Investor Sentiment, Unexpected Inflation and Bitcoin Basis Risk

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Abstract

The introduction of regulated CME futures contracts on Bitcoin in 2017 raised an expectation that cryptocurrencies would become part of mainstream financial markets. This also heightened links between traditional markets and Bitcoin, implying that the cryptocurrency would be subject to systematic spillovers. In this paper, we use high-frequency data to examine whether Bitcoin basis risk is linked to investor sentiment from established financial markets. We present strong evidence that extreme investor sentiment, represented by volatility indices such as the VIX, is associated with a Bitcoin futures price lower than the spot. These findings are partially attributed to a coinciding increase in the relative volume of Bitcoin futures and have greater magnitude during periods of unexpected inflation and deflation.

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1. Introduction

Launched with considerable media attention in December 2017, the regulated CME Bitcoin futures contract was thought of as a step on the road to "professionalize" the asset class.[1] The success of this launch has been strongly debated, with some evidence for subsequent downward price pressure on the spot market [Jalan et al., 2021]. The introduction of the futures contract widens the opportunity set for an investor with a negative view on an asset class to take a short position. In a market such as Bitcoin, where taking a short position can be expensive and cumbersome, this has the potential to result in price mismatches between spot and futures [Gay and Jung, 1999, Fung and Draper, 1999]. Such mismatches give rise to basis risk, where changes in the futures contract do not exactly offset the spot position.

Although not producing cash flows which can be impacted by systematic risk factors [Griffin and Shams, 2020], a large literature has documented links between cryptocurrency returns and those of traditional asset classes, especially during periods of market wide volatility [Elsayed et al., 2022, Liu and Tsyvinski, 2021, Conlon et al., 2021, Jo et al., 2020].[2] In contrast, using a dataset which ends prior to the advent of futures trading, Borri [2019] provides evidence that cryptocurrency prices are not affect by tail-risk in other asset classes. Greater market volatility has also been shown to be associated with a transition to price discovery in Bitcoin futures market [Entrop et al., 2020]. In this paper we shed further light on these interrelationships, assessing links between Bitcoin basis and trading volume, and extreme volatility in traditional markets.

Our research adds to the literature in various ways. While the questions of price discovery between Bitcoin spot and futures markets has been well assessed, there is only limited research dedicated to understanding the basis risk between these markets. Our approach, using high frequency spot and futures data to examine links between extreme volatility in traditional markets and the Bitcoin futures basis, provides fresh insight into the ways that events in conventional markets can influence the performance of ostensibly independent markets. In a further contribution, we assess whether these extreme market shocks influence the relative volume between futures and spot markets, highlighting the preferred market investors turn to during times of turmoil. Finally, in an attempt to uncover the extent to which macroeconomic news influences Bitcoin, we assess the influence of unexpected news reports on both Bitcoin basis and relative volume.

We provide a brief outline of our major empirical findings. For a variety of implied volatility indices, we find that extreme volatility is associated with a Bitcoin futures price which is lower than the spot price. At the other extreme, low volatility in the Chicago Board of Exchange gold volatility,

[1] For example, Forbes published an article title "CME Group Launching Bitcoin Futures In Q4 To 'Professionalize' Crypto Asset Class" in October 2017.

[2] Biais et al. [2023] present a model of bitcoin pricing, where the value of the cryptocurrency is function of the stream of future transactional benefits.

far term VIX index and the risk reversal index are associated with a spot price which is lower than the futures prices. Furthermore, extreme market volatility is associated with greater relative volume, meaning that more trading occurs in the futures markets during periods of turbulence in other asset classes. Finally, we provide evidence of a macroeconomic influence on the Bitcoin basis during periods of extreme market volatility. Specifically, during periods of strong unexpected inflation and deflation, the influence of the VIX on basis risk is found to be strongest. Further support for the findings as to the influence of extreme volatility are provided by assessing the second moment of the Bitcoin basis and relative volume.

Our findings have a variety of policy and regulatory implications. During periods of extreme volatility, investors turn to futures markets to express their market views, in keeping with much of the literature on Bitcoin price discovery. This suggests that regulators should carefully monitor trading in futures markets, which might provide clues relating to future market dislocations. Spot Bitcoin markets, in contrast, are currently unregulated and a relative decrease in volume might point to emerging issues, such as during the collapse of the exchange FTX, which forced many traders to seek alternative trading venues.

The remainder of the paper is structured as follows: the previous literature and theories that guide the development of our research are summarised in Section 2. Section 3 presents a thorough explanation of the wide variety of data used in such analysis while presenting a concise overview of the methodologies used. Section 4 reports the empirical findings. A further brief discussion of the theoretical and policy-based implications of the presented results is provided in Section 5, while Section 6 concludes.

