., Ajmi, A. N., Bouri, E., & Vo, X. V. (2020). Economic Policy Uncertainty and the Bitcoin-US Stock Nexus, Journal of Multinational Financial Management, vol. 57–58, 100656.

Mondria, J., Wu, T., & Zhang, Y. (2010). The Determinants of International Investment and Attention Allocation: Using Internet Search Query Data, Journal of International Economics, vol. 82, no. 1, pp. 85–95.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System, 2008.

Panagiotidis, T., Stengos, T., & Vravosinos, O. (2018). On the Determinants of Bitcoin Returns: A LASSO Approach, Finance Research Letters, vol. 27, pp. 235–240.

Park, D. (2024). Bitcoin's 'kimchi premium' hits two-year high in South Korea, The Block, Available Online: https://www.theblock.co/post/281018/bitcoins-kimchi-premium-hits-two-year-high.

Phan, D. H. B., Sharma, S. S., & Tran, V. T. (2018). Can Economic Policy Uncertainty Predict Stock Returns? Global Evidence, Journal of International Financial Markets, Institutions and Money, vol. 55, pp. 134–150.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry, International Journal of Electronic Commerce, vol. 20, no. 1, pp. 9–49.

Scheffel, E. M. (2016). Accounting for the Political Uncertainty Factor, Journal of Applied Econometrics, vol. 31, no. 6, pp. 1048–1064.

Sensoy, A. (2019). The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies, Finance Research Letters, vol. 28, pp. 68-73.

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, vol. 63, pp. 322–330.

Smales, L. A. (2022). Investor Attention in Cryptocurrency Markets, International Review of Financial Analysis, vol. 79, 101972.

Smith, J. (2016). An Analysis of Bitcoin Exchange Rates. Innovation Finance & Accounting eJournal.

Sun, X., Yao, X., & Wang, J. (2017). Dynamic Interaction between Economic Policy Uncertainty and Financial Stress: A Multi-Scale Correlation Framework, Finance Research Letters, vol. 21, pp. 214–221.

Tsai, I.-C. (2017). The Source of Global Stock Market Risk: A Viewpoint of Economic Policy Uncertainty, Economic Modelling, vol. 60, pp. 122–131.

Umar, M., Shahzad, F., Ullah, I., & Fanghua, T. (2023). A Comparative Analysis of Cryptocurrency Returns and Economic Policy Uncertainty Pre- and Post-Covid-19, Research in International Business and Finance, vol. 65, 101965.

Urquhart, A. (2016). The inefficiency of Bitcoin, Economics Letters, vol. 148, pp. 80–82.

Urquhart, A. (2018). What Causes the Attention of Bitcoin?, Economics Letters, vol. 166, pp. 40–44.

Vlastakis, N., & Markellos, R. N. (2012). Information Demand and Stock Market Volatility, Journal of Banking & Finance, vol. 36, no. 6, pp. 1808–1821.

Vozlyublennaia, N. (2011). The cross-section of dynamics in idiosyncratic risk. Journal of Empirical Finance, 18(3), pp. 483-502.

Wang, G.-J., Xie, C., Wen, D., & Zhao, L. (2019). When Bitcoin Meets Economic Policy Uncertainty (EPU): Measuring Risk Spillover Effect from EPU to Bitcoin, Finance Research Letters.

Wang, P., Li, X., Shen, D., & Zhang, W. (2020). How Does Economic Policy Uncertainty Affect the Bitcoin Market?, Research in International Business and Finance, vol. 53, 101234.

Wang, Y., Chen, C. R., & Huang, Y. S. (2014). Economic Policy Uncertainty and Corporate Investment: Evidence from China, Pacific-Basin Finance Journal, vol. 26, pp. 227–243.

Wang, Y., Zhang, B., Diao, X., & Wu, C. (2015). Commodity Price Changes and the Predictability of Economic Policy Uncertainty, Economics Letters, vol. 127, pp. 39–42.

Wüstenfeld, J., & Geldner, T. (2022). Economic Uncertainty and National Bitcoin Trading Activity, The North American Journal of Economics and Finance, vol. 59, 101625.

