Louvain School of Management

Bitcoin as a hedge and safe haven: A comparative analysis of European and global stock market indices

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Abstract

Over the past few years, Bitcoin has emerged as an important digital asset in the financial world. It is often compared to gold, with some saying that it can act as a hedge and/or a safe haven. For investors, it is important to determine whether this is the case. This thesis analyses the relationship between Bitcoin and European indices, comparing it with two global indices.

This study employs an econometric regression framework based on Yahoo Finance data from September 2014 to December 2025, using daily, weekly and monthly frequencies. The sample includes Bitcoin, three global equity indices and sixteen European country indices. Extreme downside movements are assessed by examining the cumulative effects of returns falling within the 10^{th}, 5^{th} and 1^{st} quantiles of the return distribution.

The main findings of this thesis can be summarised as follows: Bitcoin cannot be considered a major hedge at any time horizon, as its average co-movement with equity returns is mostly positive. Regarding its safe-haven properties, the evidence is unfavourable at the most extreme stress threshold. At the bottom 1% quantile of equity returns, the cumulative effects are positive for all nineteen indices under study at the monthly horizon, mostly positive at the daily horizon and mostly non-different from zero, i.e. uncorrelated, at the weekly horizon. At the bottom 10% and 5%, the results vary depending on the market under study. No market under study has a negative correlation with Bitcoin.

Overall, Bitcoin is best characterised as a high-risk diversifying asset rather than a reliable hedge and safe haven against equity market stress.

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Contents

1 Introduction

The global financial landscape has undergone significant transformations over the past decades, with investors continuously seeking strategies to protect their portfolios during periods of market distress. Portfolio protection mechanisms have become fundamental to modern investment management, as market participants strive to mitigate losses during financial crises. In this context, diversification strategies that incorporate assets with low or negative correlations to traditional equity markets have gained considerable attention from both academic researchers and practitioners. It is therefore important to understand the relationship between assets, particularly during turbulent market conditions. The understanding whether an asset like Bitcoin maintains independence from traditional equity markets becomes fundamental to portfolio construction. This question is particularly relevant given the growing integration of cryptocurrencies into investment portfolios and their increasing institutional adoption.

Bitcoin, as the first and most prominent cryptocurrency, has emerged as a potential candidate for portfolio diversification. Its decentralised nature, limited supply and perceived independence from traditional financial systems have led many to question whether it possesses safe-haven or hedge properties similar to traditional assets such as gold. However, the empirical evidence remains mixed, with results highly dependent on the econometric methodology, the time horizon considered and the definition of market stress.

In this context, this thesis investigates **whether Bitcoin can serve as a hedge or a safe haven for equity markets, with a particular focus on European markets, while providing a comparison with the United States and a global benchmark index**. This focus is particularly relevant given that the existing literature has predominantly concentrated on U.S. markets, leaving the European perspective relatively underexplored despite structural differences in market organisation, regulation and investor behaviour.

This study contributes to the literature in several ways. First, it provides a comprehensive analysis of Bitcoin's safe-haven and hedge properties across a broad panel of European equity markets, rather than focusing solely on aggregate indices. Second, it adopts a comparative approach by analysing both European and U.S. stock markets, allowing for the identification of potential regional differences. Third, it explicitly accounts for extreme market conditions and different temporal horizons, thereby offering a more nuanced understanding of Bitcoin's behaviour across market fluctuations.

To address this research question, the empirical analysis relies on a regression-based framework inspired by Baur and McDermott (2010), combined with a GARCH(1,1) specification to account for time-varying volatility. The model incorporates interaction terms with dummy variables corresponding to extreme market conditions, defined by the lower quantiles of equity returns (10%, 5%, and 1%). This approach allows the relationship between Bitcoin and equity markets to vary between normal periods and episodes of financial stress, thereby providing a direct test of hedge and safe-haven properties. The analysis is conducted using daily, weekly and monthly data in order to assess the robustness of the results across different time horizons.

This thesis is structured as follows: Chapter 2 provides a review of the theoretical and empirical literature on safe-haven assets and Bitcoin. Chapter 3 presents the methodology and the data. Chapter 4 reports the empirical results and discusses the findings. Chapter 5 concludes.

2 Literature review

As outlined in the introduction, Bitcoin has attracted increasing attention from investors and academics alike due to its rapid market development and growing adoption. It is also frequently claimed to have a role as a hedge and/or safe haven during periods of market stress. Yet, the available empirical evidence on these properties is mixed, which may reflect differences in sample periods, crisis definitions and econometric methodologies.

Accordingly, this literature review proceeds as follows: The section 2.1 establishes the conceptual foundations by defining hedging and safe-haven behaviour and outlining the conditions under which these can be identified. The section 2.2 discusses Bitcoin's economic nature and summarises the key factors that have been suggested as explanations for its price dynamics and volatility. The section 2.3 summarises empirical findings on Bitcoin's relationship with equity markets, emphasising differences in econometric approaches, time horizons and structural breaks. The section 2.4 then consolidates the key insights and formulates the research hypotheses that will guide the rest of the thesis.

2.1 Theoretical framework: Safe havens and hedges

The theoretical foundation for understanding the safe haven and hedge properties of financial assets was established by Baur and McDermott (2010) and Baur and Lucey (2010) in their seminal work on the relationship between gold and financial assets. These studies provide the conceptual framework that has since been widely adopted in research examining the safe haven and hedge characteristics of various assets.

According to Baur and McDermott (2010), a hedge is defined as an asset that is uncorrelated or negatively correlated with another asset on average. This means that under normal market conditions, a hedge asset should exhibit low or negative correlation with the reference asset, providing diversification benefits to investors. The hedge property is particularly valuable for portfolio construction, as it suggests that including such an asset can reduce overall portfolio risk through diversification effects.

A safe haven, by contrast, is defined as an asset that is uncorrelated or negatively correlated with another asset during periods of market stress (Baur & Lucey, 2010; Baur & McDermott, 2010). The key distinction between a hedge and a safe haven lies in the timing: while a hedge provides benefits on average, a safe haven specifically offers protection during extreme market conditions.

This theoretical framework further distinguishes between "weak" and "strong" forms. A safe haven or a hedge is considered weak when its relationship with another asset is uncorrelated. By contrast, a safe haven or a hedge is considered strong when the relationship between the two assets is negatively correlated (Baur & McDermott, 2010). This classification has become a standard approach for evaluating assets' risk-mitigation properties in the academic literature.

Building upon this theoretical classification of safe havens and hedges, it is essential to examine the intrinsic nature of Bitcoin. Understanding whether its fundamental characteristics align with those of traditional safe havens, such as gold, is a prerequisite for interpreting the empirical results presented in the following chapters.

2.2 Bitcoin: Nature and drivers

Bitcoin as an hybrid asset

Bitcoin's original purpose, as proposed by Nakamoto (2008), is a peer-to-peer payment network that relies on proof-of-work (i.e. mining) to validate transactions and maintain an immutable record of transaction histories. This architecture makes Bitcoin decentralised and usable without financial intermediaries (Weber, 2016).

Bitcoin is also frequently portrayed as a form of "digital gold" in media and financial commentary[1]. The presence of a mining process, a capped supply and an increasing marginal cost of production arguably makes Bitcoin comparable to precious metals (Selgin, 2013). However, Bitcoin is also frequently characterized as a predominantly speculative asset (Baur et al., 2018; Corbet, Lucey, et al., 2018). Yermack (2015) defines a bona fide currency as one that is largely accepted as a medium of exchange, serves as a store of value (i.e. it has low volatility) and is a stable unit of account for comparing prices. He argues that Bitcoin does not satisfy these criteria. He highlights its limited transactional use, its substantially higher volatility compared to widely used currencies, its exchange rate showing little correlation with other currencies and practical issues such as pricing conventions requiring many decimals and leading zeros. These features, in his view, reinforce Bitcoin's primarily speculative nature.

Main drivers of Bitcoin

According to Kristoufek (2015), Bakas et al. (2022) and Saiedi et al. (2021), the determinants of Bitcoin can be understood through the factors that influence its price, those that explain its volatility and those that support the adoption of the associated infrastructure, that is, the broader ecosystem enabling Bitcoin transactions, mining, exchange and payment use. In terms of price, Kristoufek (2015) emphasises the pivotal role of online attention (i.e. search queries), which has an asymmetric impact on the formation and bursting of financial bubbles. He also suggests that some market fluctuations could be linked to developments in the Chinese market and regulatory announcements made

[1] Marion Laboure, *I could potentially see Bitcoin to become the 21st century gold*, Deutsche Bank, August 2021, available at: https://www.db.com/what-next/digital-disruption/dossier-payments/i-could-potentially-see-bitcoin-to-become-the-21st-century-gold?language_id=1 (accessed 6 March 2026); *From Gold to Bitcoin: What Investors Get Wrong About Value Storage*, Forbes, 18 December 2025, available at: https://www.forbes.com/sites/digital-assets/2025/12/18/from-gold-to-bitcoin-what-investors-get-wrong-about-value-storage/ (accessed 6 March 2026).

there. However, he does not find robust and consistent evidence to support the notion of a safe-haven status in relation to the Federal Reserve Bank of Cleveland's Financial Stress Index (FSI) or gold, except for a single instance related to the Cypriot crisis at the start of 2012.

With regard to volatility, Bakas et al. (2022) demonstrate that the most robust determinants among a broad set of candidate variables are Bitcoin-related Google Trends, supply (i.e. bitcoins in circulation), U.S. consumer confidence and the S&P 500. Finally, with regard to adoption (i.e. infrastructure), Saiedi et al. (2021) define Bitcoin nodes as "any computer or data processor that connects to the Bitcoin network in order to receive and send information relating to Bitcoin's blockchain" (p. 361). They then suggest that the diffusion of Bitcoin nodes and the number of merchants accepting Bitcoin are linked to socio-institutional factors such as inflation crises, distrust of banks and distrust of the financial system. They also note that active support for Bitcoin may be higher in areas where banking services are well developed and that adoption may be partly related to its use for illicit activities. They also show that technological variables such as internet penetration, broadband access, ICT[2] market development and the availability of recent technologies significantly explain node intensity.

Moreover, the drivers of Bitcoin adoption, such as distrust in traditional banking systems and high inflation periods, provide a theoretical basis for its potential safe-haven role during specific financial crises (Saiedi et al., 2021). However, the dominance of speculative interest remains a primary driver of its volatility, which may undermine its reliability as a stable store of value during prolonged market downturns (Kristoufek, 2015; Smales, 2019).

The diversity of these price drivers, ranging from speculative interest to socio-institutional distrust, suggests that Bitcoin's market behaviour may be highly regime-dependent. This complexity goes some way to explaining why the empirical literature discussed below has produced such a wide array of findings regarding its actual performance as a diversifier and a risk-mitigation tool.

2.3 Empirical evidence of Bitcoin

The empirical literature examining Bitcoin's relationship with traditional financial markets has produced diverse and sometimes contradictory findings (Baur & Hoang, 2021; Baur et al., 2018; Błędowska-Sójka & Kliber, 2021; Bouri, Molnár, et al., 2017; Bouri et al., 2020; Hsu et al., 2024; Klein et al., 2018; Li & Miu, 2023; Pastén-Henríquez et al., 2025; Smales, 2019). Early research suggested that Bitcoin might serve as a hedge or safe haven against different assets, drawing parallels with gold's historical role (Baur et al., 2018; Błędowska-Sójka & Kliber, 2021; Klein et al., 2018). However, as the cryptocur-

[2] Information and Communications Technology

rency market has matured and Bitcoin's correlation with traditional markets has evolved, the evidence has become more nuanced.

Analysis of volatility and dynamic correlation (GARCH family)

The most widely used method for analysing Bitcoin's properties is based on GARCH family models. Klein et al. (2018) used APARCH and FIARCH models to compare Bitcoin to gold and silver, concluding that Bitcoin cannot be considered the "new gold" due to its positive correlation with stock market indices during financial crises. This observation is reinforced by Li and Miu (2023), who use a regime switching approach (MVSWARCH) to demonstrate that correlations between Bitcoin and equities increase significantly when both markets are in a state of high volatility.

Furthermore, Bouri, Molnár, et al. (2017) applied a DCC-GARCH model to conclude that Bitcoin acts primarily as a diversifier rather than a safe haven or a hedge, except in very isolated cases. Conversely, Uddin et al. (2020) point out that Bitcoin offers interesting diversification opportunities, particularly with Islamic stock indices, which monitor stocks that adhere to Shari'ah-based investment screening principles. However, the immaturity of the Bitcoin market remains an obstacle. Smales (2019) notes that excessive volatility and a lack of liquidity prevent Bitcoin from being a viable safe haven compared to gold.

While GARCH-based models provide insights into dynamic correlations, they often overlook how these relationships evolve across different investment horizons. To address this, a second strand of literature uses wavelet analysis to separate short-term fluctuations from long-term trends.

Time perspectives and wavelet analysis

Another branch of literature uses wavelet analysis to observe relationships between assets over different time horizons. Kristoufek (2015) identified, via wavelet coherence, that Bitcoin price drivers vary over time, with speculative interest measured by Google Trends playing a predominant role.

Bouri, Gupta, et al. (2017) combined this method with quantile regressions to show that Bitcoin can hedge global uncertainty, but that this effect is limited to short-term investment horizons. Similarly, Corbet, Meegan, et al. (2018) found that cryptocurrencies are relatively isolated from traditional short-term financial shocks, confirming their usefulness for tactical diversification.

Behaviour during extreme market conditions

To test the robustness of assets during stock market crashes, several authors favour quantile regressions. This method, initially applied by Baur and McDermott (2010) to establish gold's safe-haven status, has been extended to Bitcoin. Wu et al. (2019) used GARCH models with dummy variables to compare Bitcoin and gold in the face of economic policy uncertainty (EPU), finding that both assets are only weak safe havens during extreme market conditions.

However, more detailed sectoral analyses, such as that by Bouri et al. (2020) which used cross-quantilograms, suggest that certain cryptocurrencies, such as Bitcoin, Ripple and Stellar, could act as safe havens for specific sectors within the S&P 500. Nevertheless, the results are highly heterogeneous.

The robustness of Bitcoin as a safe haven was notably tested during the COVID-19 pandemic. Empirical evidence indicates that during the liquidity crisis of March 2020, Bitcoin's correlation with global equities spiked significantly, challenging the "strong safe haven" hypothesis (Li & Miu, 2023). This suggests that while Bitcoin might offer diversification during localised geopolitical shocks, its performance during systemic global crises remains highly volatile and regime dependent, often failing to provide protection when it is most needed by investors (Pastén-Henríquez et al., 2025).

Finally, recent studies (Hsu et al., 2024; Pastén-Henríquez et al., 2025) suggest that Bitcoin's role is evolving during major geopolitical crises, such as the Russia-Ukraine conflict, where it has demonstrated its capacity as a temporary safe haven.

2.4 Research hypotheses

In summary, while there is consensus that Bitcoin can provide diversification benefits due to its low average correlation with traditional assets, its status as a safe haven remains widely disputed. The divergence in empirical findings can largely be attributed to differences in econometric frameworks used to capture dependence and volatility (e.g., GARCH-family models versus wavelet-based approaches), the time horizon considered and the treatment of structural changes and regime shifts. These considerations are particularly relevant in the case of Bitcoin, given the evolving nature of the cryptocurrency market and the possibility that its relationship with traditional assets varies across volatility regimes (Klein et al., 2018; Kristoufek, 2015; Li & Miu, 2023; Smales, 2019).

Against this background, the literature provides mixed and often contradictory evidence regarding Bitcoin's role as a hedge and a safe haven. This motivates a structured empirical investigation of its behaviour across different market conditions, regions and time horizons.