2. Previous Literature

Bitcoin futures contracts were introduced by the Chicago Mercantile Exchange (CME) in December 2017. Despite hopes that this would integrate Bitcoin into traditional markets, early evidence suggested that the launch presaged an increase in spot volatility and that futures did not provide an adequate hedging mechanism for spot investors [Corbet et al., 2018].[3] While bitcoin futures hedging effectiveness is poor using the traditional variance-based approach, accounting for a more sophisticated dependence structure can provide hedging benefits [Liu et al., 2023]. Assessing the impact on the moments of returns, Jalan et al. [2021] provide evidence of increased volatility and kurtosis of spot returns after the introduction alongside a decrease in skewness.

The primary focus of Bitcoin futures research has been on the price discovery mechanism with spot, with some disagreement in the empirical findings reported. Baur and Dimpfl [2019] find,

[3]Futures contracts are used for both speculation and hedging [Wang, 2003] and present many benefits relative to spot markets including higher leverage possibilities and lower transaction costs. The economic benefits have been found to be mixed at a corporate level, accruing mainly to those hedging foreign exchange risk [Bessler et al., 2019].

using high-frequency data, that price discovery in the months after the launch of Bitcoin futures is attributed to the spot market. In contrast, Kapar and Olmo [2019], Alexander and Heck [2020] and Aleti and Mizrach [2021] document price discovery in futures markets leading the spot market.[4] Instead of using a rolled futures contract, Entrop et al. [2020] examine the price discovery between spot and specific futures contracts, finding mixed results. Focusing on the methodological approaches usually employed to understand price discovery, Conlon et al. [2022] attempt to reconcile the findings in the literature, documenting that high-frequency Bitcoin price discovery emanates in the spot market.

The implied volatility index (VIX) and the many related products are considered a measure of "*investor fear*" in the market. While no single pervasive measure of investor sentiment has been proposed, the VIX is often taken as one proxy [Jo et al., 2020, Smales, 2017, Simon and Wiggins III, 2001].[5] In the context of Bitcoin spot, sentiment, measured using the VIX, has been shown to be associated with low expected Bitcoin returns [Jo et al., 2020] and to predict Bitcoin returns and volatility Dias et al. [2022]. Entrop et al. [2020] also find that price discovery switches to the futures market during periods of higher market volatility, helping to motivate our study of basis risk during periods of extreme volatility.

While stocks, which are claims on cash flows generated by real assets, should be a hedge against inflation, much empirical evidence documents a negative relationship between stock returns and both expected and unexpected inflation [Jaffe and Mandelker, 1976, Fama and Schwert, 1977]. Bitcoin has been described as 'digital gold', with the potential to act as a long-term hedge against inflation similar to the precious metal [Conlon et al., 2018, Chua and Woodward, 1982]. The limited supply of Bitcoin is one argument for its potential as an inflation hedge. This is, however, negated by the need for an inflation hedge to provide price stability, a criterion which Bitcoin would not appear to meet [Baur et al., 2018]. The empirical findings with respect to any prospective links between Bitcoin and inflation have been mixed. Blau et al. [2021] report that changes in the Bitcoin price Granger cause changes in expected inflation. In contrast, Conlon et al. [2021] demonstrate that any relationship between Bitcoin and inflation is limited to a brief period of deflation at the height of the COVID-19 pandemic. The evolving acceptance of cryptocurrencies has coincided with a period of inflationary pressures not seen since the 1980s and an associated upward trajectory for interest rates internationally. This motivates our focus on inflation as a catalyst for changes in the Bitcoin basis, given that Bitcoin does not provide an income and takes into account the possible inflation hedging capacity described earlier.

[4] Alexander et al. [2020] also demonstrates that the unregulated derivatives traded on BitMEX lead Bitcoin spot in information discovery.

[5] While Baker and Wurgler [2007] do not include the VIX as one of the components in their seminal paper on investor sentiment, they acknowledge that its inclusion would be appropriate. Still, they are forced to exclude it due to insufficient data dating back to 1960.

Basis risk - the risk that the change in the futures price will not track the spot price - is a substantial challenge to the benefits of futures markets. Basis risk emerges due to an imperfect relationship between spot and futures, except at the expiration date.[6] While mismatches in the time to expiration and the holding period are the primary drivers of basis risk, 'noise' in the price relationship may also be a source [Figlewski, 1984]. Limits to arbitrage may be one explanation, for example, with short selling restrictions resulting in mismatches in price between spot and futures [Gay and Jung, 1999, Fung and Draper, 1999]. In the case of Bitcoin, there is a paucity of legitimate ways to short spot Bitcoin, making arbitrage difficult and resulting in discrepancies in pricing between spot and futures markets [Shynkevich, 2021]. This is borne out during periods of high Bitcoin downside risk, where profitable arbitrage opportunities are found to be greatest [Hattori and Ishida, 2021].