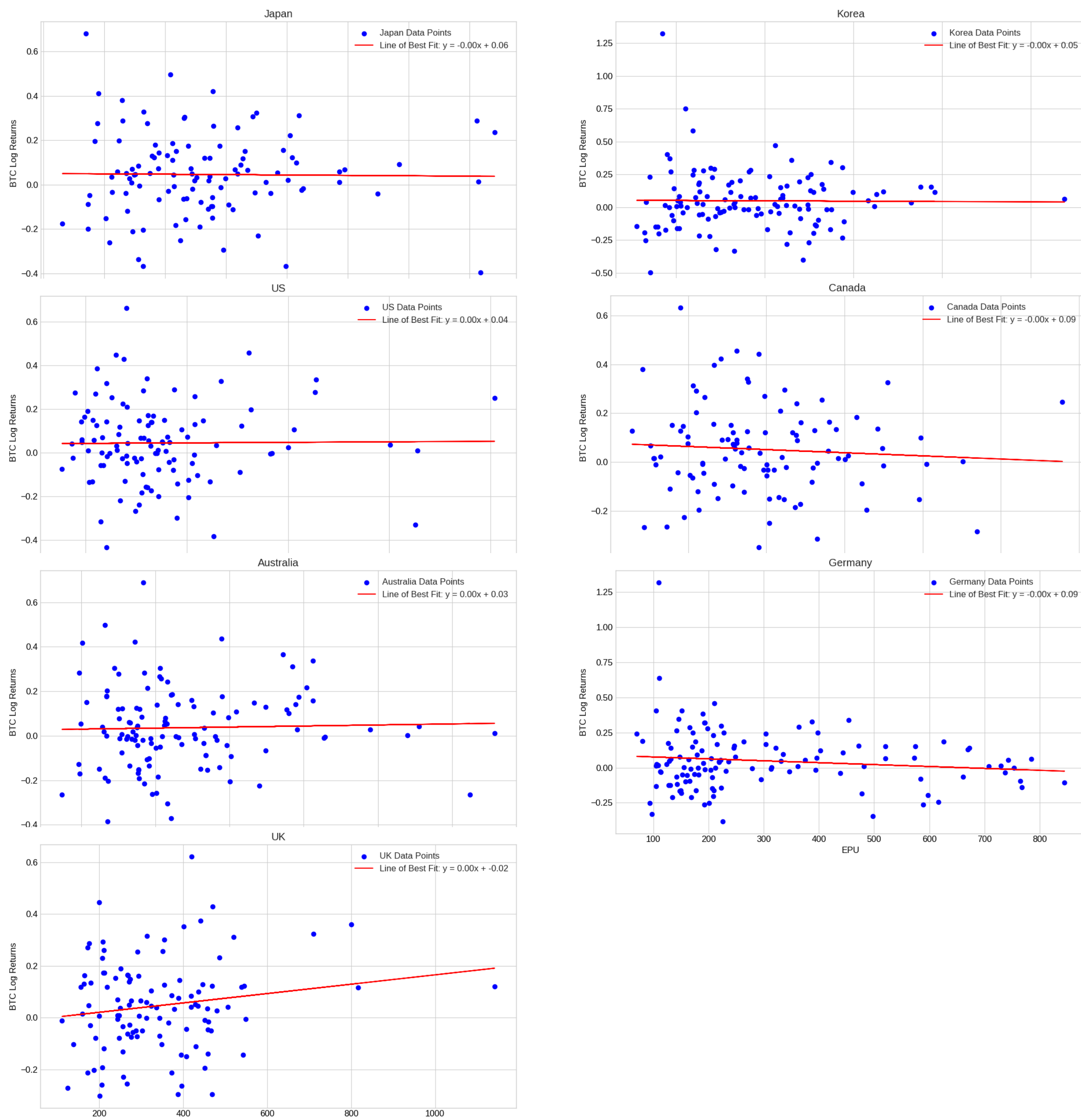
Yen, K.-C., & Cheng, H.-P. (2021). Economic Policy Uncertainty and Cryptocurrency Volatility, Finance Research Letters, vol. 38, 101428.

Zhang, G., Han, J., Pan, Z., & Huang, H. (2015). Economic Policy Uncertainty and Capital Structure Choice: Evidence from China, Economic Systems, vol. 39, no. 3, pp. 439–457.

Zhu, P., Zhang, X., Wu, Y., Zheng, H., & Zhang, Y. (2021). Investor Attention and Cryptocurrency: Evidence from the Bitcoin Market, PLOS ONE, vol. 16, no. 2, e0246331.

Appendix A

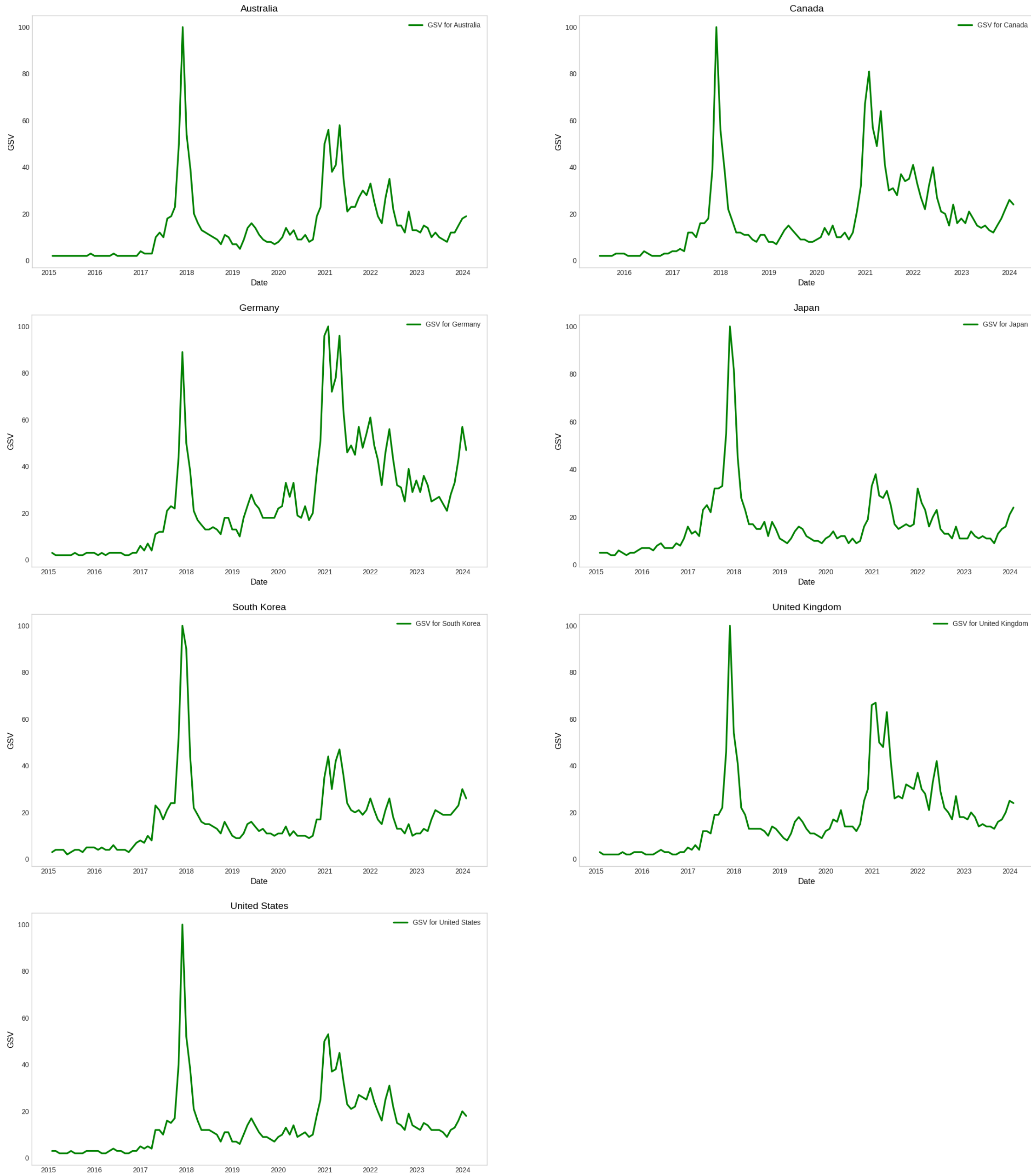
Figure A.1: Country-Specific EPU & Regional BTC Return