Building on the theoretical framework of Baur and McDermott (2010) and the empirical literature reviewed above, the following hypotheses are formulated and will be analysed and discussed in the following chapters:

Hypothesis 1: Bitcoin cannot be considered as a safe haven: during periods of stress in the equity markets, the relationship is not consistently zero or negative.

This hypothesis is supported by several studies that challenge the "digital gold" narrative. Klein et al. (2018) demonstrate that Bitcoin behaves as the "exact opposite" of gold. Similarly, Smales (2019) argues that Bitcoin's extreme volatility and lower liquidity make it unsuitable as a safe haven. Li and Miu (2023) further show that correlations between Bitcoin and equities become strongly positive when both markets enter high-volatility regimes. Moreover, Błędowska-Sójka and Kliber (2021) find that Bitcoin may at best act as a weak safe haven, but never as a strong one against major indices. Finally, Kristoufek (2015) finds no robust or persistent evidence supporting a safe-haven role.

Hypothesis 2: Bitcoin can be considered a hedge: it exhibits a negative or no correlation with equity returns in normal conditions.

There is a broad consensus in the literature that Bitcoin acts as a diversifier. Bouri et al. (2020) and Uddin et al. (2020) conclude that Bitcoin's primary role lies in its low unconditional correlation with traditional assets. This is corroborated by Klein et al. (2018), who find that correlations remain close to zero during tranquil periods and by Wu et al. (2019), who show that Bitcoin provides diversification benefits under normal market conditions.

Hypothesis 3: Bitcoin's hedge and safe-haven properties differ between European equity markets and the U.S. market

This hypothesis addresses a key gap in the literature by extending the analysis to the European market as a whole, whereas existing studies have mainly focused on selected national or regional indices. Błędowska-Sójka and Kliber (2021) find that cryptocurrencies more frequently exhibit weak safe-haven properties in European markets (e.g. the FTSE 250 and STOXX 600) than in the U.S. market. In addition, Li and Miu (2023) show that state-dependent correlations differ between the S&P 500 and the FTSE 100, suggesting regional heterogeneity driven by institutional and behavioural differences.

Hypothesis 4: Bitcoin's hedge and safe-haven properties differ across time horizons (daily, weekly, monthly)

Empirical evidence suggests that Bitcoin's relationship with traditional assets is highly sensitive to the time frequency of the data. Bouri, Gupta, et al. (2017) show, using wavelet analysis, that Bitcoin's hedging ability is primarily present at shorter horizons. Corbet, Meegan, et al. (2018) confirm that diversification benefits are mainly short-term.

Furthermore, Kristoufek (2015) demonstrate that both price drivers and co-movements vary significantly across time scales.

These hypotheses are directly tested in the empirical analysis below using the regression framework described in the next chapter (3).

3 Methodology and data

As discussed in the literature review, numerous models have been proposed to analyse the behaviour of Bitcoin and other cryptocurrencies. However, the results obtained in previous studies vary substantially depending on the econometric methodology, model specification, time horizon, sample composition and other modelling choices. Accordingly, this chapter presents the methodology adopted in this paper. It is divided into three parts: Section 3.1: econometric methodology, Section 3.2: model specification and interpretation of coefficients and Section 3.3: data and sample construction.

3.1 Econometric methodology

The objectives of the paper are to answer the question whether Bitcoin can serve as a hedge or a safe haven for equity markets, with a particular focus on European markets, while providing a comparison with the United States and a global benchmark index. To recall, a hedge is an asset that is uncorrelated or negatively correlated on average whereas a safe haven is an asset that is uncorrelated or negatively correlated in periods of market stress.

The empirical model employed in this study is based on the regression framework proposed by Baur and McDermott (2010). In this specification, extreme market conditions are identified through dummy variables, which are interacted with market returns so as to allow the asset's sensitivity to market movements to vary during periods of market stress. Such a framework is particularly suitable for assessing whether an asset behaves as a hedge in normal times and as a safe haven during extreme downturns. This methodology has been widely used in the safe haven literature (Baur & Lucey, 2010; Baur & McDermott, 2010; Iqbal, 2017; Wu et al., 2019).

The econometric models which are estimated by the maximum likelihood method, are represented as follows:

$$r_{BTC,t} = \alpha + \beta_t r_{i,t} + \varepsilon_t \tag{1}$$

$$\beta_t = \gamma_0 + \gamma_1 D(r_i q_{10}) + \gamma_2 D(r_i q_5) + \gamma_3 D(r_i q_1) \tag{2}$$

$$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2 \tag{3}$$

The equation (1) where $r_{BTC,t}$ and $r_{i,t}$ represent the return of the Bitcoin and the market i, respectively, models the relations. Furthermore, α and β_t are parameters to estimate and ε_t is the error term. Equation (2) is a dynamic process to model the parameters β_t. In the model, γ_0 reflects the usual link between Bitcoin returns and market returns. The coefficients γ_0, γ_1, γ_2, and γ_3 show how this link changes during bad market periods, defined with dummy variables $D(...)$ as returns falling into the lowest 10%, 5%, and 1% of outcomes. Equation (3) specifies a GARCH(1,1) model to capture heteroscedasticity.

The choice of this regression-based model is primarily motivated by its close alignment with the objective of the study. Since the aim is to assess whether the Bitcoin behaves as a hedge or a safe haven during episodes of market stress, a model based on interaction terms with extreme market dummies appears particularly appropriate. Unlike DCC-GARCH models, which are designed to capture time-varying conditional correlations, or wavelet approaches, which focus on dependence across different time horizons, this framework directly isolates the behaviour of the Bitcoin during extreme downturns. It therefore provides a more straightforward and economically interpretable way to test safe-haven properties. Therefore, the model is not designed to capture the full dynamic dependence structure between assets, but rather to provide a parsimonious and economically interpretable framework for testing hedge properties in normal times and safe haven properties during periods of extreme market stress.

3.2 Model specification and interpretation of coefficients

As explained, we follow Baur and McDermott (2010) to assess whether Bitcoin behaves as a hedge and/or a safe haven for different markets. The key component of the econometric model lies in equation (2), which is as follows:

$$\beta_t = \gamma_0 + \gamma_1 D(r_i q_{10}) + \gamma_2 D(r_i q_5) + \gamma_3 D(r_i q_1)$$

where $D(r_i q_{10})$, $D(r_i q_5)$ and $D(r_i q_1)$ are dummy variables equal to one when stock market returns fall below the 10%, 5% and 1% lower quantiles of their distribution, respectively, and zero otherwise. This specification allows the relationship between Bitcoin and the stock market to differ between normal periods and episodes of severe market stress.

Hedge property

The coefficient γ_0 captures the average sensitivity of Bitcoin returns to stock market returns under normal market conditions. Therefore, γ_0 is used to assess the hedge property. If γ_0 is negative and statistically significant, Bitcoin is interpreted as a strong hedge. If γ_0 is not statistically different from zero, Bitcoin is interpreted as a weak hedge, since its returns are on average uncorrelated with stock market movements. By contrast, if γ_0 is positive and statistically significant, Bitcoin cannot be considered a hedge. This interpretation is consistent with the theoretical definition according to which a hedge must display a non-positive average correlation with the reference market.

Safe-haven property

The safe-haven property is evaluated through the total effect of stock market returns during extreme negative market conditions. Because the dummy variables are nested, the safe-haven effect at each threshold is assessed through the cumulative impact of the relevant coefficients rather than through any single coefficient taken separately. Hence, the effect associated with the 10% quantile is given by $\gamma_0 + \gamma_1$, the effect associated with the 5% quantile by $\gamma_0 + \gamma_1 + \gamma_2$, and the effect associated with the 1% quantile by $\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$. To determine whether these cumulative effects are statistically distinguishable from zero, we rely on Wald tests for linear restrictions. Specifically, we test $H_0 : \gamma_0 + \gamma_1 = 0$, $H_0 : \gamma_0 + \gamma_1 + \gamma_2 = 0$ and $H_0 : \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 = 0$ for the 10%, 5%, and 1% quantiles of the returns, respectively. This approach follows the logic that the overall effect in extreme market conditions is obtained by summing the relevant coefficients up to the quantile under consideration.

Accordingly, Bitcoin is classified as a strong safe haven when the total effect at a given quantile is negative and statistically significant, since this indicates that Bitcoin moves in the opposite direction to the stock market during extreme downturns. It is classified as a weak safe haven when the total effect is not statistically different from zero, which implies that Bitcoin remains uncorrelated with the market in stressful periods. Finally, if the total effect is positive and statistically significant, Bitcoin is not a safe haven, because its returns co-move positively with stock market returns when protection is most needed.

Special attention should be paid to non-significant results. Since the null hypothesis of the Wald test is that the relevant total effect is equal to zero, a non-significant result should not be interpreted as proof that the true coefficient is exactly zero. Rather, it indicates that the estimated effect cannot be statistically distinguished from zero at the chosen significance level. Under the theoretical framework proposed by Baur and McDermott (2010), such outcomes may still be classified as evidence of weak safe-haven or weak hedge properties.

Table 3.1
Interpretation of hedge and safe-haven coefficients

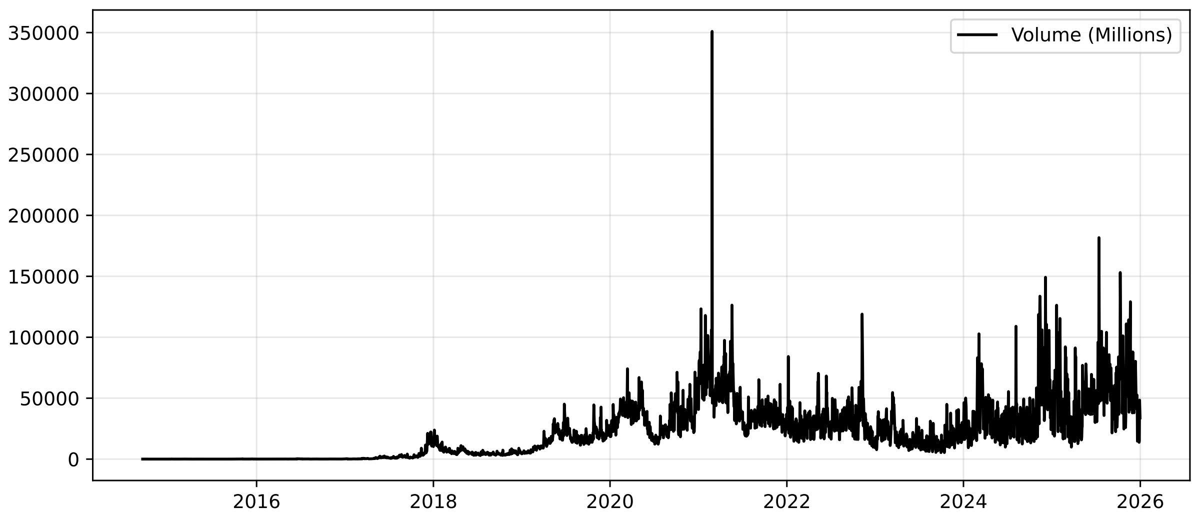
Property	**Coefficient / Total effect**	**Interpretation**
Hedge	$\gamma_0 < 0$ and statistically significant	Strong hedge
Hedge	γ_0 not statistically different from 0	Weak hedge
Hedge	$\gamma_0 > 0$ and statistically significant	Not a hedge
Safe haven at $q10$	$\gamma_0 + \gamma_1 < 0$ and statistically significant	Strong safe haven at the 10% quantile
Safe haven at $q10$	$\gamma_0 + \gamma_1$ not statistically different from 0	Weak safe haven at the 10% quantile
Safe haven at $q10$	$\gamma_0 + \gamma_1 > 0$ and statistically significant	Not a safe haven at the 10% quantile
Safe haven at $q05$	$\gamma_0 + \gamma_1 + \gamma_2 < 0$ and statistically significant	Strong safe haven at the 5% quantile
Safe haven at $q05$	$\gamma_0 + \gamma_1 + \gamma_2$ not statistically different from 0	Weak safe haven at the 5% quantile
Safe haven at $q05$	$\gamma_0 + \gamma_1 + \gamma_2 > 0$ and statistically significant	Not a safe haven at the 5% quantile
Safe haven at $q01$	$\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 < 0$ and statistically significant	Strong safe haven at the 1% quantile
Safe haven at $q01$	$\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$ not statistically different from 0	Weak safe haven at the 1% quantile
Safe haven at $q01$	$\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 > 0$ and statistically significant	Not a safe haven at the 1% quantile

3.3 Data and sample construction

The empirical analysis focuses on Bitcoin as the asset of interest, with the objective of assessing whether it exhibits hedge and safe haven properties with respect to major equity markets. To this end, Bitcoin is compared with a set of stock market indices representing both global and European equity markets. Specifically, the analysis includes the MSCI World, MSCI Europe, and the S&P 500, together with a broad panel of European national equity indices covering Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Lithuania, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. All data are obtained from Yahoo Finance, which determines the coverage of European equity markets included in the analysis. Details on the indices, tickers, currencies, frequencies and sample periods are reported in Table 3.2

The sample period runs from 17 September 2014 to 31 December 2025. The full sample is retained for the correlation analysis, including Pearson and rolling correlations. However, for the regression-based model analysis, the sample is restricted to the period from 18 December 2017 to 31 December 2025. This choice is justified by the fact that the period preceding December 2017 corresponds to an earlier stage in Bitcoin's development, characterised by lower market depth and a less mature market structure. As shown in Figure 3.1, trading volume increased markedly around this date, suggesting that Bitcoin entered a new phase of market development and became a more established asset.

Figure 3.1
Bitcoin daily trading volume in millions (September 2014 - December 2025)



To account for potential horizon effects, the analysis uses daily, weekly and monthly data. This multi-frequency approach enables the results to be evaluated at various time horizons. It also helps to determine whether the observed daily correlation structure persists when short-term noise is smoothed through lower-frequency aggregation, thus enabling us to assess whether hypothesis 4 holds.

Asset returns are computed as logarithmic returns (continuously compounded returns), using the standard formula based on the first difference of log prices. This measure is widely used in empirical finance because it provides a convenient and theoretically consistent representation of price variations.

Regarding data processing, one of the main challenges arises from the fact that Bitcoin is traded continuously, 24 hours a day and 7 days a week, whereas stock market indices are only traded from Monday to Friday during official market hours. To ensure consistency across assets, weekend observations are removed from the daily Bitcoin series, as is commonly done in the literature. Weekly returns are computed on a Friday-to-Friday basis for the stock and on a Sunday-to-Sunday basis for the Bitcoin, while monthly returns are calculated using the last closing price observed in each month. In those both cases, Bitcoin and equity index data are aligned so that returns are measured over comparable intervals. Finally, following the safe-haven literature, indices are kept in local currency terms rather than systematically converted into USD. This choice avoids mechanically introducing a common USD component into both Bitcoin and equity returns, which could artificially increase co-movement and blur the identification of safe-haven dynamics.

Table 3.2
Summary of the datasets for the analysis.