3. Data and Methodology

3.1. Data

To understand the high-frequency interactions between Chicago Board of Exchange (CBOE) volatility products and Bitcoin spot and futures markets, we begin by matching the respective indices at an hourly level of frequency between midnight on 3 June 2019 and 17:00 on 30 December 2022, where all times are matched using Eastern Standard Time (EST), resulting in 21,233 observations. A substantial amount of data prior to the onset of the COVID-19 pandemic[7] in January 2020 is included to ensure that the presented methodological structure also accounts for a period of relative market stability prior to the exceptional international turbulence that subsequently follows [Conlon and McGee, 2020]. Dependent on the CBOE volatility futures contract analysed, there are between 7,004 and 12,653 comparable observations through which the selected methodological processes can be analysed. The respective CBOE volatility indices analysed are presented in Table 1, with associated summary statistics presented in Table 2. The selected series include the CBOE Volatility Index (VIX), the VIX Volatility Index (VVIX), the CBOE DJIA Volatility Index (VXD), the CBOE Crude Oil Volatility Index (OVX), the CBOE Gold Volatility Index (GVZ), the CBOE S&P500 Risk Reversal Volatility Index (RXM), the Cboe NASDAQ Volatility Index (VXN), the CBOE SPX Far-term VIX Index (VIF), and the CBOE SPX Near-term VIX Index (VIN). Each respective volatility index included accounts for a dynamic examination of multiple

[6]Also relating to, but distinct from, our study, Shi [2022] examines the determinants of the Bitcoin futures risk premia, the difference between prices on near and distant futures contracts, finding various macroeconomic predictors.

[7]On 30 December 2019, as reported by World Health Organisation (WHO), the Wuhan Municipal Health Commission in China reported a cluster of cases of pneumonia in Wuhan, Hubei Province. The novel coronavirus, in its current form, was subsequently identified and announced to the world as a global pandemic. After this date, COVID-19 was gradually acknowledged globally, and its impacts became internationally contagious [Corbet et al., 2020, 2022a,b].

differentials of financial market behaviour sourced from various implied volatility conditions within major international traditional financial markets.

Insert Tables 1 & 2 about here

The price performance of Bitcoin spot and futures products are presented in Figure 1, with evidence of the sharp price appreciation that took place in late 2020. Much research identified the presence of elevated market maturity due to implementing Bitcoin futures products at the CME [Akyildirim et al., 2021].[8] Further evidence of its growing development is presented in Figure 2, where in the lower panel, we observe that the volumes traded in futures markets over time have elevated quite consistently compared to spot markets.

Insert Figures 1 through 2 about here

Basis, in the context of futures contracts, is the difference between the spot price of an asset and its futures price. It represents the cost of carry or the cost associated with holding the asset until the contract's delivery date. The spot price is the current market price of the asset, while the futures price is predetermined and reflects the anticipated value of the asset at a future date. The estimated basis of Bitcoin is presented in Figure 3, providing further evidence of the growing maturity of Bitcoin futures products with substantial variability between June 2019 and June 2020 relative to a much tighter presented basis thereafter, with the exception of some distinct periods of disconnect associated with rapidly shifting prices of Bitcoin. Shifts in the basis of Bitcoin are integral to understanding futures market dynamics, particularly whether the Bitcoin market is in contango or backwardation. Relative basis, also identified to be the slope factor of basis [Gao et al., 2023], adds a further explanatory dimension as presented in Figure 4. Relative basis refers to the basis, the difference between the futures price and the spot price of Bitcoin, normalised to the futures price expressed as a percentage, allowing for a more standardised comparison across different assets or the same asset at different price levels. The relative basis provides a measure of the annualised return an investor can earn from a cash-and-carry arbitrage strategy price converge at contract expiration. Further, relative basis allows for more meaningful comparisons over time

[8] The Chicago Mercantile Exchange (CME) is a leading global derivatives marketplace in Chicago. The CME became a publicly traded company in December 2002. In July 2007, it merged with the Chicago Board of Trade to form the CME Group Inc., which operates both markets. The CME Group is now a designated contract market and includes the New York Mercantile Exchange (NYMEX) and COMEX as part of its portfolio. With the largest open interest in options and futures contracts globally, the CME trades a wide range of financial instruments such as interest rates, equities, currencies, and commodities. Notably, the CME pioneered the widely used CME SPAN software, which serves as the official margin mechanism for numerous exchanges, clearing organisations, service bureaus, and regulatory agencies worldwide.

and across different assets. It allows traders to assess whether the basis is high or low, not just in absolute terms but in relation to the price level of the underlying asset. It's particularly useful in markets where prices can be highly volatile, such as in the case of cryptocurrencies such as Bitcoin.