Note: These figures display the scatterplots of Economic Policy Uncertainty (EPU) against Bitcoin log returns for seven selected countries—Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States. Each plot includes data points representing the observed values and a line of best fit to illustrate the relationship between EPU and Bitcoin log returns. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Appendix B

Figure B.1: Google Search Volume (GSV) for Bitcoin in Selected Countries (2015-2024)



Note: GSV refers to the search of the word "Bitcoin" in each country. These figures illustrate the Google Search Volume (GSV) for Bitcoin in seven countries—Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States—from 1 January 2015 to 1 February 2024, except Canada (1 July 2015 to 1 February 2024). The GSV index is scaled between 0 and 100, with 100 representing the peak search interest for Bitcoin within the specified time frame and location. Each graph shows the trend and variability in search volume, highlighting periods of significant spikes that correspond to increased public and market interest.

Appendix C

This Appendix shows the methodology and results of the Bitcoin return univariate regression.

We use the following model:

$$BTCR_{it} = \beta_0 + \beta_1 \text{Predictor}_{it} + \epsilon_i \tag{6.1}$$

Where $BTCR_{it}$ is Bitcoin returns at country i in month t. We use the following predictors:

Predictor	**Description**
ΔGSV_{it}	Google Search Volume for Bitcoin at country i in month t
ΔEPU_{it}	Economic Policy Uncertainty Index at country i in month t
ΔVIX_{it}	Market Volatility Index at country i in month t
ΔGPR_{it}	Geopolitical Risk Index at country i in month t
$\Delta UCRY_{it}$	Cryptocurrency Uncertainty Index at country i in month t
ΔFX_{it}	Foreign Exchange rate changes at country i in month t

This Appendix contains the univariate regression results using BTC returns as the dependent variable (from Eq. 6.1). We observe near-zero and insignificant coefficients for EPU, UCRY, VIX and GPR across all markets. For FX, only Canada was significant at the 10% level. Furthermore, GSV was significant for all markets at the 1% level, with stronger positive relationships in Canada, Japan and the US. Germany exhibited the weakest relationship between GSV and BTC returns.

Due to data availability of the UCRY Policy index we initially tested a sample period for all markets that ended 1 June 2023. However, after observing near zero and insignificant UCRY coefficients across all markets, we dropped UCRY from our multivariate model and ran the complete data set from 1 January 2015 to 1 February 2024. These findings echo those of Smales (2022), who contends that crypto uncertainty does not impact BTC, but rather exerts influence on smaller cryptocurrencies. BTC was recently designated as a commodity by the CFTC and is not undergoing scrutiny for being classified as a security, as is the case with Ripple, Ethereum, and numerous other cryptocurrencies.

Table C.1: Results for Predictor: ΔGSV

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.041***	0.043***	0.040**	0.042**	0.042**	0.042***	0.040**
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
ΔGSV	0.287***	0.333***	0.215***	0.336***	0.309***	0.255***	0.296***
	(0.048)	(0.048)	(0.052)	(0.067)	(0.056)	(0.051)	(0.050)
Adj. R-squared	0.242	0.310	0.130	0.181	0.211	0.179	0.237
F-statistic	35.798	47.345	17.286	25.117	30.203	24.839	34.855
Observations	110	104	110	110	110	110	110

Table C.2: Results for Predictor: ΔEPU

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.047***	0.051***	0.047***	0.047***	0.047**	0.047***	0.045**
	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)
ΔEPU	0.007	-0.021	-0.069	-0.102	0.053	0.061	-0.040
	(0.043)	(0.058)	(0.053)	(0.105)	(0.062)	(0.057)	(0.061)
Adj. R-squared	-0.009	-0.009	0.006	-0.000	-0.002	0.001	-0.005
F-statistic	0.024	0.127	1.690	0.947	0.747	1.151	0.432
Observations	110	104	110	110	110	110	110