Market/Asset	Index	Ticker (Yahoo)	Currency	Frequency	Sample Start	Sample End
Bitcoin	Bitcoin	BTC-USD	$	Daily, weekly and monthly	September 17, 2014	December 31, 2025
World	MSCI World Index	^990100-USD-STRD	$	Daily, weekly and monthly	September 17, 2014	December 31 2025
USA	S&P500	^GSPC	$	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Europe	MSCI Europe	^125904-USD-STRD	$	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Austria	ATX	^ATX	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Belgium	BEL20	^BFX	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Finland	OMXH25	^OMXH25	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
France	CAC40	^FCHI	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Germany	DAX	^GDAXI	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Greece	Athex	GD.AT	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Ireland	ISEQ	^ISEQ	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Italy	FTSE MIB	FTSEMIB.MI	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Lithuania	OMX Vilnius	OMXVGI	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Netherlands	AEX	^AEX	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Norway	OBX	OBX.OL	NOK	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Portugal	PSI20	PSI20.LS	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Spain	IBEX 35	^IBEX	€	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Sweden	OMX Stockholm 30	^OMX	SEK	Daily, weekly and monthly	September 17, 2014	December 31, 2025
Switzerland	SMI	^SSMI	CHF	Daily, weekly and monthly	September 17, 2014	December 31, 2025
UK	FTSE 100	^FTSE	£	Daily, weekly and monthly	September 17, 2014	December 31, 2025

4 Empirical Analysis

This chapter presents the main empirical findings of the thesis. The analysis is structured as follows: Section 4.1 reports descriptive statistics for all return series. Section 4.2 provides a graphical examination of price and return dynamics over the full sample period. Section 4.3 analyses unconditional Pearson correlations and rolling correlations to provide preliminary evidence on the degree of co-movement between Bitcoin and equity markets. Finally, Section 4.4 presents the results of the regression-based model, and Section 4.5 discusses the implications for the four research hypotheses and compare them to the literature review.

4.1 Descriptive Statistics

Table 4.1 reports descriptive statistics for the daily return series of Bitcoin and the 19 equity market indices over the full sample period from September 2014 to December 2025.

Table 4.1
Descriptive statistics for daily returns. *Daily logarithmic returns are reported. The sample covers September 17, 2014 to December 31, 2025. European equity indices are denominated in local currency; MSCI World, MSCI Europe, S&P 500, and Bitcoin are denominated in US dollars. Annualised volatility (approximated as $\sigma \times \sqrt{252}$) amounts to approximately 68.3% for Bitcoin, compared to a range of 15.6%–19.6% for the equity indices.*

	Mean (%)	Median (%)	St. Dev.	Min. (%)	Max. (%)	Obs.
Bitcoin	0.207	0.148	4.477	-46.473	22.512	2538
Global indices						
MSCI World	0.037	0.078	1.033	-10.440	8.406	2538
MSCI Europe	0.017	0.074	1.212	-14.407	8.524	2538
S&P500	0.049	0.076	1.190	-12.765	9.089	2538
European stock indices						
Austria	0.033	0.080	1.374	-14.675	10.206	2538
Belgium	0.018	0.058	1.181	-15.328	7.361	2538
Finland	0.026	0.071	1.195	-10.679	6.665	2538
France	0.024	0.080	1.261	-13.098	8.056	2538
Germany	0.037	0.084	1.286	-13.055	10.414	2538
Greece	0.025	0.110	1.934	-17.713	19.533	2538
Ireland	0.039	0.080	1.338	-18.467	8.332	2538
Italy	0.030	0.118	1.490	-18.546	8.551	2538
Lithuania	0.042	0.038	0.628	-9.834	6.339	2538
Netherlands	0.032	0.081	1.160	-11.376	8.591	2538
Norway	0.041	0.071	1.157	-8.951	6.284	2538
Portugal	0.014	0.052	1.164	-10.267	7.532	2538
Spain	0.018	0.075	1.316	-15.151	8.225	2538
Sweden	0.028	0.084	1.200	-11.173	6.849	2538
Switzerland	0.016	0.060	1.023	-10.134	6.780	2538
UK	0.015	0.064	1.039	-11.512	8.666	2538

A first key finding concerns the dispersion of returns. Bitcoin exhibits a daily standard deviation of 4.477%, which is substantially higher than that of any equity index in the sample. Among equity markets, volatility ranges from 1.023% for Switzerland to 1.374% for Austria, which is a relatively narrow range. Only Lithuania and Greece differ markedly, with values of 0.628% and 1.934%, respectively, although these levels remain far below that of Bitcoin. This confirms the well-documented stylised fact that Bitcoin returns fluctuate far more intensely than traditional equity returns (Klein et al., 2018; Smales, 2019).

Differences also emerge in terms of average performance. Bitcoin records the highest mean daily return in the sample (0.207%), whereas the equity indices range from 0.014% for Portugal to 0.049% for the S&P 500. A similar pattern holds for median returns: Bitcoin posts a median daily return of 0.148%, exceeding the medians of all equity indices, which range from 0.038% for Lithuania to 0.118% for Italy. This suggests that, on average and over the long run, Bitcoin has delivered higher returns than equity markets, although this has come at the cost of considerably higher risk.

The contrast becomes even more pronounced when examining the tails of the return distribution. Bitcoin records a minimum daily return of −46.473% and a maximum of 22.512%, underscoring the possibility of extremely large gains or losses over very short horizons. By comparison, equity indices exhibit much narrower ranges. On the downside, the most negative daily returns are observed for Italy (−18.546%), Ireland (−18.467%), and Greece (−17.713%), while on the upside Greece stands out with a maximum daily return of 19.533%, well above the rest of the European sample. Germany, for example, which is just after Greece, has a maximum daily return of 10.414%. Lithuania appears at the other extreme, combining the lowest standard deviation with relatively limited tail movements, from −9.834% to 6.339%.

When considering weekly and monthly return series (Tables A.1 and A.2 in the Appendix), the magnitude of the worst drawdowns for Bitcoin remains broadly comparable across frequencies (approximately −41% at the weekly and −47% at the monthly level), whereas the upper tail expands substantially, with maximum gains reaching +52.5% at the weekly and +52.8% at the monthly frequency.

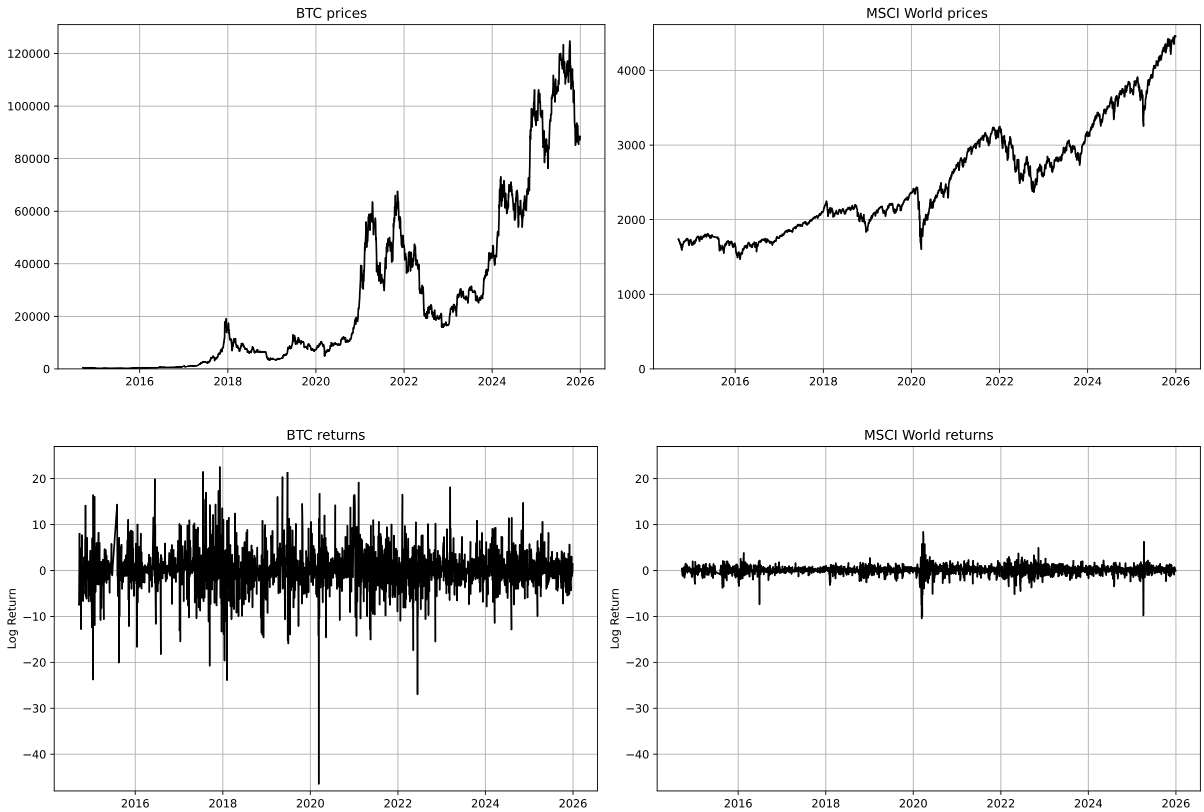
Taken together, these statistics illustrate Bitcoin's distinctive risk-return profile: a higher average return accompanied by higher volatility and much more pronounced tail risk than traditional equity markets. They also suggest a relative homogeneity across European markets, aside from two exceptions: Lithuania, which is characterised by unusually low volatility and a more distinct market profile and Greece, which displays comparatively high volatility among European indices.

These features are directly relevant for the analysis of Bitcoin as a safe haven, as European countries with similar characteristics may be expected to exhibit comparable safe-haven patterns, while Lithuania and Greece may display more distinct properties.

4.2 Graphical analysis of price and return dynamics

Before turning to formal correlation analysis and regression-based testing, it is instructive to examine the price and return dynamics of Bitcoin and the equity indices over the full sample period. Figure 4.1 shows two complementary representations of the data from September 2014 to December 2025. The upper panel plots the daily closing prices, in USD, of Bitcoin and the MSCI World Index together, enabling direct visual comparison of their absolute price trajectories. The lower panel shows the log returns for the same series, facilitating the comparison of fluctuations and performance across the two assets.

Figure 4.1
Daily prices and returns of Bitcoin and MSCI World (September 2014 - December 2025). *The top panel reports daily closing prices. The bottom panel reports the daily log returns. The others indices present the same pattern and interpretation. They are available in Appendix (A.1, A.2)*



While the MSCI World Index is used here as a representative benchmark for global equity markets, it is important to note that the other European indices considered in this study exhibit highly similar dynamics relative to Bitcoin. Their graphical patterns are therefore omitted for brevity and provided in Appendix (A.1, A.2).

A first striking observation concerns the markedly different price trajectories of Bitcoin and the MSCI World Index. Bitcoin follows a highly nonlinear and explosive growth path, characterised by pronounced boom-and-bust cycles, whereas the MSCI World Index displays a smoother and more gradual upward trend. The scale of price variation also differs substantially, reflecting fundamentally different underlying market structures and valuation mechanisms.

These differences are even more apparent when examining return series. Bitcoin exhibits significantly higher volatility, with frequent and extreme fluctuations compared to the relatively stable behaviour of the MSCI World Index. This is consistent with the descriptive statistics reported in Table 4.1, where Bitcoin returns display a much wider range and higher dispersion. Large positive and negative spikes are recurrent in the Bitcoin series, highlighting its exposure to substantial shocks, whereas equity market returns remain comparatively contained.

Despite these differences, a preliminary visual inspection suggests some degree of co-movement during major global crises. Notably, both Bitcoin and the MSCI World Index experienced noticeable price declines, reflected in negative returns, during key events in the period under study, such as the COVID-19 pandemic in 2020 and the onset of the Russia-Ukraine conflict in 2022. This simultaneous downward movement provides initial evidence that Bitcoin may not be entirely insulated from global financial stress, an aspect that will be formally investigated in the subsequent empirical analysis.

Finally, it is worth noting that similar patterns emerge when considering lower-frequency data. The weekly and monthly series (Appendix A.4, A.5, A.9 and A.10) exhibit comparable dynamics, with Bitcoin remaining substantially more volatile than equity indices and displaying analogous reactions during major stress episodes. This consistency across frequencies reinforces the robustness of the stylised facts highlighted in this preliminary analysis.

4.3 Pearson and rolling correlations

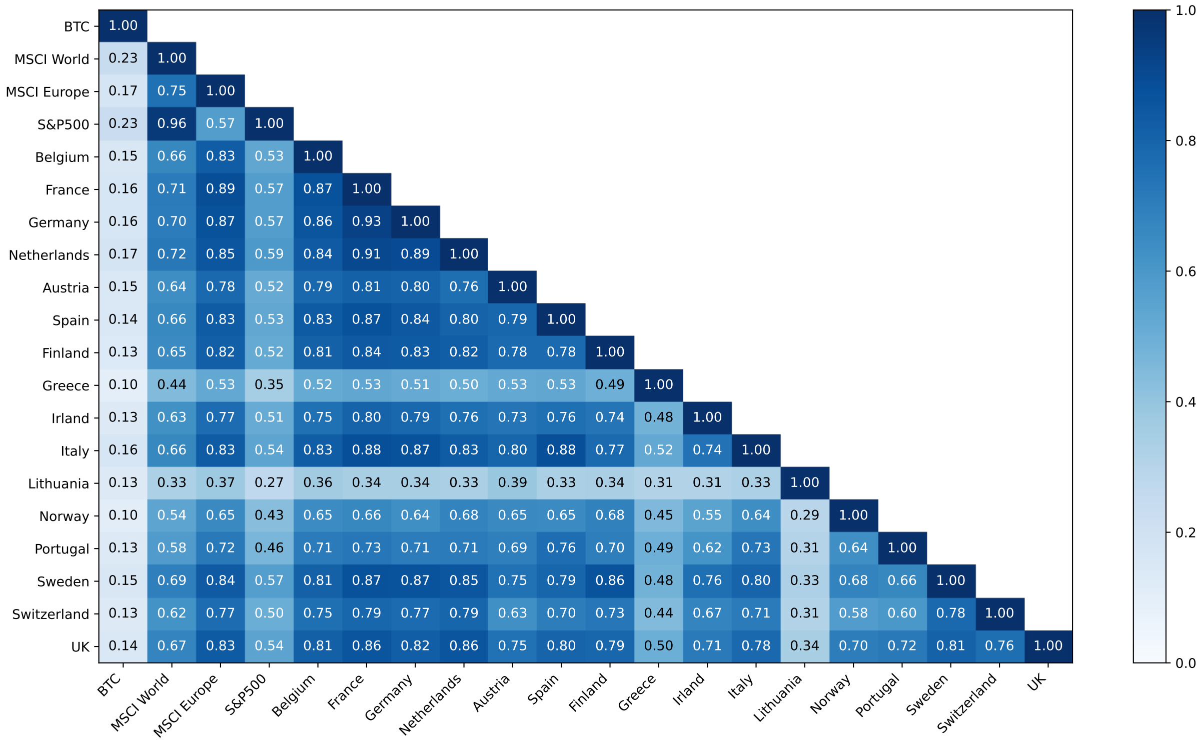
Prior to estimating the regression-based model, it is useful to assess the degree of co-movement between Bitcoin and the equity indices using standard correlation measures. This section employs two complementary approaches: unconditional Pearson correlations over the full sample period and one-year rolling window correlations, which allow the time-varying nature of these relationships to be examined.

Pearson correlations

Figure 4.2 presents the Pearson correlation matrix for daily returns over the full sample period (2014-2025). The matrix displays pairwise correlation coefficients for all twenty assets in the panel, with shading intensity proportional to the magnitude of the correlation.

The most notable result is the consistently low correlation between Bitcoin and all equity market indices. At the daily frequency, the pairwise Pearson coefficients between Bitcoin and the equity indices range from 0.10 (Greece and Norway) to 0.23 (MSCI World and S&P 500). These figures are substantially lower than the correlations observed among

Figure 4.2
Pearson correlation matrix for daily returns, September 2014 - December 2025.



the equity indices themselves. For example, the correlation reaches 0.96 between the MSCI World and the S&P 500, and correlations among the large Western European indices are also typically high. Two markets merit special attention in this regard. Lithuania exhibits markedly lower correlations not only with Bitcoin (0.13) but also with most European country indices (generally in the 0.29-0.48 range), suggesting that its stock market may be driven by local factors to a greater extent than its peers. Greece similarly shows relatively low correlations with Bitcoin (0.10) and with other European indices, though its divergence is less pronounced than that of Lithuania.