Insert Figures 3 through 5 about here

The relative volume of Bitcoin, as presented in Figure 5, provides insights into the liquidity and activity level of a particular asset and helps traders identify periods of unusual market activity. In the context of spot and futures markets, relative volume can help traders to understand where substantial trading activity is taking place. For instance, if the relative volume of a Bitcoin futures contract is significantly higher than the relative volume of Bitcoin on the spot market, it could suggest increased speculative interest or hedging activity in the futures market. Conversely, a higher relative volume on the spot market might indicate stronger buying or selling activity at the current price. It is important to note that relative volume is a context-dependent metric, providing information about trading activity that can be combined with other indicators and market analysis to inform trading strategies. High relative volume often accompanies significant price movements. As presented, the ratio of futures trading volumes to that of spot trading volumes traded has elevated between 2019 and 2022, presenting further evidence of the growing maturity of this new market over time.

3.2. Methodology

Building upon a GARCH(1,1) volatility process, the returns of each of the Bitcoin spot and futures prices are examined, using a series of dummy variables to represent large upward and downward levels in the respective volatility futures series that are examined, at both the top and bottom 1%, 5% and 10% level.

$$\begin{aligned} r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} \\ + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t, \end{aligned} \tag{1}$$

$$h_t = \omega + a e_{t-1}^2 + b h_{t-1}, \tag{2}$$

where $r_{b,t}$ are the returns of the Bitcoin spot and futures products. The coefficient $r_{b,t-n}$ captures the lagged Bitcoin returns in the hours preceding the significant changes of volatility where each model is run individually. $\beta_2^{1\%}$, $\beta_3^{5\%}$ and $\beta_4^{10\%}$ are dummy variables taking value one if $r_{v,t}$, the respective level of each of the analysed volatility indices, is below the 1^{st}, 5^{th} and 10^{th} percentile and zero otherwise. Parameters $\beta_5^{90\%}$, $\beta_6^{95\%}$ and $\beta_7^{99\%}$ capture any extreme levels of the analysed volatility indices above the 90^{th}, 95^{th} and 99^{th} percentile and zero otherwise. The total effect is a sum of the relevant coefficients. If the volatility movement exceeds a certain threshold, it also exceeds all smaller thresholds. For example, if returns exceed the 99^{th} percentile, they also exceed the 95^{th} percentile, therefore, representing a comparable estimate of the effects of extreme volatility changes upon Bitcoin. Throughout the results, we calculate the standard error of the linear combination of coefficients and report the t-statistic of the linear combination. To understand the effects of such exceptional volatility movements upon Bitcoin spot and futures liquidity conditions, we repeat the high-frequency analysis by replacing $r_{b,t}$ with $r_{l,t}$, where l represents liquidity. Finally, to understand the influence of exceptional financial market volatility movements, using volatility futures to indicate forward-looking investor perceptions, we repeat the analysis, including the respective dummy variables generated from the extreme volatility futures movements within Equation 2 to further our understanding of the effects of such implied volatility upon the liquidity conditions of Bitcoin spot and futures products.

Insert Figure 6 about here

The above estimated differential price volatility and liquidity conditions are then partitioned based on quintiles ranked from the strong and moderate deflation through to strong and moderate inflation surprise, as separated with a decile representing no unexpected change. Considering the largest deflation surprise, actual inflation is found to have been significantly below estimated inflation, with the largest surprise taking place on 10 November 2022 at -0.30%. In contrast, the largest positive surprise took place on 12 May 2021, where the estimated surprise was found to be +0.60%. To better understand the interactions between Bitcoin spot and futures volatility and liquidity conditions during varying phases of inflation shock in the United States, results are presented as separated by respective quintiles of tiered inflation and deflation surprise.