Table C.3: Results for Predictor: ΔVIX

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.047***	0.051***	0.046***	0.047**	0.047**	0.047***	0.044**
	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)
ΔVIX	-0.146	-0.045	-0.037	-0.043	-0.023	-0.047	-0.064
	(0.090)	(0.097)	(0.084)	(0.085)	(0.091)	(0.066)	(0.070)
Adj. R-squared	0.014	-0.008	-0.007	-0.007	-0.009	-0.005	-0.001
F-statistic	2.600	0.215	0.197	0.260	0.066	0.505	0.851
Observations	110	104	110	110	110	110	110

Table C.4: Results for Predictor: ΔGPR

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.047***	0.051***	0.046***	0.047***	0.047**	0.046***	0.044**
	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)
ΔGPR	0.038	0.021	0.036	0.029	-0.004	0.083	0.072
	(0.026)	(0.039)	(0.040)	(0.034)	(0.040)	(0.058)	(0.073)
Adj. R-squared	0.011	-0.007	-0.002	-0.003	-0.009	0.009	-0.000
F-statistic	2.203	0.288	0.832	0.722	0.012	2.007	0.983
Observations	110	104	110	110	110	110	110

Table C.5: Results for Predictor: ΔUCRY

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.034*	0.049**	0.034*	0.043**	0.033*	0.043**	0.033*
	(0.018)	(0.019)	(0.017)	(0.019)	(0.019)	(0.018)	(0.019)
ΔUCRY	0.803	0.229	1.053	0.457	0.925	0.075	0.925
	(1.331)	(1.517)	(1.311)	(1.567)	(1.394)	(1.474)	(1.394)
Adj. R-squared	-0.006	-0.010	-0.003	-0.009	-0.005	-0.010	-0.005
F-statistic	0.364	0.023	0.645	0.085	0.441	0.003	0.441
Observations	113	96	113	103	113	103	113

Table C.6: Results for Predictor: ΔFX

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.049***	0.053***	0.047***	0.046**	0.048**	0.046***	0.046**
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)
ΔFX	1.099*	1.683*	0.663	-0.486	0.291	-0.275	-1.190
	(0.591)	(0.864)	(0.805)	(0.694)	(0.701)	(0.678)	(0.914)
Adj. R-squared	0.022	0.026	-0.003	-0.005	-0.008	-0.008	0.006
F-statistic	3.457	3.792	0.677	0.489	0.173	0.164	1.693
Observations	110	104	110	110	110	110	110

Note: These tables present the univariate regression results of Bitcoin returns against various independent variables across seven countries: Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States for the variables GSV, EPU, VIX, GPR, UCRY, and FX. The constant and the coefficient for each independent variable are reported alongside their standard errors in parentheses. The adjusted R-squared (Adj. R^2), F-statistic, and the number of observations (No. Obs.) are also included. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% significance, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Appendix D

This Appendix shows the methodology and results of the Bitcoin volatility univariate regression.

We use the following model:

$$BTCVol_{it} = \beta_0 + \beta_1 \text{Predictor}_{it} + \epsilon_i \tag{6.2}$$

Where $BTCVol_{it}$ is Bitcoin volatility at country i in month t. We use the following predictors:

Predictor	**Description**
ΔGSV_{it}	Google Search Volume for Bitcoin at country i in month t
ΔEPU_{it}	Economic Policy Uncertainty Index at country i in month t
ΔVIX_{it}	Market Volatility Index (VIX) at country i in month t
ΔGPR_{it}	Geopolitical Risk Index at country i in month t
$\Delta UCRY_{it}$	Cryptocurrency Uncertainty Index at country i in month t
ΔFX_{it}	Foreign Exchange rate changes at country i in month t

This Appendix contains univariate regression results using BTC volatility as the dependent variable (from Eq. 6.2). Similar to the univariate regressions for BTC returns, UCRY, VIX, GPR and FX were all near zero and insignificant. EPU was also near zero and insignificant for all markets. Again, GSV was significant at 1% for all markets. A 1% increase in GSV correlates to a 25% increase in monthly volatility on average. Furthermore, the constant term is significant across all regressions, indicating some baseline level of monthly volatility of approximately 14%.

Table D.1: Results for Predictor: ΔGSV

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.136***	0.135***	0.136***	0.143***	0.141***	0.136***	0.138***
	(0.010)	(0.009)	(0.010)	(0.011)	(0.011)	(0.009)	(0.010)
ΔGSV	0.239***	0.272***	0.202***	0.251***	0.221***	0.221***	0.246***
	(0.030)	(0.029)	(0.032)	(0.044)	(0.039)	(0.031)	(0.031)
Adj. R-squared	0.359	0.452	0.265	0.228	0.221	0.318	0.357
F-statistic	61.972	85.881	40.381	33.248	31.980	51.893	61.506
Observations	110	104	110	110	110	110	110

Table D.2: Results for Predictor: ΔEPU

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.141***	0.141***	0.142***	0.146***	0.145***	0.140***	0.142***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)	(0.012)
ΔEPU	-0.023	-0.034	-0.031	0.091	0.040	-0.011	0.028
	(0.029)	(0.039)	(0.035)	(0.070)	(0.043)	(0.037)	(0.041)
Adj. R-squared	-0.003	-0.002	-0.002	0.006	-0.001	-0.008	-0.005
F-statistic	0.632	0.760	0.781	1.692	0.847	0.089	0.463
Observations	110	104	110	110	110	110	110