This low unconditional correlation is broadly consistent with Hypothesis 2, which posits that Bitcoin exhibits weak or non-positive dependence with equity returns in normal market conditions, thereby providing potential diversification or hedging benefits to investors.

A secondary observation concerns the divergence in correlation levels between the S&P 500 and the European indices. Whereas the Pearson correlation between the MSCI World and the S&P 500 is very high (0.96), the correlations between the S&P 500 and the individual European markets are noticeably lower. For most European markets, these coefficients fall in the range of 0.43 (Norway) to 0.59 (Netherlands), with Lithuania (0.27) and Greece (0.35) representing notable exceptions. This structural difference in the correlation motivates Hypothesis 3, which conjectures that Bitcoin's hedge and safe-haven properties may differ across geographic regions.

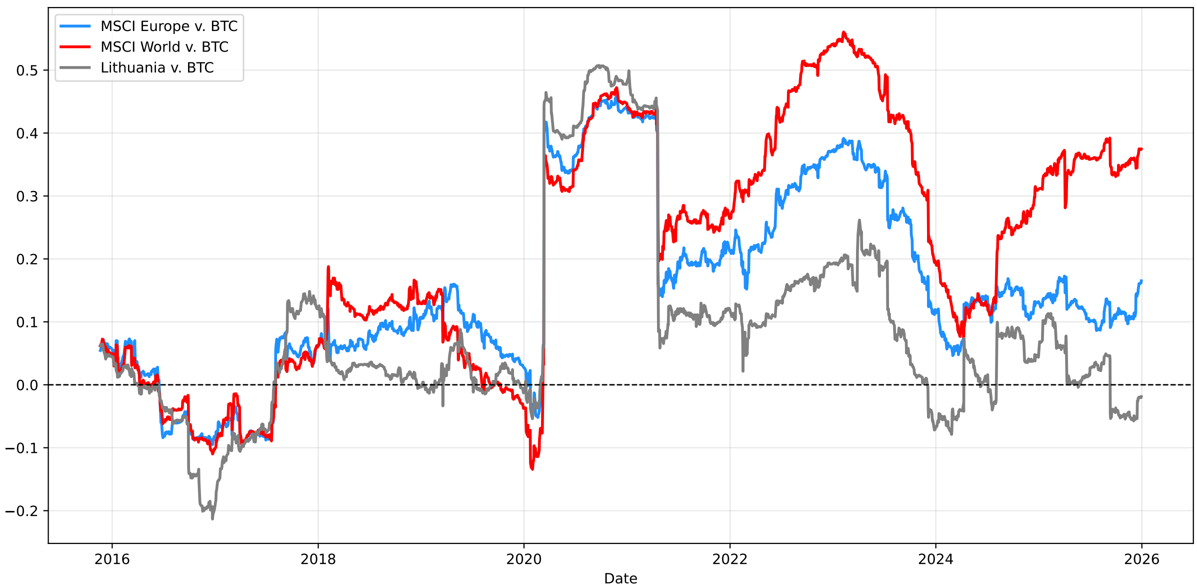
At the weekly and monthly frequencies (Appendix A.6 and A.11), the broad structure of the correlation matrix is preserved. Correlations between stock indices remain high, while Bitcoin's pairwise correlations with markets remain low. Notably, the unconditional correlation between Bitcoin and the MSCI World rises from 0.23 at the daily frequency to 0.24 at the weekly and 0.36 at the monthly frequency, suggesting that co-movement between Bitcoin and stock markets is somewhat more pronounced over longer time horizons. This horizon-dependence provides preliminary evidence in favour of Hypothesis 4, which posits that Bitcoin's relationship with equity markets varies across investment frequencies.

However, unconditional Pearson correlations suffer from a well-known limitation: they summarise the co-movement between two series using a single average value, thereby obscuring potential regime shifts and crisis-induced changes in the correlation structure (Klein et al., 2018). In particular, if the correlation between Bitcoin and the stock market increases during periods of financial crises – precisely when investors need protection the most – a low unconditional Pearson coefficient could create the misleading impression that Bitcoin has strong diversification potential.

Rolling correlations

To adress this limitation, Figure 4.3 plots one-year rolling correlations between Bitcoin and selected equity indices at the daily frequency, namely MSCI Europe, MSCI World and Lithuania. Rolling correlations for all remaining equity market indices are available in the Appendix (A.3).

Figure 4.3
1-Year rolling correlation estimates between Bitcoin and equity market indices (MSCI Europe, MSCI World and Lithuania), daily frequency. *The rest of the equity market indices are available in Appendix A.3.*



The rolling correlations reveal a markedly more complex picture. Between 2016 and early 2020, correlations between Bitcoin and the indices are generally low and fluctuating around zero, which is consistent with the diversification narrative and supports Hypothesis 2. However, during episodes of market stress, the pattern changes substantially. Around March 2020, at the height of the COVID-19 crisis, rolling correlations spike sharply across the pairs with MSCI World, MSCI Europe and Lithuania, reaching levels above 0.40. A similar, though less acute, pattern emerges around the 2022 market correction. These spikes indicate that Bitcoin's correlation with equity markets increases precisely during periods when portfolio protection is most valuable. This finding challenges the safe haven narrative and is consistent with Hypothesis 1.

Another notable feature is the sustained increase in correlation between Bitcoin and both the MSCI World and the S&P 500 (Appendix A.3) from late 2024 onwards. This may reflect the growing institutional adoption of Bitcoin and its increasing integration into global capital markets. In contrast, correlations with individual European country indices have remained comparatively low and more stable throughout the sample, providing preliminary support for Hypothesis 3 regarding potential regional heterogeneity. Lithuania, in particular, stands apart: its rolling correlation with Bitcoin is consistently lower than that of other European markets throughout the sample period, occasionally turning markedly negative, a pattern not observed for any other index. This idiosyncratic behaviour reinforces the observation made in the Pearson correlation analysis and suggests that Lithuania may warrant separate treatment in the interpretation of results.

Finally, the rolling correlation patterns at the weekly and monthly frequencies, presented in the Appendix (A.7, A.8, A.12 and A.13), display broadly similar dynamics, though with somewhat smoother trajectories due to reduced high-frequency noise. The spikes associated with crisis episodes remain visible at the weekly frequency but are substantially attenuated at the monthly frequency, where the rolling correlation window encompasses fewer distinct observations.

Taken together, the preliminary evidence from both Pearson and rolling correlations suggests that, while Bitcoin shows low average co-movement with stock markets, which is consistent with its potential for diversification, its correlation rises substantially during market downturns. This time-varying behaviour justifies the use of the regression-based model presented below. This model is specifically designed to determine whether Bitcoin acts as a hedge during normal times and as a safe haven during periods of extreme market volatility.

4.4 Model results

Having characterised the return trends and correlation structure of the variables, this section presents the results of the regression-based model described in Section 3. The model is estimated separately for each index and at three time horizons: daily, weekly, and monthly. For each index, Table 4.2, Table 4.3, and Table 4.4 report the estimated hedge coefficient $\hat{\gamma}_0$ as well as the cumulative effects $\hat{\gamma}_0 + \hat{\gamma}_1$, $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2$ and $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2 + \hat{\gamma}_3$, which correspond to Bitcoin's sensitivity to stock market returns when the latter falls below the 10%, 5%, and 1% lower quantiles of their distribution, respectively.

Daily frequency

Table 4.2 presents the results at the daily horizon.

At the daily frequency, the evidence is clear and consistent across all indices. The hedge coefficient $\hat{\gamma}_0$ is positive and statistically significant at the 1% level for all markets. This implies that on average Bitcoin returns co-move positively with stock market returns across the full panel. In contrast to the Pearson correlation, which shows that Bitcoin exhibits a low correlation and therefore has the potential to act as a hedge, this result shows a significant positive value for all $\hat{\gamma}_0$ and unequivocally rejects the hypothesis that Bitcoin acts as a hedge at the daily horizon, regardless of whether global, US or European markets are considered.

The picture at the safe-haven thresholds is slightly more nuanced but broadly consistent. For the global indices – MSCI World and S&P 500 – the cumulative effects at the 10% and 5% quantiles are positive and statistically significant, indicating that Bitcoin moves in the same direction as these markets under mild to moderate stress. For the MSCI Europe Index, the cumulative effect at the 5% quantile (0.2291) is positive but does not reach statistical significance, which is consistent with a weak safe-haven classification at that threshold in the framework. At the most extreme 1% quantile, all three global indices exhibit large, positive and highly significant cumulative effects, indicating the complete absence of safe-haven behaviour under the most severe stress conditions. Bitcoin therefore cannot be considered a safe haven for these indices at the 1% threshold.

For the European country indices, the results are more heterogeneous, particularly at the 10% quantile. In most cases – including Austria, Finland, France, Germany, the Netherlands, Greece, Lithuania, Netherlands and the United Kingdom – the cumulative effect at the 10% threshold is positive, though not statistically significant. This suggests that the hypothesis of a zero effect cannot be rejected, which is consistent with Bitcoin being classified as a weak safe haven against those markets at that threshold. Belgium and Ireland even display negative, though insignificant, cumulative effects at the 10% threshold (-0.0827 and -0.0439, respectively), which is interpreted as weak safe haven. For Italy, Norway, Portugal, Spain and Sweden, the cumulative effect at the 10% quantile is positive and statistically significant, confirming the absence of safe-haven behaviour for Bitcoin at this threshold.

At the 5% quantile, the cumulative effect of the coefficients exhibits variation. The effect is no longer statistically significant for Austria, Belgium, Greece, Lithuania, Nor-

Table 4.2
Estimated coefficients at the daily frequency. *The table reports the estimated hedge coefficient $\hat{\gamma}_0$ and the cumulative safe-haven effects at the 10%, 5%, and 1% lower quantile thresholds, computed as $\hat{\gamma}_0 + \hat{\gamma}_1$, $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2$, and $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2 + \hat{\gamma}_3$, respectively. Significance of cumulative effects is assessed via Wald tests.*

	Daily frequency			
	Hedge ($\hat{\gamma}_0$)	q10 ($\sum_0^1 \hat{\gamma}_i$)	q05 ($\sum_0^2 \hat{\gamma}_i$)	q01 ($\sum_0^3 \hat{\gamma}_i$)
Global indices				
MSCI World	0.9548***	0.9139***	0.9981***	1.0763***
MSCI Europe	0.5298***	0.7368***	0.2291	0.9040***
S&P500	0.8146***	0.6022***	0.8327***	0.9464***
European stock indices				
Austria	0.3885***	0.3762	0.1648	0.7496*
Belgium	0.4727***	−0.0827	0.1341	0.6801*
Finland	0.4388***	0.2859	0.2971*	0.8569*
France	0.4913***	0.1499	0.3784**	1.0507***
Germany	0.4352***	0.2671	0.3683**	1.1012***
Greece	0.2228***	0.0819	0.2073	0.1354
Ireland	0.3454***	−0.0439	0.2558*	0.9814***
Italy	0.3665***	0.6172***	0.2242*	0.9960***
Lithuania	0.3101*	0.5757	0.3363	0.3247
Netherlands	0.5700***	0.2856	0.4657**	1.2512***
Norway	0.2257***	0.4608**	0.1125	0.2640
Portugal	0.3502***	0.4356*	0.0850	0.3927
Spain	0.4289***	0.3868*	0.0323	1.1066***
Sweden	0.4554***	0.4978**	0.0168	0.9337***
Switzerland	0.4164***	−0.1817	0.6238**	0.6318
UK	0.4358***	0.2946	0.2667	1.0554**

Model:
$r_{BTC,t} = \alpha + \beta_t r_{i,t} + \varepsilon_t$
$\beta_t = \gamma_0 + \gamma_1 D(r_i q_{10}) + \gamma_2 D(r_i q_5) + \gamma_3 D(r_i q_1)$
$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2$
Notes: *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

way, Portugal, Spain, Sweden and the UK. Therefore, at this threshold, Bitcoin can be considered a weak safe haven for these markets.

At the more extreme 1% quantile threshold, the results change considerably for most European markets. The cumulative effects for France, Germany, Ireland, Italy, the Netherlands, Spain, Sweden and the UK are large, positive and statistically significant. This indicates that, during the most extreme sell-offs, Bitcoin tends to rise alongside these markets – the opposite of a safe haven. However, the 1% cumulative effect remains insignificant for Greece, Lithuania, Norway, Portugal and Switzerland. This is consistent with Bitcoin being classified as a weak safe haven against these indices at the most extreme threshold.

Weekly frequency

Table 4.3 reports the results at the weekly horizon.

Table 4.3
Estimated coefficients at the weekly frequency. *The table reports the estimated hedge coefficient $\hat{\gamma}_0$ and the cumulative safe-haven effects at the 10%, 5%, and 1% lower quantile thresholds, computed as $\hat{\gamma}_0 + \hat{\gamma}_1$, $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2$, and $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2 + \hat{\gamma}_3$, respectively. Significance of cumulative effects is assessed via Wald tests.*

	Weekly frequency			
	Hedge ($\hat{\gamma}_0$)	q10 ($\sum_0^1 \hat{\gamma}_i$)	q05 ($\sum_0^2 \hat{\gamma}_i$)	q01 ($\sum_0^3 \hat{\gamma}_i$)
Global indices				
MSCI World	1.0613***	0.5946	1.2424***	0.7785
MSCI Europe	0.7345***	1.5692	0.8562**	1.4096
S&P500	0.8918***	0.6416	1.1575***	0.6068
European stock indices				
Austria	0.6857***	1.5772***	0.0605	1.2680**
Belgium	0.7057***	0.9182	−0.3892	1.2452
Finland	0.8358***	1.6054***	0.2331	1.6299***
France	0.7929***	1.2824**	0.4409	1.1616
Germany	0.9352***	1.2358*	0.7013***	1.1023
Greece	0.5059***	0.8829**	0.6789**	0.7412***
Ireland	0.7157***	1.7529***	0.5912**	0.6471
Italy	0.7386***	1.4285**	0.6188*	0.8901
Lithuania	0.9112***	1.3537	1.7876*	1.4987
Netherlands	1.0376***	1.2457	0.8572	1.1945
Norway	0.6373***	0.7379	1.0439*	1.2243*
Portugal	0.6320***	0.6040	−0.1609	1.6001*
Spain	0.7316***	1.7658***	0.5908	1.3776***
Sweden	0.7544***	1.5999***	0.7431	0.9188
Switzerland	0.7673***	3.0475***	0.4687	1.1529**
UK	0.9780***	1.4978	0.1661	1.3785

Model:
$r_{BTC,t} = \alpha + \beta_t r_{i,t} + \varepsilon_t$
$\beta_t = \gamma_0 + \gamma_1 D(r_i q_{10}) + \gamma_2 D(r_i q_5) + \gamma_3 D(r_i q_1)$
$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2$
Notes: *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

The weekly results confirm the main finding of the daily analysis. The hedge coefficient $\hat{\gamma}_0$ remains positive and highly significant for all indices. This indicates that the relationship between bitcoin and the indices is positive, thus rejecting the hedge hypothesis for all stock indices at this horizon.

At the safe-haven thresholds, the pattern of results is broadly similar to the daily case, though there are some shifts in statistical significance. For the global indices, the 10% cumulative effect is largely insignificant, suggesting weak safe-haven behaviour for the Bitcoin against the majority of the markets at this threshold. In contrast, the 5% effect is positive and significant, indicating an absence of safe-haven properties under moderately severe stress. At the most extreme 1% quantile, the cumulative effects remain positive but do not reach conventional levels of statistical significance. This suggests that Bitcoin exhibits weak safe-haven properties against these indices.