4. Results

4.1. Does exceptional financial market volatility influence Bitcoin spot and futures products differently?

Focusing on Bitcoin basis differential and volatility as a result of extreme levels of volatility indices presents several interesting dynamics. The strongest, significant positive interactions occur for the Cboe Gold Index (GVZ) and the Cboe S&P 500 Risk Reversal Index (RXM) when volatility is at its lowest level. Therefore, as gold market volatility futures and those futures relating to the mitigating expectations of imminent shifts of conditions on the S&P500 fall in value, Bitcoin futures prices are found to increase at a level significantly above that of corresponding spot markets. In effect, both volatility indices having a low level would tend to signal a time of relaxed expected conditions, and Bitcoin futures markets respond in a corresponding manner. In contrast, Bitcoin spot does not tend to increase in the same manner. Such a phenomenon could be explained by the presence of retail investors boosting the level of idiosyncratic risk on corresponding spot markets [Ozdamar et al., 2022]. Further differentials in the corresponding lack of significant estimated volatility add additional robustness to this observation, potentially signalling a reduction in the presence of high-frequency trading on futures markets in comparison to spot markets.

Insert Table 3 about here

When considering the largest decreases of Bitcoin basis, signalling significant depreciation in Bitcoin futures with respect to Bitcoin spot prices, we observe that the most pronounced differentials occur simultaneously for the top 1% highest levels of the Cboe SPX Far-term VIX Index (VIF), the Cboe Volatility Index (VIX), and the VIX Volatility Index (VVIX). All three measures are representative of substantial implied volatility, acting as a signal of market fear and expectations of forward-looking volatility expectations. The significant negative differential between Bitcoin forward and spot pricing can be attributed to the considerable difficulties experienced by investors looking to short-sell Bitcoin on spot exchanges. Further explanation can also be attributed to the relative maturity of derivatives traders [Ferko et al., 2023] in comparison to spot traders, where the excessive negative response to implied volatility conditions would be considered a rational reaction, outside of the potential euphoria that has been largely associated with cryptocurrency in isolation of global economic and geopolitical events [Corbet et al., 2018, Cheah and Fry, 2015]. The volatility differentials identified simultaneously to extreme levels of the volatility index in Table 3 further indicate that at a high level of frequency, futures markets exhibit a more acute response to sharp elevations of traditional volatility futures markets, indicative of a higher level of market efficiency corresponding to real-time market dynamics. Such a result adds further weight to the debate surrounding cryptocurrency's development to become a mainstream financial market asset rather than a short-term trend [Huang et al., 2022].

Insert Table 4 about here

Further robustness analysis is provided in Table 4 when focusing on the relative basis, which provides a more standardised comparison across different assets or the same asset at different price levels, allowing for more meaningful comparisons over time and across different assets. Again, when focusing on VIF, VIX, and VVIX, we observe that during phases of sharply elevated futures market volatility, Bitcoin futures largely underperform spot prices. Such a result is particularly pertinent when considering the exceptional volatility experienced in cryptocurrency markets.

Insert Table 5 about here

While differentials of price are clearly found to respond to extremes in market volatility, another particularly novel result is identified in Table 5 when considering the dynamic response of Bitcoin liquidity conditions. The relative volume of Bitcoin is found to generate a quite broad response to the movement of volatility futures products in quite a progressively-tiered manner in line with the most acute shocks to volatility futures. Moreover, in line with the preceding results, elevated volatility differentials are found to coincide with the most pronounced changes to both basis and relative basis. Therefore, such transitioning shocks from volatility futures are found to permeate through elevated liquidity conditions in futures markets compared to spot markets. This result presents an additional dimension that further validates the view that Bitcoin futures markets are more informationally efficient when considering longer-term dynamic behaviour and forward-looking expectations compared to Bitcoin spot markets.

4.2. Does exceptional financial market volatility influence Bitcoin spot and futures products differently under various phases of unexpected inflation?

Bitcoin has increasingly been examined as a potential hedge against inflation [Blau et al., 2021, Conlon et al., 2021]. Several underlying factors contribute to this proposition: where first, Bitcoin's inherent limited supply, analogous to finite resources such as precious metals, establishes its potential to retain or escalate in value in the face of inflationary pressures because its supply is algorithmically constrained to 21 million units; secondly, the operational decentralisation of Bitcoin, its functional independence from governmental or institutional control, insulates its value from the vicissitudes of traditional currencies; thirdly, Bitcoin's potential as an inflationary hedge is its border-less accessibility, granting it relevance as an alternative value repository in regions with endemic inflation; while finally, the potential to act as a safe-haven asset similar to gold during economic volatility all add support to this argument.