Table D.3: Results for Predictor: ΔVIX

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.141***	0.141***	0.142***	0.146***	0.145***	0.140***	0.142***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)	(0.012)
ΔVIX	0.023	-0.058	0.041	-0.006	0.026	0.018	0.026
	(0.063)	(0.065)	(0.056)	(0.057)	(0.063)	(0.044)	(0.048)
Adj. R-squared	-0.008	-0.002	-0.004	-0.009	-0.008	-0.008	-0.006
F-statistic	0.128	0.777	0.523	0.011	0.174	0.167	0.297
Observations	110	104	110	110	110	110	110

Table D.4: Results for Predictor: ΔGPR

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.141***	0.141***	0.141***	0.146***	0.145***	0.140***	0.142***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)	(0.012)
ΔGPR	0.004	0.019	-0.004	-0.008	-0.014	0.054	0.037
	(0.018)	(0.026)	(0.027)	(0.023)	(0.028)	(0.038)	(0.050)
Adj. R-squared	-0.009	-0.005	-0.009	-0.008	-0.007	0.009	-0.004
F-statistic	0.055	0.529	0.025	0.127	0.267	2.001	0.549
Observations	110	104	110	110	110	110	110

Table D.5: Results for Predictor: ΔUCRY

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.034*	0.049**	0.034*	0.043**	0.033*	0.043**	0.033*
	(0.018)	(0.019)	(0.017)	(0.019)	(0.019)	(0.018)	(0.019)
ΔUCRY	0.803	0.229	1.053	0.457	0.925	0.075	0.925
	(1.331)	(1.517)	(1.311)	(1.567)	(1.394)	(1.474)	(1.394)
Adj. R-squared	-0.006	-0.010	-0.003	-0.009	-0.005	-0.010	-0.005
F-statistic	0.364	0.023	0.645	0.085	0.441	0.003	0.441
Observations	102	102	102	102	102	102	102

Table D.6: Results for Predictor: ΔFX

	Australia	Canada	Germany	Japan	South Korea	UK	US
const	0.141***	0.141***	0.142***	0.147***	0.145***	0.139***	0.143***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)	(0.012)
ΔFX	-0.007	-0.309	0.266	0.261	0.250	-0.412	-0.254
	(0.413)	(0.597)	(0.540)	(0.466)	(0.490)	(0.445)	(0.627)
Adj. R-squared	-0.009	-0.007	-0.007	-0.006	-0.007	-0.001	-0.008
F-statistic	0.000	0.268	0.242	0.314	0.261	0.860	0.164
Observations	110	104	110	110	110	110	110

Note: These tables present the univariate regression results of Bitcoin volatility against various independent variables across seven countries: Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States for the variables GSV, EPU, VIX, GPR, UCRY, and FX. The constant and the coefficient for each independent variable are reported alongside their standard errors in parentheses. The adjusted R-squared (Adj. R^2), F-statistic, and the number of observations (No. Obs.) are also included. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% significance, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Appendix E

This Appendix shows the methodology and results of the Premia univariate regression.

We use the following model:

$$Premia_{it} = \beta_0 + \beta_1 \text{Predictor}_{it} + \epsilon_i \tag{6.3}$$

Where $Premia_{it}$ is the premia at country i in month t. We use the following predictors:

Predictor	**Description**
ΔGSV_{it}	Google Search Volume for Bitcoin at country i in month t
ΔEPU_{it}	Economic Policy Uncertainty Index at country i in month t
ΔVIX_{it}	Market Volatility Index (VIX) at country i in month t
ΔGPR_{it}	Geopolitical Risk Index at country i in month t
$\Delta UCRY_{it}$	Cryptocurrency Uncertainty Index at country i in month t
ΔFX_{it}	Foreign Exchange rate changes at country i in month t

Table E.1: Results for Predictor: ΔGSV

	Australia	Canada	Germany	Japan	South Korea	UK
const	-0.587***	0.298*	-0.035	-0.116	-1.570***	0.479
	(0.204)	(0.162)	(0.120)	(0.328)	(0.369)	(0.458)
ΔGSV	-1.206*	-0.822	-0.487	-1.068	-2.710**	-0.254
	(0.642)	(0.532)	(0.383)	(1.355)	(1.269)	(1.542)
Adj. R-squared	0.023	0.013	0.006	-0.003	0.032	-0.009
F-statistic	3.532	2.388	1.613	0.621	4.562	0.027
Observations	110	104	110	110	110	110

Table E.2: Results for Predictor: ΔEPU

	Australia	Canada	Germany	Japan	South Korea	UK
const	-0.613***	0.279*	-0.050	-0.130	-1.623***	0.478
	(0.206)	(0.163)	(0.120)	(0.327)	(0.375)	(0.456)
ΔEPU	0.377	-0.250	0.105	1.395	1.093	-1.258
	(0.501)	(0.535)	(0.368)	(1.921)	(1.256)	(1.541)
Adj. R-squared	-0.004	-0.008	-0.008	-0.004	-0.002	-0.003
F-statistic	0.564	0.219	0.082	0.527	0.757	0.667
Observations	110	104	110	110	110	110

Table E.3: Results for Predictor: ΔVIX

	Australia	Canada	Germany	Japan	South Korea	UK
const	-0.606***	0.278*	-0.045	-0.131	-1.621***	0.489
	(0.204)	(0.163)	(0.119)	(0.328)	(0.374)	(0.444)
ΔVIX	1.976*	0.610	0.781	0.131	2.036	4.556**
	(1.059)	(0.886)	(0.578)	(1.546)	(1.840)	(1.745)
Adj. R-squared	0.022	-0.005	0.008	-0.009	0.002	0.051
F-statistic	3.479	0.474	1.826	0.007	1.224	6.817
Observations	110	104	110	110	110	110