The pattern diverges somewhat for the European country indices. For almost all markets, the cumulative effects at the 1% threshold are statistically insignificant, which is consistent with a weak safe-haven classification for Bitcoin. However, Austria, Finland, Greece, Spain, Norway and Portugal display positive and significant effects at the 1% quantile, confirming the absence of safe-haven behaviour for Bitcoin against these indices at the most extreme threshold. The case of Belgium is particularly notable: while the 5% cumulative effect is negative (−0.3892), it does not reach statistical significance, Bitcoin only acts as a weak safe haven for this country.

Compared to the daily results, the weekly frequency provides slightly more evidence in favour of a weak safe-haven classification, particularly at the 1% and, in some cases, 5% thresholds. However, the overall conclusion remains that, during market downturns, Bitcoin does not reliably offer protection, as there is generally at least one quantile with a positive relationship for each market.

Monthly frequency

Table 4.4 presents the results at the monthly horizon.

The monthly results provide evidence against both the hedge and safe-haven hypotheses, though with a more nuanced picture regarding the former. The hedge coefficient $\hat{\gamma}_0$ is positive and statistically significant for ten of the nineteen indices considered (MSCI World, S&P 500, Belgium, France, Germany, Greece, Italy, the Netherlands, Norway and Sweden), whereas it fails to reach conventional significance for the remaining nine (MSCI Europe, Austria, Finland, Ireland, Lithuania, Portugal, Spain, Switzerland and the United Kingdom). The hedge property of the Bitcoin at the monthly horizon is therefore more balanced than at shorter frequencies.

More strikingly, at the most extreme 1% quantile, all nineteen cumulative effects are positive and highly significant, with coefficients ranging from approximately 0.9017 (Austria) to 2.7953 (Netherlands). This implies that during the worst monthly stock market episodes, Bitcoin returns not only remain positive in direction relative to stock markets, but do so in a strongly co-moving manner across the entire sample of markets. The absence of any safe-haven property at the 1% monthly threshold is particularly informative, as monthly returns aggregate away short-lived noise and are therefore more likely to reflect structural co-movement.

At the intermediate 10% and 5% thresholds, the evidence is mixed: some indices display insignificant cumulative effects (consistent with weak safe-haven classification), while others – particularly the Netherlands at the 5% level (3.1341) and France at the 10% level (1.6967) – show large positive and significant effects. These mixed results contrast sharply with the uniformly negative picture at the 1% quantile.

Table 4.4
Estimated coefficients at the monthly frequency. *The table reports the estimated hedge coefficient $\hat{\gamma}_0$ and the cumulative safe-haven effects at the 10%, 5%, and 1% lower quantile thresholds, computed as $\hat{\gamma}_0 + \hat{\gamma}_1$, $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2$, and $\hat{\gamma}_0 + \hat{\gamma}_1 + \hat{\gamma}_2 + \hat{\gamma}_3$, respectively. Significance of cumulative effects is assessed via Wald tests.*

	Monthly frequency			
	Hedge ($\hat{\gamma}_0$)	q10 ($\sum_0^1 \hat{\gamma}_i$)	q05 ($\sum_0^2 \hat{\gamma}_i$)	q01 ($\sum_0^3 \hat{\gamma}_i$)
Global indices				
MSCI World	1.8068***	0.0326	2.1839**	2.0124***
MSCI Europe	0.8321	0.8147	2.2291**	1.9854***
S&P500	1.9084***	1.2743	0.9902**	2.1511***
European stock indices				
Austria	0.9462	−0.4461	0.5109	0.9017***
Belgium	1.1924**	1.0055	−0.5372	1.6527***
Finland	0.4360	−0.3425	1.7534	1.7997***
France	1.1629**	1.6967***	1.7874	1.6500***
Germany	1.8386**	−0.5968	0.9996	1.6116***
Greece	1.3250***	−0.8732	0.7983	1.1167***
Ireland	0.8072	−0.0710	1.7656**	1.4216***
Italy	1.2454***	−0.5328	2.2814	1.1745***
Lithuania	0.4007	2.0325	0.7059	2.4366***
Netherlands	1.5872***	0.2838	3.1341***	2.7953***
Norway	1.4210**	−0.6254	1.9252	2.1240***
Portugal	0.9630	1.5738***	0.1067	1.9455***
Spain	0.4440	−0.3855	2.6159**	1.2497***
Sweden	1.5683**	−0.1021	0.4375	2.4861***
Switzerland	0.8629	1.4983	2.4154	1.2908***
UK	1.3301	−1.0800	2.4949*	2.0830***

Model:
$r_{BTC,t} = \alpha + \beta_t r_{i,t} + \varepsilon_t$
$\beta_t = \gamma_0 + \gamma_1 D(r_i q_{10}) + \gamma_2 D(r_i q_5) + \gamma_3 D(r_i q_1)$
$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2$
Notes: *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Overall, the monthly results reinforce the conclusion from the daily and weekly analyses: Bitcoin does not act as a strong safe haven for any of the markets under consideration and this conclusion is most robust at the extreme tails of the return distribution. The hedge rejection is also confirmed at the monthly frequency for the majority of indices, though the evidence is less uniform than at the daily and weekly horizons

4.5 Discussion of hypotheses

This section summarises the descriptive statistics, correlation and regression-based evidence in light of the four hypotheses formulated in Section 2.4.

Hypothesis 1: Bitcoin cannot be considered as a safe haven: during periods of stress in the equity markets, the relationship is not consistently zero or

negative. The results *strongly support* this hypothesis. Across all three time horizons, none of the markets under study exhibit a significant negative cumulative effect. All markets exhibit at least two significant and positive relationships with Bitcoin at one of the three thresholds and for one of the three time horizons. The rolling correlation analysis further supports this conclusion, as the significant spikes in correlation observed during the March 2020 and 2022 crises demonstrate that Bitcoin's correlation with equities increases precisely when portfolio protection is most valuable. This is the opposite of what would be expected from a safe haven.

These results are consistent with the findings of Klein et al. (2018), Smales (2019), and Li and Miu (2023), who studied indices like the S&P 500 Index, MSCI World Index, among others. Similarly, these studies document that Bitcoin's correlation with equity markets becomes strongly positive during periods of high volatility and market stress, rendering it unsuitable as a reliable safe haven. While isolated instances of insignificant cumulative effects at milder thresholds (10% and 5%) are consistent with a weak safe-haven classification in a technical sense, the overall pattern does not support the view that Bitcoin reliably protects investors during market downturns.

Hypothesis 2: Bitcoin can be considered a hedge: it exhibits a negative or no correlation with equity returns in normal conditions. This hypothesis is *not supported* by the results. Initially, the Pearson correlation analysis, which revealed low yet consistently positive correlations across all pairs, suggested that Bitcoin could potentially act as a hedge against equity markets. However, the model results do not support this interpretation. In fact, the hedge coefficient, $\hat{\gamma}_0$, is positive and statistically significant across all three frequencies for the vast majority of indices, directly contradicting the hypothesis that Bitcoin exhibits zero or negative average co-movement with equity markets. The monthly frequency reveals greater heterogeneity, with nine out of the nineteen hedge coefficients failing to reach statistical significance. Nevertheless, all point estimates remain positive, and the overall direction of the evidence is unambiguous.

This finding contradicts earlier studies, such as those by Baur et al. (2018), which documented the uncorrelated nature of Bitcoin with the MSCI World Index and the FTSE 100. However, the sample period from July 2010 to July 2017 covers an earlier stage in Bitcoin's development. It is therefore reasonable to argue that its relationship with the financial market has changed over time, with Bitcoin becoming more deeply integrated into financial markets and losing its hedge property (Hsu et al., 2024).

Hypothesis 3: Bitcoin's hedge and safe-haven properties differ between European equity markets and the U.S. market This hypothesis is *partially supported* by the results. The hypothesis conjectured that Bitcoin's tail-risk relationships would differ between European and US markets. The results provide mixed evidence on this point.

At the daily and weekly frequencies, the US and global indices (S&P 500, MSCI World) display somewhat more uniformly positive and significant cumulative effects across all quantile thresholds, while the individual European country indices exhibit slightly more heterogeneous outcomes with isolated instances of insignificant cumulative effects at the 10% and 5% thresholds that are consistent with a weak safe-haven classification. Furthermore, the rolling correlation analysis revealed that correlations between Bitcoin and European indices, especially country-level ones, have historically been lower and more stable than those with the S&P 500 and MSCI World, particularly in the post-2024 period. Lithuania is a particularly striking case: its rolling correlation with Bitcoin remains almost consistently lower than that of any other index in the panel throughout the sample, occasionally turning negative, which sets it distinctly apart from the U.S. market.

However, at the monthly frequency, the differences across regions largely disappear and the dominance of positive, significant cumulative effects is uniform across all nineteen indices. This suggests that any regional differentiation is horizon-specific, rather than reflecting a structural difference in Bitcoin's relationship with European versus US equity markets. Overall, the hypothesis receives only partial support.

Hypothesis 4: Bitcoin's hedge and safe-haven properties differ across time horizons (daily, weekly, monthly) The results *support* this hypothesis. The analysis reveals significant differences in the estimated coefficients and their levels of significance across the three frequencies. The most notable horizon effect concerns the hedge coefficient: the magnitude of $\hat{\gamma}_0$ decrease substantially from the daily to the monthly frequency for most indices, suggesting that positive co-movement between Bitcoin and equity markets is more nuanced over longer horizons. At the 1% quantile, the monthly cumulative effects are consistently the largest in absolute value across the panel, whereas at daily and weekly frequencies, the picture is more nuanced, with fluctuations in some markets emphasising the fact that properties change across frequencies. Consider, for example, the relationship between Bitcoin and Greece. At the daily horizon, Bitcoin is considered a weak safe haven at all quantiles. At the weekly frequency, however, the relationship between the two assets becomes significantly positive at all quantiles, indicating a clear change in Bitcoin's safe-haven property.

The Pearson correlation analysis further supports this finding: the unconditional correlation between Bitcoin and the MSCI World increases from 0.23 at the daily frequency to 0.36 at the monthly frequency. Additionally, while the rolling correlation patterns at the monthly frequency are qualitatively similar to the daily case, they show attenuated crisis-related spikes and a smoother co-movement profile.

These findings are consistent with Bouri, Gupta, et al. (2017), who documents that, to the extent that it exists at all, Bitcoin's hedging capacity is primarily a short-term phenomenon and with Corbet, Lucey, et al. (2018), who notes that cryptocurrencies offer diversification benefits mainly in the short term. In the present sample, however, even the short-horizon evidence is insufficient to classify Bitcoin as a hedge, let alone a safe haven.

5 Conclusion

This thesis investigated whether Bitcoin can serve as a hedge or a safe haven for equity markets, with a particular focus on European markets, while providing a comparison with the United States and a global benchmark index. Using a regression-based framework inspired by Baur and McDermott (2010), the model was estimated on a panel of nineteen indices at daily, weekly and monthly frequencies over the period December 2017 to December 2025.

The results deliver a clear and consistent message. Bitcoin cannot be considered a reliable hedge at any horizon or for any market in the sample: the average sensitivity of Bitcoin returns to market returns is positive and statistically significant throughout the panel. Regarding its safe-haven properties, the picture is more nuanced, but the overall conclusion remains unfavourable. At the most extreme stress threshold (the bottom 1% quantile), the cumulative effects are positive and highly significant for all nineteen monthly frequency indices. This generality is somewhat reduced for daily and weekly data, but it still implies that Bitcoin amplifies rather than offsets losses when protection is most needed. At milder thresholds, a subset of European markets – particularly small ones such as Greece, Lithuania, Norway and Portugal – yield insignificant cumulative effects, which supports a weak safe-haven classification. Bitcoin is therefore not a perfect safe haven against equity markets. These findings align with Klein et al. (2018), Li and Miu (2023), and Smales (2019) are consistent with a broader theoretical reading: as Bitcoin's institutional adoption deepens and its integration into global capital markets grows, the independence from traditional assets that once gave it diversification appeal appears to have eroded.

Several limitations should be acknowledged. The sample, while spanning major stress episodes, remains relatively short, particularly at the monthly frequency (134 observations), which constrains statistical power. In addition, Bitcoin's market behaviour may evolve over time as the asset matures and its investor base changes, meaning that estimates obtained over one sample period may not fully generalise to other market environments. The scope of the analysis is also deliberately narrow, as it focuses exclusively on equity markets and excludes other major asset classes such as sovereign bonds, which remain central benchmarks in the safe-haven literature. Finally, the analysis is restricted to developed markets, so the results may not extend to emerging economies, where market structures, volatility dynamics and investor behaviour may differ substantially.

Building on these limitations, several extensions appear promising. First, future research could broaden the asset universe by incorporating sovereign bond markets, making it possible to assess whether Bitcoin behaves differently relative to fixed-income assets than it does relative to equities and to benchmark its role against more traditional safe-haven instruments. Second, extending the analysis to emerging markets would help determine whether the Bitcoin-equity relationship under stress is specific to developed economies or varies across different institutional and financial environments. Third, examining other major crypto-assets would help assess whether Bitcoin's apparent safe-haven gap is specific to Bitcoin itself or reflects a broader feature of digital assets as a class.

From a practical standpoint, these findings suggest that Bitcoin should not be viewed as a systematic portfolio hedge or a reliable safe haven in times of crisis. While its low average correlation with equity markets does support a limited role as a diversifying asset under normal market conditions, and its asymmetric return profile may justify an allocation for risk-tolerant investors, the broader evidence remains unfavourable to a safe-haven interpretation. During periods of severe market stress, Bitcoin tends to move in tandem with declining equity markets rather than offsetting them. This pattern is particularly pronounced at the monthly horizon, rendering Bitcoin an unreliable source of protection precisely when it is needed most.

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A Appendix

Daily

Figure A.1
Daily closing prices for market indices (September 2014 - December 2025).

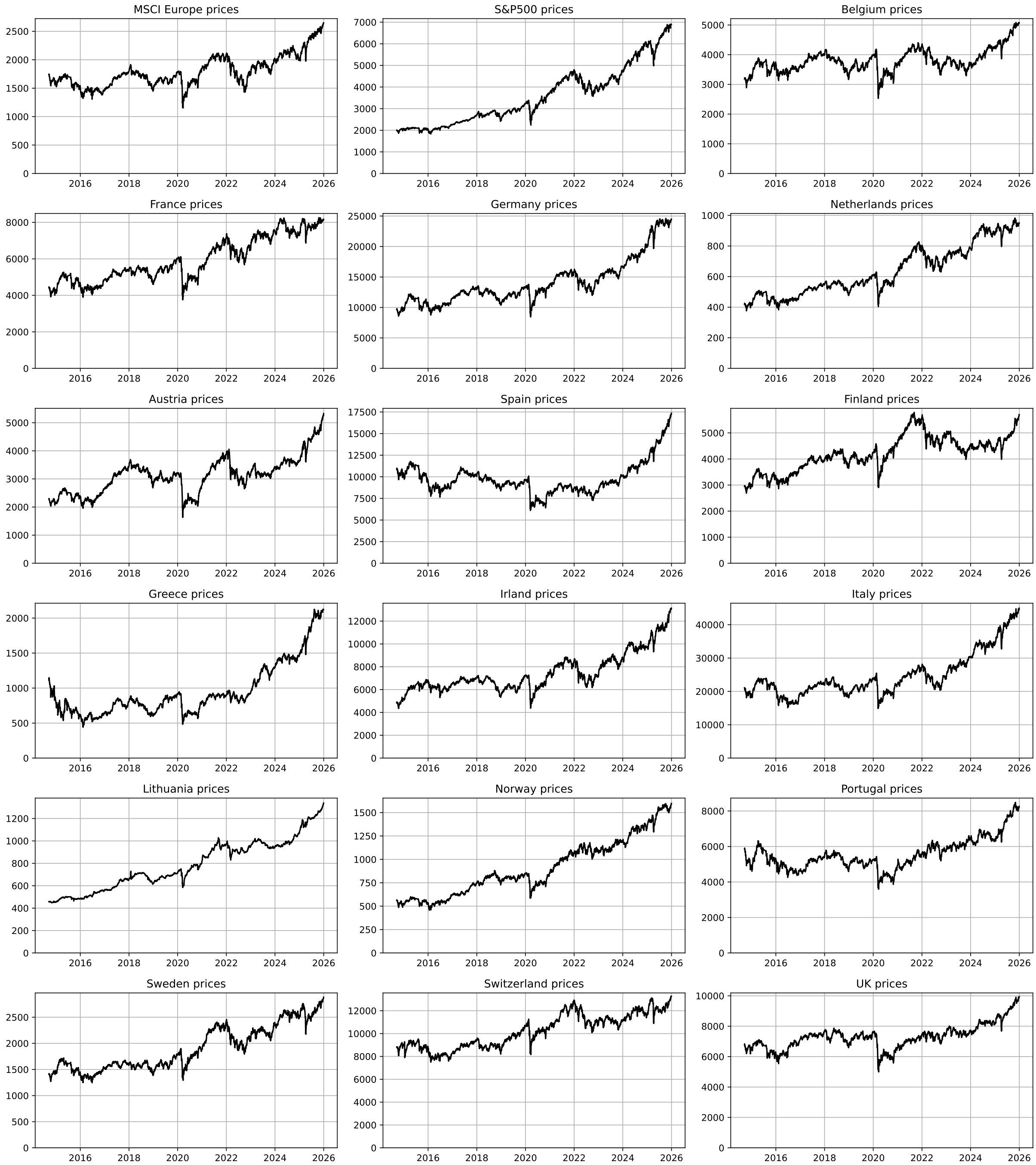


Figure A.2
Daily returns for market indices (September 2014 - December 2025).