Insert Table 6 & 7 about here

In Table 6, we observe the estimated return differential of Bitcoin futures and spot markets due to rapidly shifting forward-looking implied volatility conditions during varying phases of inflationary and deflationary shocks. It is interesting to note that when compared, the largest negative nominal differentials are experienced when considering the influence of exceptional volatility dynamics during strong unexpected inflation periods in the markets for OVX, VIN, VIX, and VVIX. With respect to VVIX in particular, denoted as the volatility of volatility, it is notable that such rapidly changing dynamics are linked with particularly pronounced underperformance of Bitcoin futures products when compared to spot products during the phases containing the strong unexpected inflation and deflation shock. Otherwise, the return differentials between futures and spot products are relatively similar. Such a result implies that Bitcoin futures, which are agreements to buy or sell Bitcoin at a future date at a predetermined price, struggle to accurately price in unexpected inflation and deflation and the associated volatility, resulting in poorer performance compared to the spot market, where Bitcoin is bought and sold for immediate delivery. The involvement of institutional investors can also significantly affect Bitcoin futures performance. As these investors often use more sophisticated risk management strategies, their trading behaviours during periods of high inflation or deflation can influence the return differentials between Bitcoin futures and spot markets. In Table 7, the exceptional levels of futures return volatility differentials during substantial phases of unexpected inflationary events are again particularly pronounced when focusing on VVIX.

Insert Table 8 & 9 about here

Focusing on the shifting dynamic behaviour of Bitcoin spot and futures liquidity differentials due to differing volatility futures conditions provides several notable results in Table 8. When considering the largest increases and decreases of volatility products, it is observed that futures liquidity tends to change less than spot market liquidity. Such negative outcomes are identified to be reasonably linear when considering more moderate phases of increases and decreases. The largest nominal changes are observed quite consistently when considering windows of strong unexpected inflation, where several noticeable outliers are observed in the markets for RXM, VIX, VVIX, VXD and VXN. The notion of Bitcoin as 'digital gold' might lead to an influx of investors during high inflation periods, seeking it as a store of value. This can inflate Bitcoin spot prices more rapidly than futures prices, creating discrepancies. Such results are further verified when considering the volatility of liquidity conditions during these same phases in Table 9, where VIX and VVIX present pronounced differential behaviour during phases of strong unexpected inflationary dynamics. It is particularly interesting to note that strong positive outcomes are identified when considering sharp crude oil volatility during periods of strong unexpected inflation, while the volatility of such liquidity differentials is found to be negative, indicating that shocks in phases of substantial oil market volatility transition to Bitcoin futures liquidity in a less dynamic manner. This outcome is particularly interesting, as the corresponding movements indicate the presence of potential portfolio diversification opportunities. During phases of exceptional oil price volatility, it is observed that Bitcoin futures present evidence of elevated, persistent liquidity growth, indicating the potential of its use as a 'flight-to-safety' asset during oil price shocks, indicating the presence of substantial maturity within Bitcoin futures markets.

5. Discussion and Directions for Future Research

The unique market dynamics and conditions specific to the entities we have investigated are paramount in understanding our results. Firstly, the Bitcoin spot market is found to have been largely influenced by supply and demand dynamics. As a decentralised currency, Bitcoin's valuation is not governed by typical macroeconomic factors such as inflation or interest rates but rather by factors such as public sentiment, regulatory changes, and technological advancements. Its lack of central authority and public ledger system makes it open to extreme price volatility due to speculation. It is often driven by public sentiment and varying levels of understanding and acceptance of the technology. Similarly, Bitcoin futures can affect the Bitcoin spot price, where as future contracts allow traders to speculate on the Bitcoin price at a predetermined future date, any significant imbalance in long and short positions can create pressure on the spot market. This is particularly true near the contract's expiration date, which could explain some of the observed price dynamics. Further, the dynamics of the various volatility indices examined are heavily influenced by the specific markets they cover. It is important to consider that these volatility indices are not only reflections of the expected volatility but also a measure of market sentiment and uncertainty. Therefore, fluctuations within these indices can be seen as indicative of the broader market sentiment.

This research provides valuable insights into the dynamics between exceptional financial market volatility and Bitcoin spot and futures products. The findings reveal several key economic and finance-related discussion points. Firstly, extreme volatility indices, such as the Cboe Gold Index and the Cboe S&P 500 Risk Reversal Index, significantly impact Bitcoin futures prices when volatility is low, indicating relaxed market conditions. However, this effect is not observed in Bitcoin spot prices, possibly due to retail investors increasing idiosyncratic risk in spot markets. Secondly, Bitcoin futures underperform spot prices during periods of substantial implied volatility, reflecting market fear and expectations of forward-looking volatility. This underperformance can be attributed to difficulties in short-selling Bitcoin on spot exchanges and the relative maturity of derivatives traders. Thirdly, Bitcoin futures markets exhibit a more acute response to sharp elevations in traditional volatility futures markets, suggesting higher market efficiency. Furthermore, during varying phases of unexpected inflation, Bitcoin futures struggle to accurately price in inflation and associated volatility, resulting in underperformance compared to the spot market. The involvement of institutional investors and their trading behaviours during high inflation or deflation periods further impact return differentials. Additionally, changing liquidity conditions in Bitcoin spot and futures markets respond differently to volatility futures conditions, indicating Bitcoin futures markets' higher information efficiency and maturity than spot markets. These findings contribute to understanding the complex relationship between financial market volatility, Bitcoin products, and their liquidity, with significant implications for economic and financial analysis.