Table E.4: Results for Predictor: ΔGPR

	Australia	Canada	Germany	Japan	South Korea	UK
const	-0.611***	0.279*	-0.051	-0.128	-1.617***	0.469
	(0.207)	(0.164)	(0.120)	(0.326)	(0.376)	(0.457)
ΔGPR	-0.084	-0.074	0.226	-0.797	0.239	0.943
	(0.308)	(0.356)	(0.275)	(0.626)	(0.810)	(1.594)
Adj. R-squared	-0.009	-0.009	-0.003	0.006	-0.008	-0.006
F-statistic	0.075	0.044	0.672	1.623	0.087	0.350
Observations	110	104	110	110	110	110

Table E.5: Results for Predictor: ΔUCRY

	Australia	Canada	Germany	Japan	South Korea	UK
const	0.045**	0.052**	0.039**	0.050**	0.041**	0.048**
	(0.020)	(0.022)	(0.021)	(0.023)	(0.022)	(0.021)
ΔUCRY	1.103	0.629	1.353	0.757	1.225	0.375
	(1.400)	(1.600)	(1.450)	(1.620)	(1.510)	(1.560)
Adj. R-squared	0.015	0.011	0.017	0.010	0.014	0.009
F-statistic	1.024	0.543	1.145	0.785	1.021	0.633
Observations	102	102	102	102	102	102

Table E.6: Results for Predictor: ΔFX

	Australia	Canada	Germany	Japan	South Korea	UK
const	-0.721***	0.245*	-0.089	-0.245	-1.722***	0.426
	(0.146)	(0.144)	(0.090)	(0.300)	(0.346)	(0.455)
ΔFX	-52.197***	-39.246***	-38.252***	-53.955***	-59.165***	-25.659
	(4.971)	(7.098)	(4.215)	(11.596)	(13.118)	(18.242)
Adj. R-squared	0.501	0.223	0.427	0.159	0.151	0.009
F-statistic	110.255	30.570	82.352	21.648	20.341	1.978
Observations	110	104	110	110	110	110

Note: These tables present the univariate regression results of the calculated spread (Eq. X) against various independent variables across seven countries: Australia, Canada, Germany, Japan, South Korea, the United Kingdom, and the United States for the variables GSV, EPU, VIX, GPR, UCRY, and FX. The constant and the coefficient for each independent variable are reported alongside their standard errors in parentheses. The adjusted R-squared (Adj. R^2), F-statistic, and the number of observations (No. Obs.) are also included. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10% significance, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Appendix F

Table F.1: Bitcoin Return Panel Regression

Variable	Coefficient	Standard Error
const	0.029***	(0.000)
ΔADS	0.001	(0.591)
ΔCredit spread	-0.223***	(0.000)
Δ10-2Y TERM	0.003	(0.221)
ΔFX	0.124	(0.601)
ΔEPU	0.005	(0.775)
ΔGPR	0.030**	(0.014)
ΔVIX	-0.072***	(0.008)
ΔGSV	0.243***	(0.000)
BTC lag	0.256***	(0.000)

Panel Regression Summary	
Fixed Effects	Yes
R-squared (Within)	0.316
R-squared (Between)	-0.077
R-squared (Overall)	0.316
F-statistic	37.974
F-statistic (P-value)	0.000
No. Observations	757

Note: This table presents the results of the Bitcoin Return Panel Regression with country fixed effects. The coefficients indicate the relationship between each predictor and Bitcoin returns, with their respective standard errors in parentheses. Significant coefficients are marked as *p<0.1, **p<0.05, ***p<0.01. Fixed effects are used to control for unobserved heterogeneity across different countries, accounting for time-invariant differences in investor attention and uncertainty. The F-test for Poolability indicates no benefit to using a panel regression versus a pooled OLS regression, with an F-statistic of 0.021 and a P-value of 1.000. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table F.2: Bitcoin Volatility Panel Regression

Variable	Coefficient	Standard Error
const	0.136***	(0.000)
ΔADS	0.001	(0.319)
ΔCredit spread	0.064**	(0.046)
Δ10-2Y TERM	-0.002	(0.189)
ΔFX	-0.189	(0.238)
ΔEPU	-0.012	(0.332)
ΔGPR	0.006	(0.506)
ΔVIX	0.019	(0.291)
ΔGSV	0.238***	(0.000)
BTC Vol lag	0.015	(0.630)

Panel Regression Summary	
Fixed Effects	Yes
R-squared (Within)	0.324
R-squared (Between)	-0.900
R-squared (Overall)	0.324
F-statistic	39.516
F-statistic (P-value)	0.000
No. Observations	757

Note: This table presents the results of the Bitcoin Volatility Panel Regression with country fixed effects. The regression model includes multiple predictor variables. Significant coefficients are marked as *p<0.1, **p<0.05, ***p<0.01. Fixed effects are used to control for unobserved heterogeneity across different countries, accounting for time-invariant differences in investor attention and uncertainty. The F-test for Poolability indicates no significant benefit to using a panel regression versus a pooled OLS regression, as the F-statistic is 0.099 with a P-value of 0.996. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table F.3: Premia Panel Regression Results