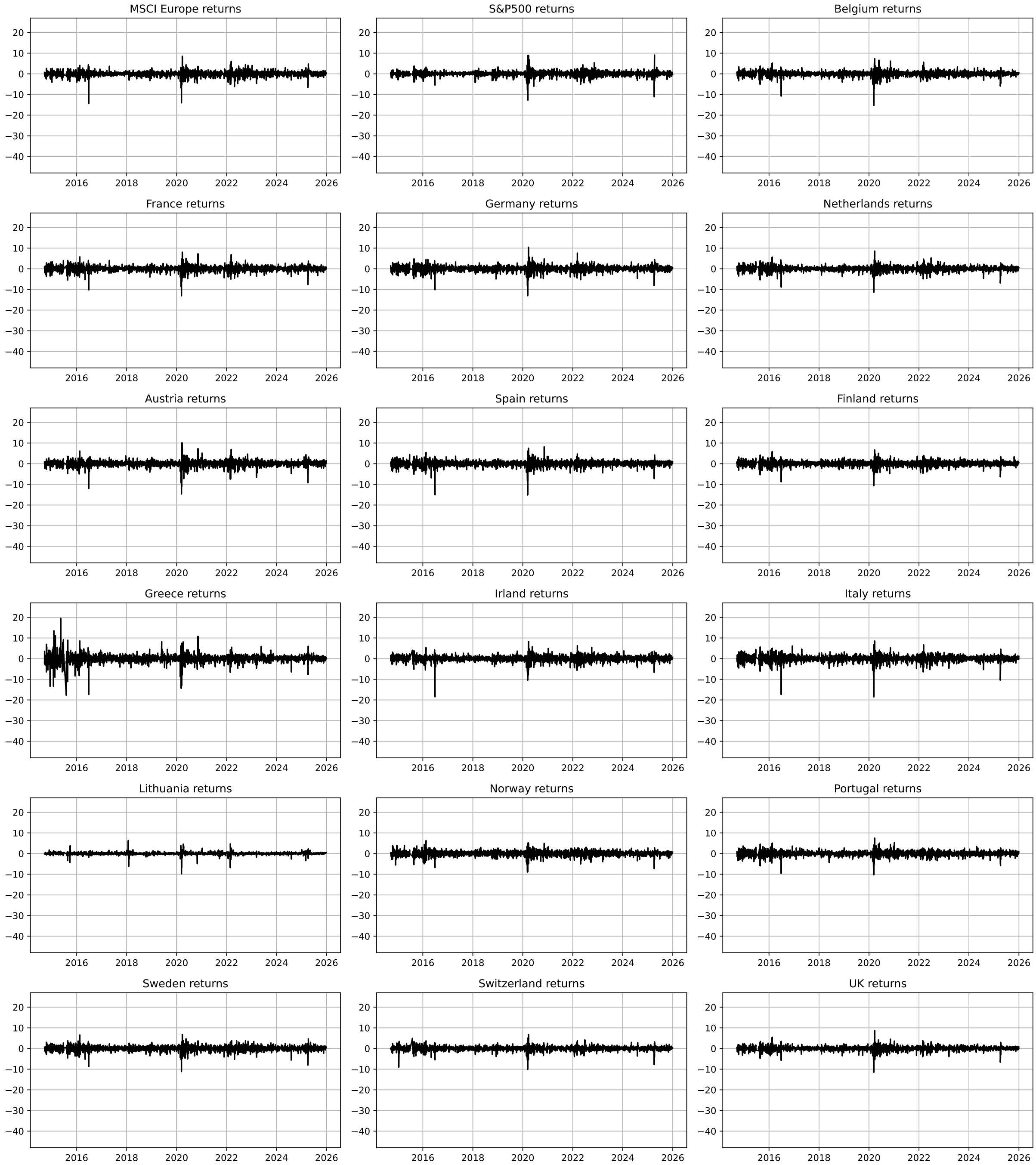
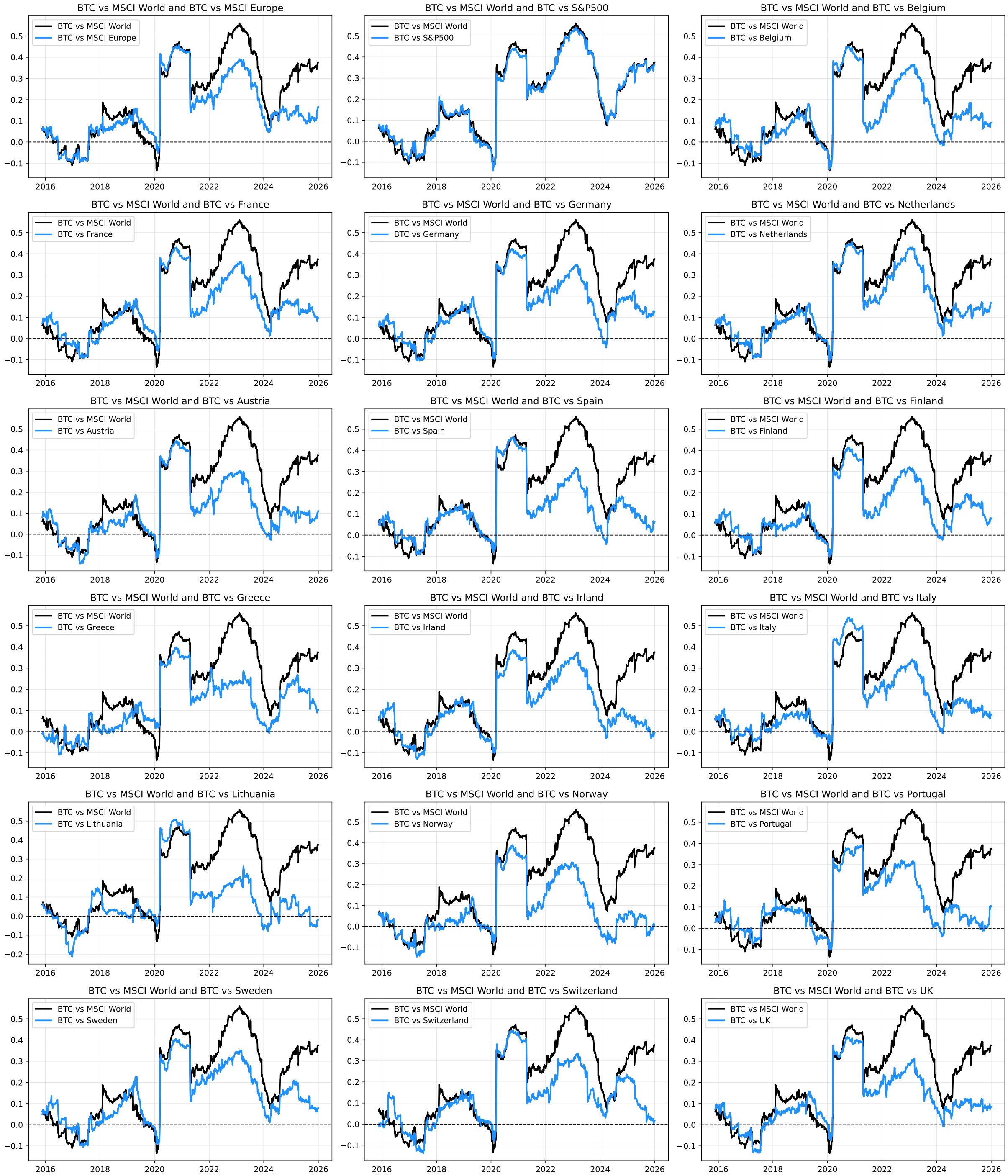


Figure A.3
1-Year rolling correlation estimates between Bitcoin and equity market indices, daily frequency.



Weekly

Table A.1
Descriptive statistics for weekly returns. *Weekly logarithmic returns are reported. The sample covers September 19, 2014 to January 09, 2026. European equity indices are denominated in local currency; MSCI World, MSCI Europe, S&P 500, and Bitcoin are denominated in US dollars. Annualised volatility, computed as* $\sigma \times \sqrt{52}$*, reaches approximately 72.2% for Bitcoin, whereas it ranges from about 16.9% to 19.1% across the equity indices.*

	Mean (%)	Median (%)	St. Dev.	Min. (%)	Max. (%)	Obs.
Indices (in US$)						
Bitcoin	1.062	0.666	10.006	-40.789	52.497	511
MSCI World	0.186	0.357	2.349	-13.302	11.211	511
MSCI Europe	0.086	0.221	2.648	-22.697	9.369	511
S&P500	0.243	0.473	2.473	-16.228	13.092	511
Markets (in local currency)						
Austria	0.167	0.291	3.081	-26.795	11.277	511
Belgium	0.095	0.270	2.595	-23.013	10.005	511
Finland	0.130	0.410	2.617	-22.564	7.594	511
France	0.123	0.263	2.754	-22.142	10.164	511
Germany	0.185	0.347	2.825	-22.330	10.329	511
Greece	0.128	0.335	4.136	-22.544	16.452	511
Ireland	0.194	0.327	2.858	-19.653	10.134	511
Italy	0.153	0.415	3.060	-26.524	10.378	511
Lithuania	0.217	0.200	1.566	-10.517	13.568	511
Netherlands	0.165	0.327	2.551	-20.492	8.220	511
Norway	0.204	0.342	2.424	-17.061	7.013	511
Portugal	0.072	0.166	2.616	-19.669	7.772	511
Spain	0.092	0.416	2.861	-23.378	12.481	511
Sweden	0.145	0.268	2.576	-16.845	8.162	511
Switzerland	0.082	0.232	2.270	-15.155	7.391	511
UK	0.077	0.191	2.232	-18.593	8.843	511

Figure A.4
Weekly prices for Bitcoin and equity market indices (September 2014 - December 2025).

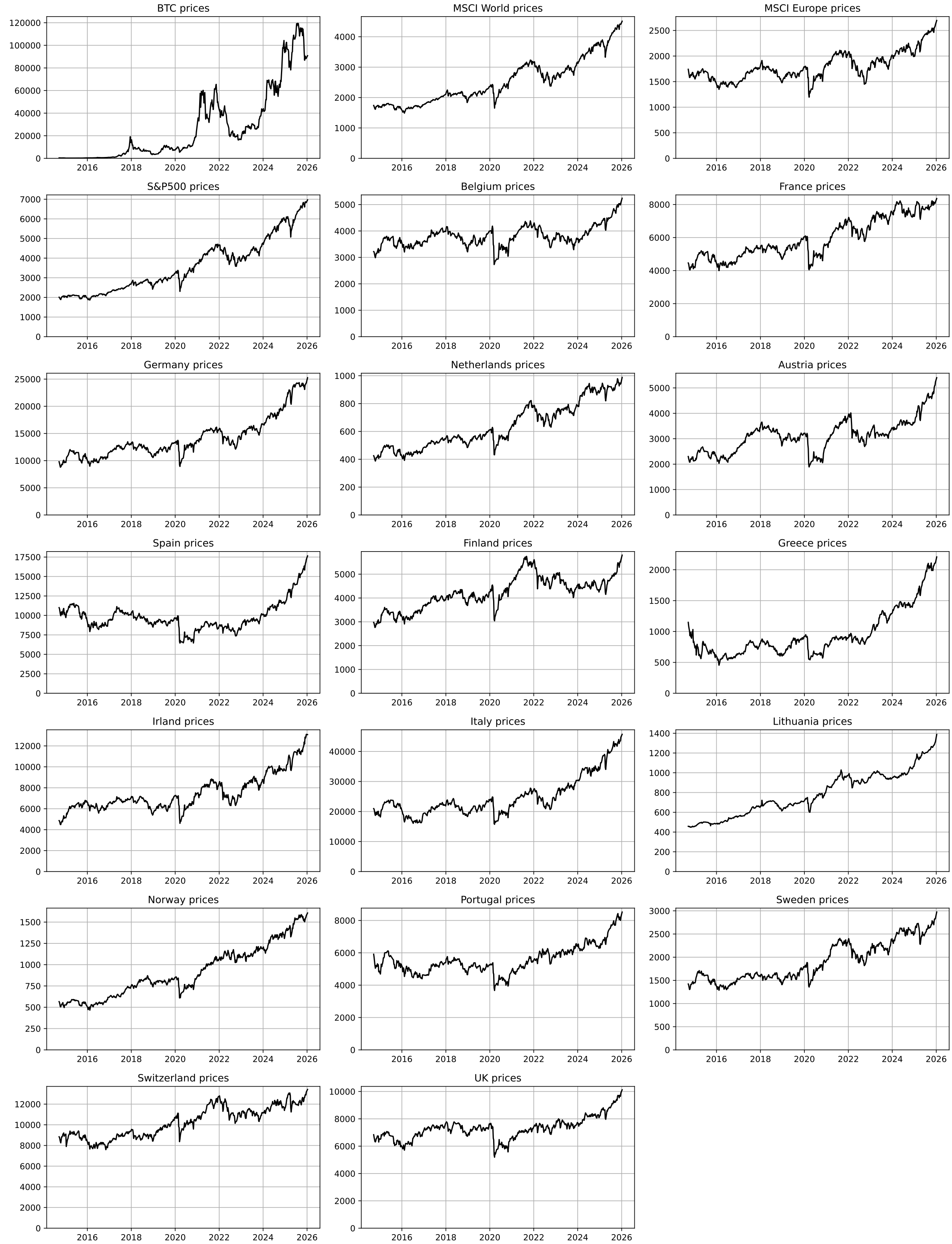


Figure A.5
Weekly returns for Bitcoin and equity market indices (September 2014 - December 2025).