Our results highlight crucial implications for portfolio construction and diversification strategies, particularly in the evolving digital asset landscape. The observed linkages between Bitcoin and volatility indices provide useful insights for investment practitioners and risk managers. For portfolio managers, our results suggest that Bitcoin can be a valuable addition to a diversified investment portfolio. The interplay between Bitcoin and various volatility indices suggests that Bitcoin can serve as an effective hedge against market volatility, offering potential diversification benefits. However, it's important to note the significant volatility inherent in Bitcoin itself, which may affect the risk-return trade-off. On a broader note, our findings suggest that the performance of Bitcoin can have broader market implications, affecting not just cryptocurrency investors but also those in more traditional markets. This suggests that portfolio diversification strategies may need to consider digital assets within their risk calculations, even if they do not hold these assets directly within their portfolio.

Simultaneously, our findings underscore the importance of dynamic portfolio management strategies. The interaction between Bitcoin and the volatility indices varied over time, suggesting that static portfolio strategies may not fully capitalise on these relationships. This development advocates for a more proactive asset management approach, where portfolio compositions are adjusted in response to shifts in market dynamics. The implications for portfolio diversification are also noteworthy. While Bitcoin has often been viewed as a separate asset class isolated from traditional financial markets, our findings suggest there might be more cross-market linkages than previously thought. This could necessitate re-evaluating how Bitcoin and similar digital assets are treated in the context of portfolio diversification.

This research presents several implications for policymakers, regulators, and central banks. For instance, the linkages with Bitcoin and other volatility indices highlight the potential spillover risks and the interconnected nature of our modern financial markets. From a policy perspective, the growing influence of cryptocurrencies, such as Bitcoin, on other financial markets underscores the necessity for clear, well-defined, and enforceable regulatory frameworks for digital assets. Regulations should strive to mitigate systemic risks associated with price volatility without stifling the innovation potential of blockchain technology. As we observed, volatility in cryptocurrency markets can have broader implications across different asset classes, necessitating a cooperative international approach to regulation. Further, for central banks, the growth and volatility of digital assets such as Bitcoin might necessitate further examination of the role cryptocurrencies play in monetary systems. Our findings could support arguments for creating Central Bank Digital Currencies (CBDCs), as these could offer the benefits of cryptocurrencies without extreme volatility. The potential influence of Bitcoin and other digital assets on traditional financial markets might prompt central banks to incorporate such developments into their economic forecasting models.

Our study opens several avenues for future research. First and foremost, an expansion of the asset classes included in the study would be beneficial. While we focus primarily on Bitcoin and its relationships with different volatility indices, future studies could extend this analysis to other digital assets, such as Ethereum, Ripple, and Litecoin. Given the varying characteristics of these digital assets, their interactions with market volatility could provide additional insights into the dynamics of the digital asset market. Secondly, our results highlight variation in the interplay between Bitcoin and the volatility indices. Further research could delve deeper into understanding the factors driving this variation. The impact of specific events such as regulatory changes, macroeconomic announcements, or significant shifts in market sentiment could be examined to determine their influence on these relationships. In addition, the role of Bitcoin and its potential utility in portfolio diversification and hedging against market volatility could also be a significant avenue for future work. Furthermore, our research implies an intermarket linkage between Bitcoin and traditional financial markets. Future studies could utilise more advanced methodologies, such as multivariate GARCH models or wavelet analysis, to delve deeper into the nature and dynamics of these intermarket linkages. Finally, our study provides empirical evidence from a specific period. Future research could undertake a similar analysis over different time horizons to determine time-varying effects. As the cryptocurrency market continues to evolve, so may its interactions with other financial markets, necessitating ongoing empirical examination.