Variable	**Coefficient**	**Standard Error**
const	-0.221**	(0.032)
ΔADS	0.008	(0.650)
ΔCredit spread	-0.518	(0.539)
Δ10-2Y TERM	0.076*	(0.093)
ΔFX	-47.342***	(0.000)
ΔEPU	-0.307	(0.348)
ΔGPR	-0.286	(0.171)
ΔVIX	0.196	(0.697)
ΔGSV	-0.382	(0.266)
Spread lag	0.478***	(0.000)

Panel Regression Summary	
Fixed Effects	Yes
R-squared (Within)	0.364
R-squared (Between)	0.722
R-squared (Overall)	0.381
F-statistic	40.335
F-statistic (P-value)	0.000
No. Observations	648

Note: This table presents the results of the Premia Panel Regression with country-fixed effects. The regression model includes multiple predictor variables. Significant coefficients are marked as *p<0.1, **p<0.05, ***p<0.01. Fixed effects are used to control for unobserved heterogeneity across different countries, accounting for time-invariant differences in investor attention and uncertainty. The results are presented in percentage terms (x.xx%). The F-test for Poolability indicates significant country-specific factors that should be accounted for, with an F-statistic of 2.523 and a P-value of 0.028. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Appendix G

Table G.1: Fama French Five-Factor Model Results

	Dependent variable: BTC Return				
	(1)	(2)	(3)	(4)	(5)
const	0.037**	0.037**	0.037**	0.039**	0.040**
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
Mkt-RF	0.793**	0.796**	0.767*	0.844**	0.745*
	(0.366)	(0.388)	(0.389)	(0.399)	(0.411)
SMB		-0.000	0.002	-0.002	-0.002
		(0.006)	(0.007)	(0.008)	(0.008)
HML			-0.005	-0.003	0.001
			(0.005)	(0.005)	(0.007)
RMW				-0.008	-0.008
				(0.009)	(0.009)
CMA					-0.010
					(0.010)
Adj. R-squared	0.033	0.024	0.023	0.021	0.021
No. Observations	110	110	110	110	110

Note: This table shows the spanning regression results from the Fama & French 5 Factor Model : $E(R_{\mathrm{BTC},t}) = R_f + \beta_{\mathrm{MKT}} + \ldots + \varepsilon_t$, t = monthly. The dependent variable is the US Total Market Bitcoin Return. The sample period of our analysis is from 1 January 2015 to 1 February 2024. The regression coefficients (α, Mkt-RF, SMB, HML, RMW, and CMA) are reported along with their standard errors in parentheses. The adjusted R-squared (Adj. R^2) and the number of observations (No. Obs.) are also provided. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix H

Table H.1: QQ Results for EPU 2016-2020

Quantile	Australia	Canada	Germany	Japan	South Korea	UK	US
0.05	-0.104	-0.168	-0.225	-0.242	-0.110	-0.032	-0.130
0.10	-0.035	-0.081	-0.110	-0.323	-0.011	0.067	-0.180
0.15	-0.004	-0.105	-0.140	-0.412	0.001	-0.005	-0.051
0.20	0.018	-0.212	-0.127	-0.476	0.080	0.108	-0.031
0.25	0.071	-0.193	0.065	-0.494	0.160	0.114	0.053
0.30	0.070	-0.188	0.043	-0.186	0.163	0.122	0.058
0.35	0.049	-0.133	0.019	-0.124	0.111	0.139	0.043
0.40	0.092	-0.076	0.102	-0.206	0.070	0.169	-0.000
0.45	0.096	-0.087	0.081	0.035	0.071	0.183	0.050
0.50	0.027	0.043	0.059	0.054	0.092	0.149	0.059
0.55	0.019	0.028	0.029	0.072	0.095	0.139	0.054
0.60	0.010	0.068	-0.002	-0.006	0.082	0.141	0.065
0.65	0.019	0.063	-0.053	0.116	0.044	0.092	0.052
0.70	0.005	0.016	-0.007	0.110	0.034	0.004	-0.002
0.75	-0.015	0.073	-0.011	0.271	-0.002	0.044	0.019
0.80	-0.060	0.154	-0.107	-0.131	0.097	0.188	0.186
0.85	0.029	-0.102	-0.187	-0.061	-0.099	0.284*	-0.017
0.90	-0.042	0.178	-0.210	-0.355*	-0.019	0.313**	0.049
0.95	-0.123	0.132	-0.255	-0.669	-0.079	0.140	-0.048

Note: This table presents QQ regression results for EPU and BTC returns across the selected countries from July 2016 to May 2020 (period from second to third BTC halving). The coefficients for different quantiles are marked with * and ** indicating statistical significance at the 10% and 5% levels, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table H.2: QQ Results for EPU 2020-2024

Quantile	Australia	Canada	Germany	Japan	South Korea	UK	US
0.05	0.180	0.082	-0.077	-0.228	0.102	0.114	0.092
0.10	0.168	0.130	0.022	-0.261	-0.008	0.231	-0.033
0.15	0.196*	0.162	0.188	-0.392**	0.057	0.211	-0.078
0.20	0.187*	0.176	-0.028	-0.310*	0.148	0.149	-0.075
0.25	0.116	0.128	-0.117	-0.186	0.128	0.106	-0.022
0.30	0.124	0.095	-0.089	-0.145	0.092	0.078	-0.081
0.35	0.083	0.033	-0.072	-0.097	0.075	0.007	-0.086
0.40	0.065	0.031	-0.037	-0.030	0.016	0.019	-0.061
0.45	0.088	0.039	-0.072	-0.033	0.062	0.003	-0.021
0.50	0.078	0.014	-0.097	0.002	0.079	0.039	-0.088
0.55	0.070	0.009	-0.156	0.024	0.081	0.007	-0.113
0.60	-0.074	-0.071	-0.201	0.049	0.088	-0.007	-0.190
0.65	-0.075	-0.116	-0.168	0.127	0.042	-0.044	-0.170
0.70	-0.039	-0.126	-0.153	0.142	-0.026	-0.050	-0.185
0.75	-0.088	-0.111	-0.119	0.113	-0.069	-0.086	-0.226
0.80	-0.033	-0.177**	-0.154	0.150	-0.058	-0.100	-0.243*
0.85	-0.081	-0.175**	-0.164	0.173	0.069	-0.137	-0.313**
0.90	-0.074	-0.144	-0.238	0.078	0.016	-0.102	-0.397***
0.95	0.064	-0.260	-0.357	0.015	0.029	-0.221	-0.496