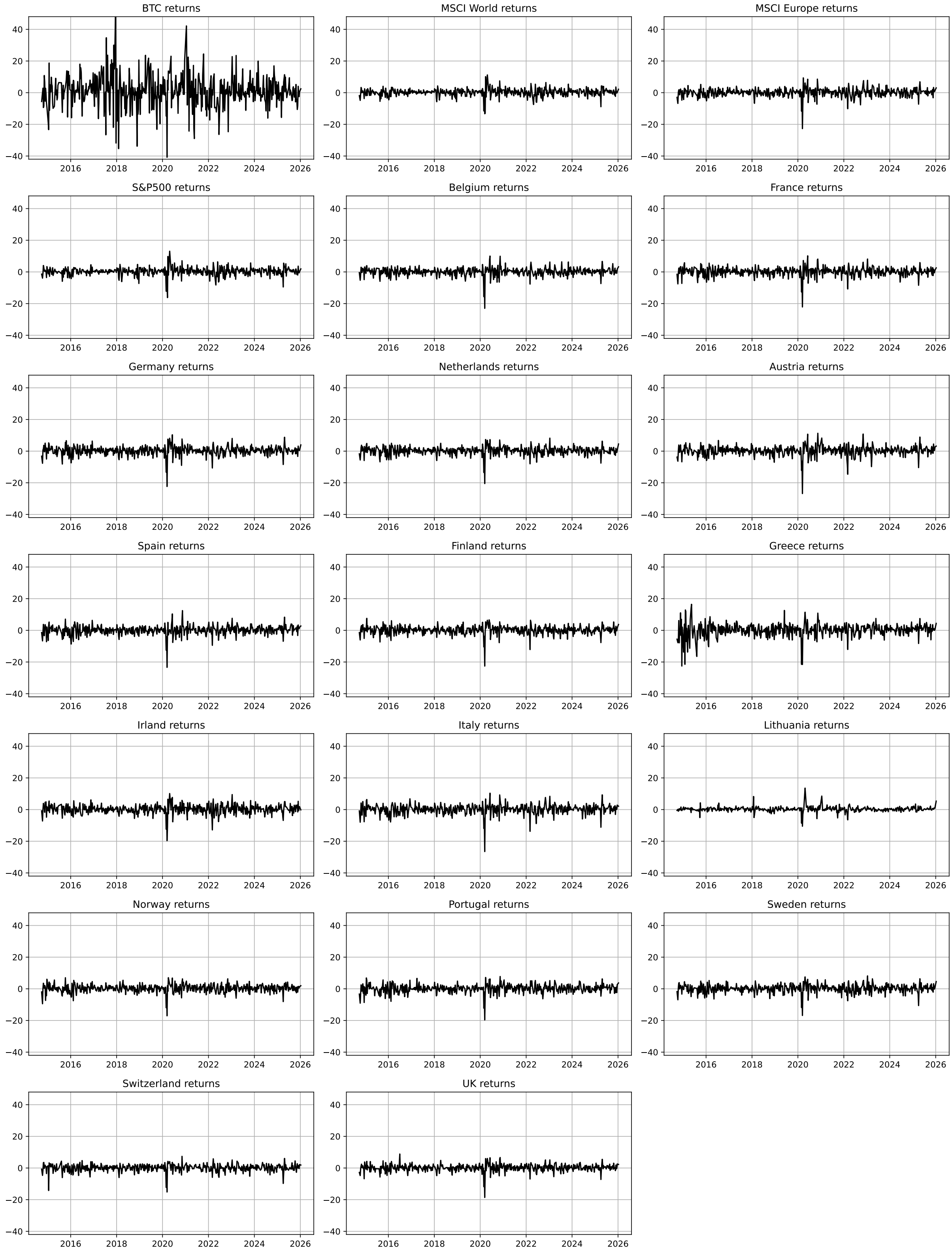


Figure A.6
Pearson correlation matrix for weekly returns, September 2014 - December 2025.

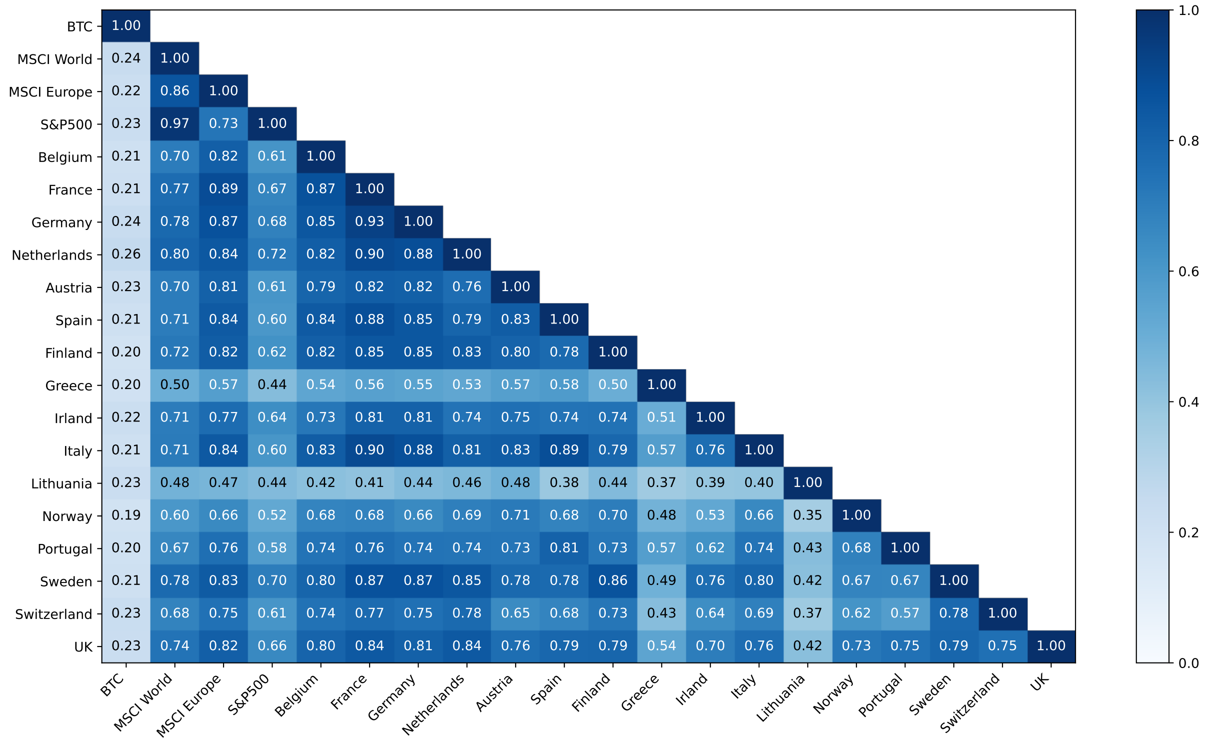


Figure A.7
1-Year rolling correlation estimates between Bitcoin and equity market indices (MSCI World and Lithuania), weekly frequency.

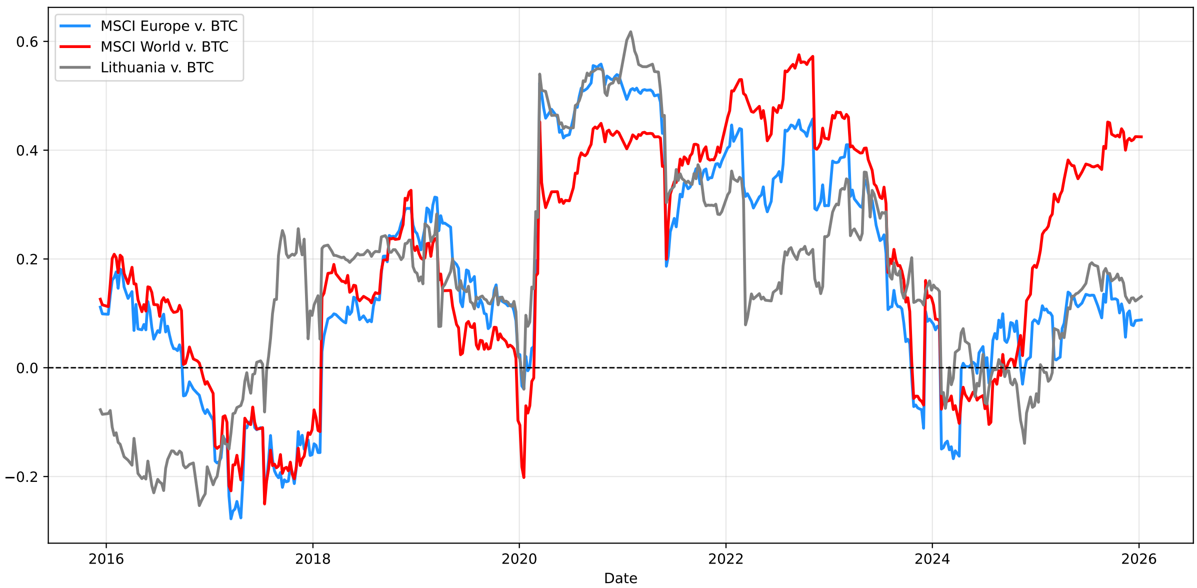
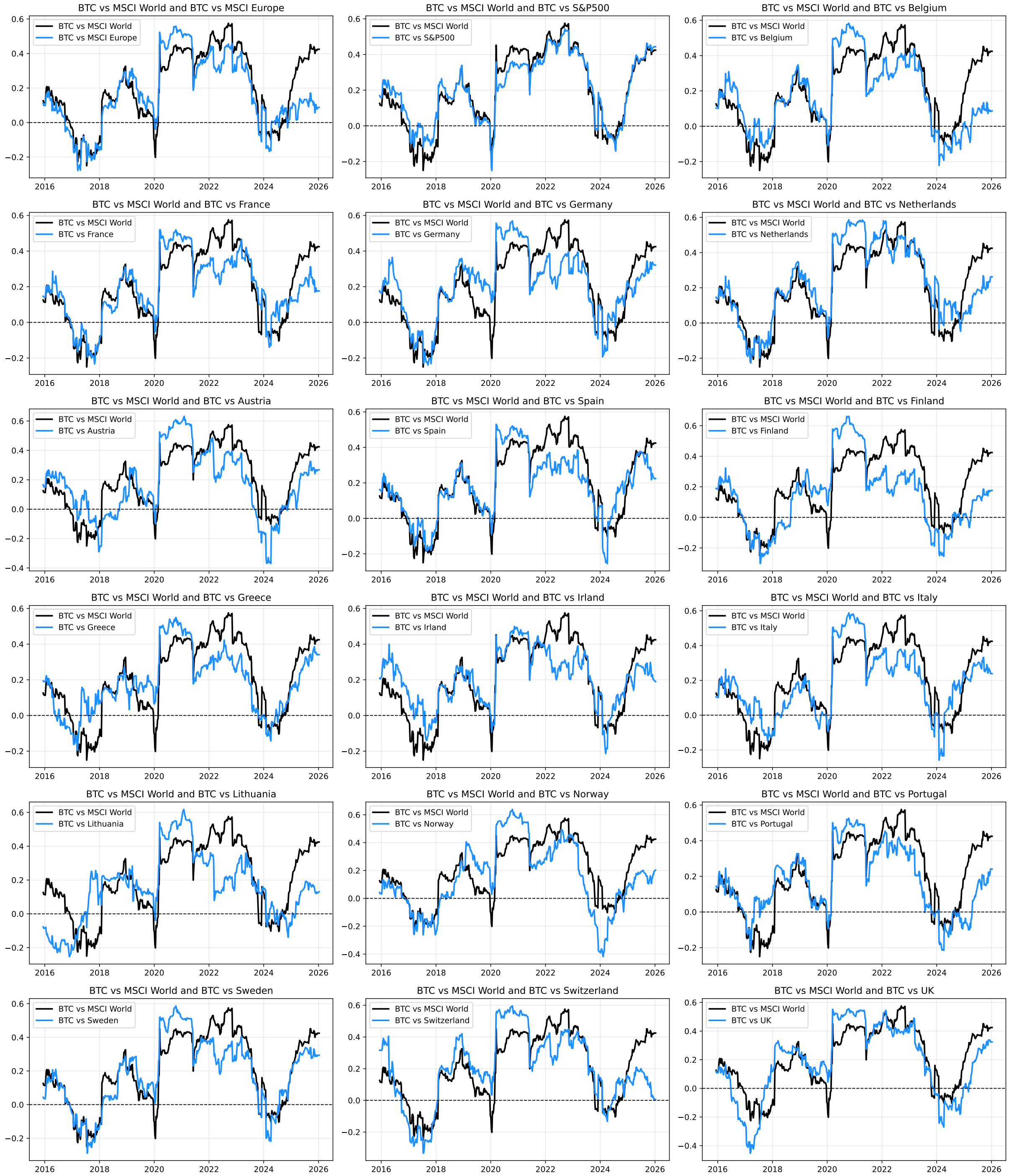


Figure A.8
1-Year rolling correlation estimates between Bitcoin and equity market indices, weekly frequency.



Monthly

Table A.2
Descriptive statistics for Monthly returns. *Monthly logarithmic returns are reported. The sample covers September 30, 2014 to December 31, 2025. European equity indices are denominated in local currency; MSCI World, MSCI Europe, S&P 500, and Bitcoin are denominated in US dollars. Annualised volatility, computed as $\sigma \times \sqrt{12}$, reaches approximately 67.8% for Bitcoin, whereas it ranges from about 14.5% to 15.9% across the equity indices.*

	Mean (%)	Median (%)	St. Dev.	Min. (%)	Max. (%)	Obs.
Indices (in US$)						
Bitcoin	4.046	3.078	19.562	-47.431	52.844	134
MSCI World	0.716	1.256	4.192	-14.468	11.917	134
MSCI Europe	0.336	0.719	4.576	-15.935	15.599	134
S&P500	0.929	1.640	4.276	-13.367	11.942	134
Markets (in local currency)						
Austria	0.659	1.278	5.917	-33.116	21.732	134
Belgium	0.340	0.913	4.307	-18.425	18.646	134
Finland	0.495	0.755	4.241	-17.423	11.790	134
France	0.457	0.708	4.552	-18.885	18.331	134
Germany	0.709	0.790	4.834	-17.958	13.985	134
Greece	0.516	1.618	8.222	-25.713	25.772	134
Irland	0.738	1.278	5.168	-21.618	11.134	134
Italy	0.572	0.812	5.559	-25.411	20.661	134
Lituania	0.800	0.695	3.028	-12.936	13.948	134
Netherlands	0.608	0.639	3.980	-10.949	12.674	134
Norway	0.785	1.085	3.888	-14.134	14.589	134
Portugal	0.272	0.631	4.583	-15.792	15.460	134
Spain	0.350	0.528	5.139	-25.121	22.459	134
Sweden	0.537	0.983	4.249	-11.845	11.010	134
Switzerland	0.303	0.641	3.403	-7.794	8.870	134
UK	0.302	0.812	3.404	-14.858	11.647	134

Figure A.9
Monthly prices for Bitcoin and equity market indices (September 2014 - December 2025).