Note: This table presents QQ regression results for EPU and BTC returns across the selected countries from May 2020 to February 2024 (period from third halving to end of the dataset). The coefficients for different quantiles are marked with * and ** indicating statistical significance at the 10% and 5% levels, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table H.3: QQ Results for GSV 2016-2024

Quantile	Australia	Canada	Germany	Japan	South Korea	UK	US
0.05	0.181	0.042	-0.019	0.209	0.300	0.012	-0.026
0.10	-0.020	0.024	-0.003	0.258	0.470***	0.083	-0.013
0.15	0.317***	0.051	0.026	0.444**	0.513***	0.225***	0.036
0.20	0.252**	0.389***	0.220**	0.478**	0.496***	0.338***	0.301***
0.25	0.421***	0.401***	0.191**	0.530***	0.563***	0.340***	0.335***
0.30	0.417***	0.381***	0.184*	0.550***	0.479***	0.340***	0.282***
0.35	0.382***	0.401***	0.140	0.632***	0.484***	0.398***	0.276***
0.40	0.376***	0.378***	0.283***	0.608***	0.471***	0.375***	0.315***
0.45	0.367***	0.390***	0.264**	0.470***	0.435***	0.351***	0.334***
0.50	0.351***	0.422***	0.260**	0.471***	0.406***	0.342***	0.338***
0.55	0.348***	0.410***	0.309***	0.553***	0.375***	0.319***	0.340***
0.60	0.356***	0.394***	0.262**	0.510***	0.371***	0.298***	0.304***
0.65	0.387***	0.404***	0.271**	0.563***	0.438***	0.280***	0.305***
0.70	0.375***	0.356***	0.287***	0.517***	0.408***	0.272***	0.295***
0.75	0.423***	0.377***	0.313***	0.492***	0.441***	0.308***	0.315***
0.80	0.426***	0.468***	0.339***	0.525***	0.507***	0.347***	0.404***
0.85	0.366***	0.471***	0.371***	0.533***	0.463***	0.321***	0.406***
0.90	0.351***	0.432***	0.345***	0.586***	0.481***	0.301**	0.445***
0.95	0.391	0.427	0.450	0.647	0.504	0.390	0.461

Note: This table presents QQ regression results for GSV and BTC returns across the selected countries from July 2016 to May 2020 (period from second to third BTC halving). The coefficients for different quantiles are marked with * and ** indicating statistical significance at the 10% and 5% levels, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).

Table H.4: QQ Results for GSV 2020-2024

Quantile	Australia	Canada	Germany	Japan	South Korea	UK	US
0.05	0.032	0.019	0.027	-0.230	0.150	0.050	-0.196
0.10	-0.107	-0.161	-0.238*	-0.191	-0.172	-0.168	-0.189
0.15	-0.158	-0.244*	-0.238	-0.104	-0.154	-0.174	-0.282*
0.20	-0.073	-0.050	-0.076	-0.112	-0.107	-0.112	-0.125
0.25	0.044	-0.069	-0.130	-0.071	0.046	-0.106	-0.070
0.30	0.095	0.166	0.119	0.122	0.005	0.125	0.101
0.35	0.126	0.290***	0.174	0.125	0.047	0.054	0.124
0.40	0.216**	0.223**	0.249**	0.177	0.071	0.163	0.140
0.45	0.223**	0.205*	0.288***	0.204*	0.208	0.266**	0.200
0.50	0.227**	0.287***	0.267**	0.252**	0.216	0.210*	0.251*
0.55	0.258***	0.291***	0.282***	0.290**	0.239	0.284**	0.328**
0.60	0.308***	0.374***	0.335***	0.333***	0.326**	0.259**	0.341***
0.65	0.279***	0.357***	0.315***	0.372***	0.365**	0.384***	0.399***
0.70	0.267***	0.359***	0.330***	0.404***	0.344**	0.371***	0.303**
0.75	0.309***	0.363***	0.301**	0.369***	0.285*	0.367***	0.314**
0.80	0.351***	0.359***	0.291**	0.310**	0.322*	0.361***	0.323**
0.85	0.347***	0.393***	0.312**	0.406***	0.375**	0.356***	0.344**
0.90	0.327***	0.351***	0.370**	0.331*	0.351*	0.336**	0.373**
0.95	0.222	0.256	0.282	0.271	0.221	0.253	0.273

Note: This table presents QQ regression results for GSV and BTC returns across the selected countries from May 2020 to February 2024 (period from third halving to end of the dataset). The coefficients for different quantiles are marked with * and ** indicating statistical significance at the 10% and 5% levels, respectively. The sample period of our analysis is 1 January 2015 to 1 February 2024 for all markets except Canada (1 July 2015 to 1 February 2024).