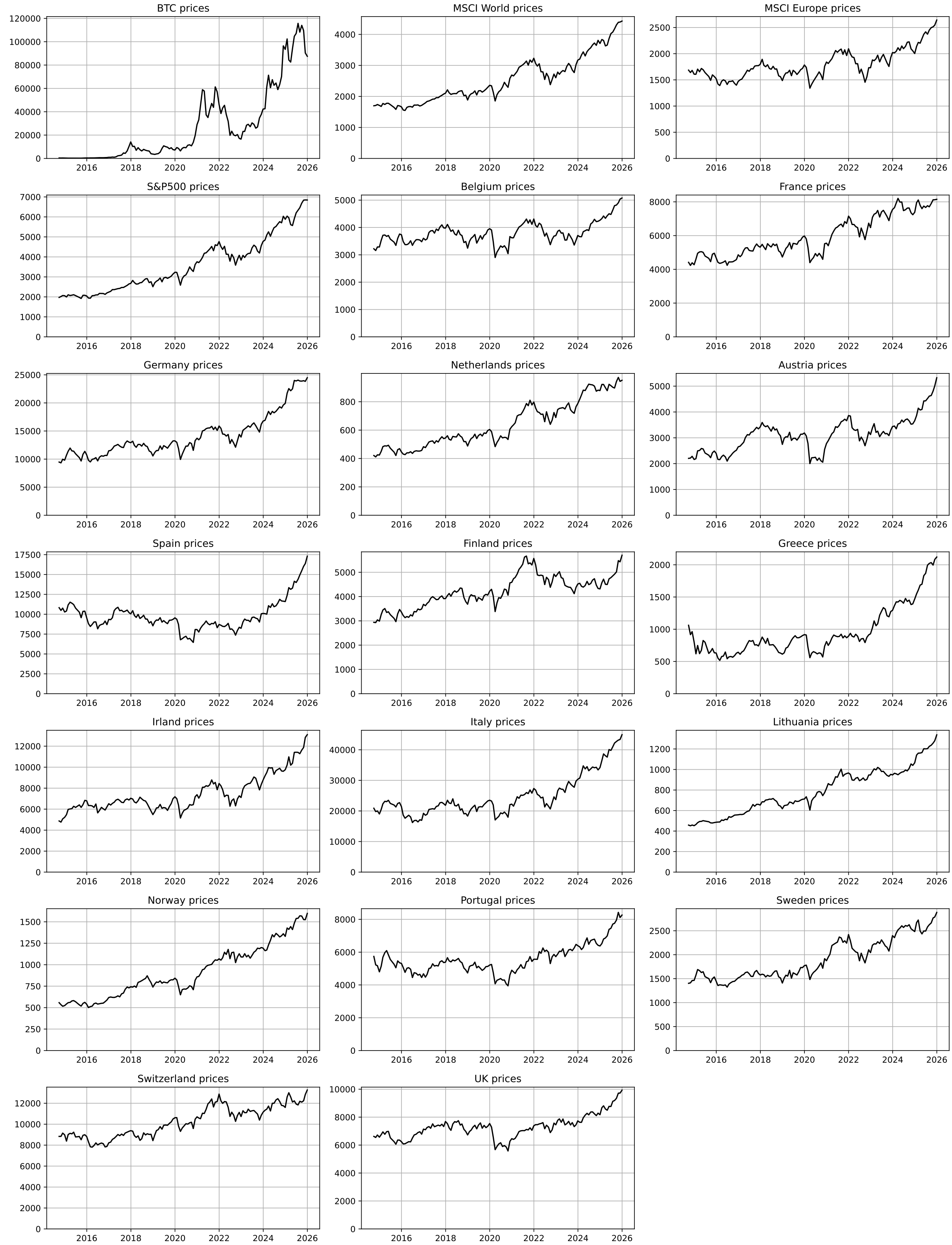


Figure A.10
Monthly returns for Bitcoin and equity market indices (September 2014 - December 2025).

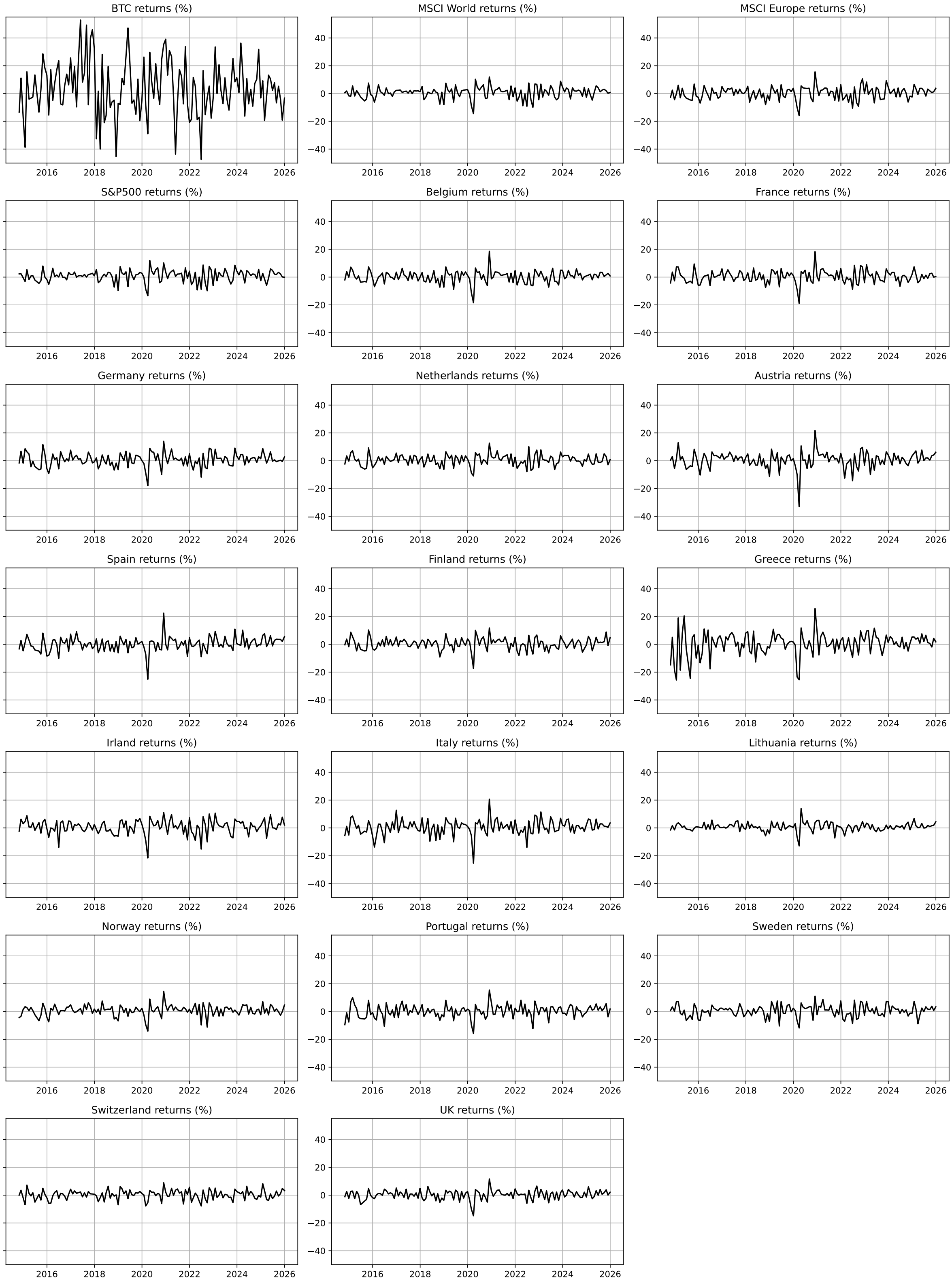


Figure A.11
Pearson correlation matrix for monthly returns, September 2014 - December 2025.

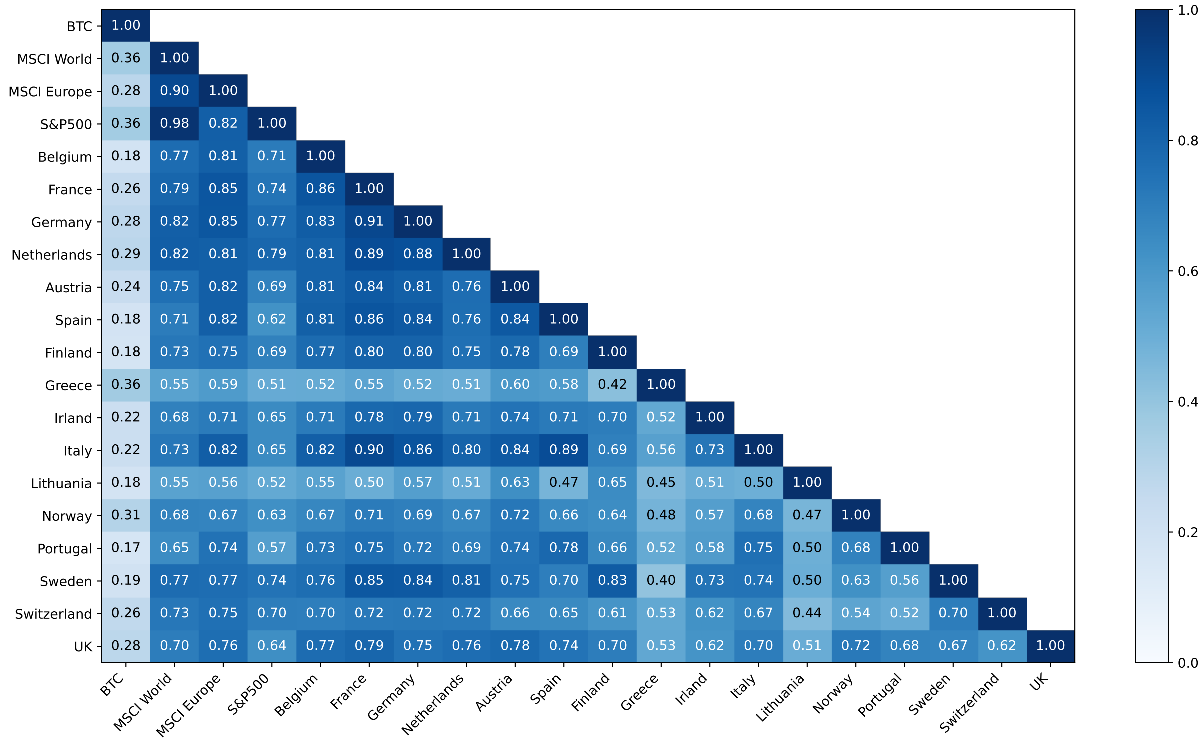


Figure A.12
1-Year rolling correlation estimates between Bitcoin and equity market indices (MSCI World and Lithuania), monthly frequency.

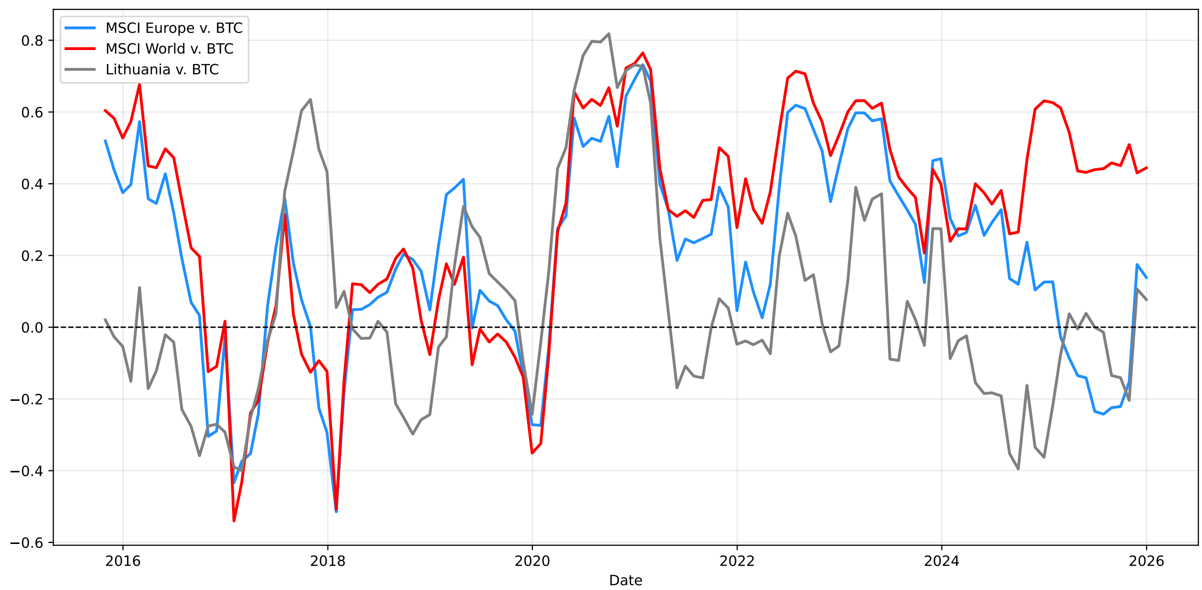
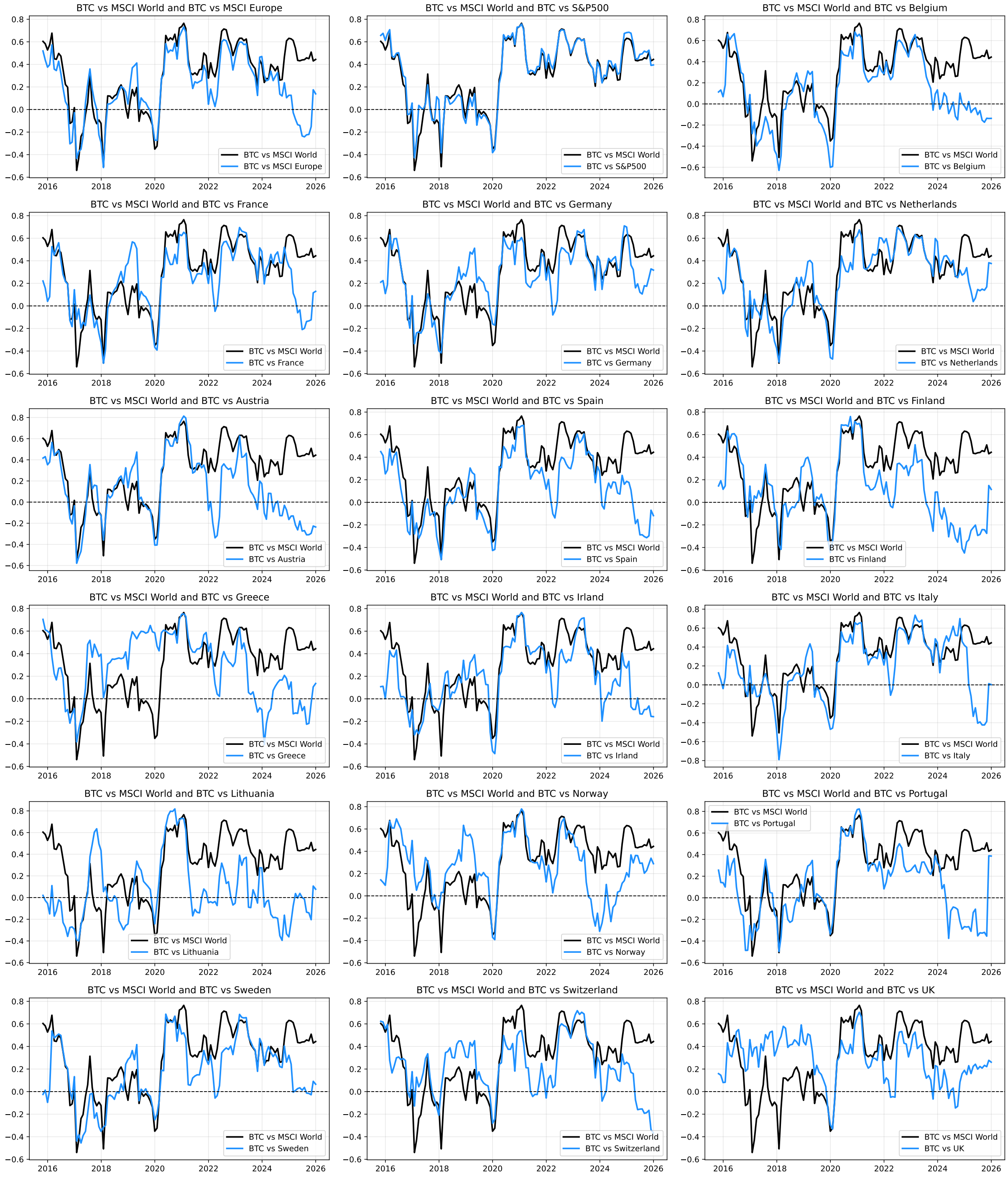


Figure A.13
1-Year rolling correlation estimates between Bitcoin and equity market indices, Monthly frequency.



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