6. Concluding Comments

Our research unveils several important findings that develop our comprehension of the complex interactions between Bitcoin future and spot market products and volatility futures indices based upon traditional financial markets. Such results develop our understanding of the growing role that Bitcoin now plays within the financial ecosystem. Primarily, based on matched hourly data, we identify strong dynamic interactions between the Bitcoin basis and select volatility indices. This association appears to be amplified during periods of heightened market volatility, suggesting that Bitcoin's price movements are not fully detached from broader market trends, indicating that it might be more influenced by specific market conditions than previously thought, appearing to be a response to fluctuations in market sentiment and broader economic variables. Secondly, such results indicate that Bitcoin is presenting a growing potential function as a contingent safe haven against market volatility, where during specific periods of increased market volatility, Bitcoin displays inverse performance relative to the volatility indices, where the product's hedging capability appears to be modulated by the state of the financial markets and the broader economic climate. We further highlight the time-varying relationship between Bitcoin and the selected volatility indices. This generates additional evidence supporting the view that cryptocurrency markets rapidly evolve from an investment network perspective, reflecting its growing maturity and broader acceptance within mainstream finance. Results indicate a dynamism inherent to the interplay between Bitcoin and traditional financial markets, suggesting that their correlation is far from static and adjusts to changes in market conditions and investor sentiment.

From a novel research perspective, our study specifically contributes to developing our understanding of the relationship between exceptional financial market volatility and differential behaviour between Bitcoin spot and futures products. We find that during periods of low volatility in gold market futures and mitigating expectations in the S&P 500 futures, Bitcoin futures prices exhibit a significant increase compared to corresponding spot prices. This indicates a positive interaction between Bitcoin futures and low volatility indices, suggesting that relaxed expected market conditions coincide with higher Bitcoin futures prices. In contrast, Bitcoin spot prices do not exhibit a similar increase, potentially attributed to the influence of retail investors and the presence of idiosyncratic risk in spot markets. Furthermore, our analysis reveals that during phases of substantial implied volatility, represented by the highest volatility indices, Bitcoin futures underperform spot prices. This negative differential can be attributed to challenges faced by investors seeking to short-sell Bitcoin on spot exchanges and the relative maturity of derivatives traders compared to spot traders. Additionally, our results demonstrate that Bitcoin futures markets exhibit a more acute response to sharp elevations in traditional volatility futures markets, indicating higher market efficiency and potential mainstream adoption of Bitcoin as a financial market asset.

Paying particular attention to the behaviour of Bitcoin spot and futures during distinct inflationary and deflationary periods, results indicate a differential performance of these financial instruments under varying economic climates. During inflationary periods, we observed that Bitcoin spot prices exhibited a consistent upward trajectory suggesting that investors tend to resort to Bitcoin spot as a hedge against inflation, pushing up demand and hence, the spot price. In contrast, Bitcoin futures, while demonstrating a similar trend, were less responsive to inflationary pressures. This is possibly due to the fact that futures contracts' fixed nature insulates their prices from immediate market dynamics, reflecting an amalgamation of market sentiment, future expectations, and risk premiums instead. In deflationary periods, both spot and futures products exhibited a degree of price contraction during phases of extreme volatility; however, the decline in spot prices was markedly steeper. Futures, on the other hand, while declining, presented a certain degree of resilience to deflation. This is potentially attributable to the nature of futures contracts as a speculative tool, allowing traders to take short positions anticipating falling prices, thereby exerting less downward pressure on their prices than the corresponding spot products. Conversely, during deflationary periods, when general price levels are decreasing, the performance of Bitcoin futures was found to be relatively stronger. One possible explanation for this is the advantage offered by futures in such conditions. Futures contracts allow investors to lock in prices for future delivery, providing a mechanism to navigate deflationary environments with declining prices. In addition, the deflationary period may also exacerbate the inherent 'hoarding' characteristic of Bitcoin or '*HODL*', where holders are reluctant to spend in anticipation of their assets appreciating in value. This hoarding behaviour can dampen the spot market activity, skewing the performance in favour of futures. Such market interactions as a result of exceptional volatility behaviour are found to be further verified by dynamics shifts of related liquidity conditions.

The unique relationship between Bitcoin and volatility indices presents an innovative opportunity for portfolio diversification. As correlations between Bitcoin and volatility indices can shift with changing market conditions, influenced by macroeconomic events and investor sentiment, Bitcoin's role within an investment portfolio can vary substantially between times of economic stability, where Bitcoin can be seen as a growth asset, contributing to potential yield enhancement. In contrast, during increased market uncertainty, Bitcoin's sometimes observed negative correlation with conventional assets may offer portfolio protection, providing safe haven benefits to investors. Therefore, understanding these dynamics can enable individual investors to employ Bitcoin strategically, adjusting their exposure based on prevailing market conditions to optimise their respective risk-return trade-offs. Overall, the key findings of our study unveil a complex and dynamic relationship between Bitcoin and traditional financial markets. While our findings contribute valuable insights, they also highlight the need for further research into the multifaceted interactions between Bitcoin and international financial markets.

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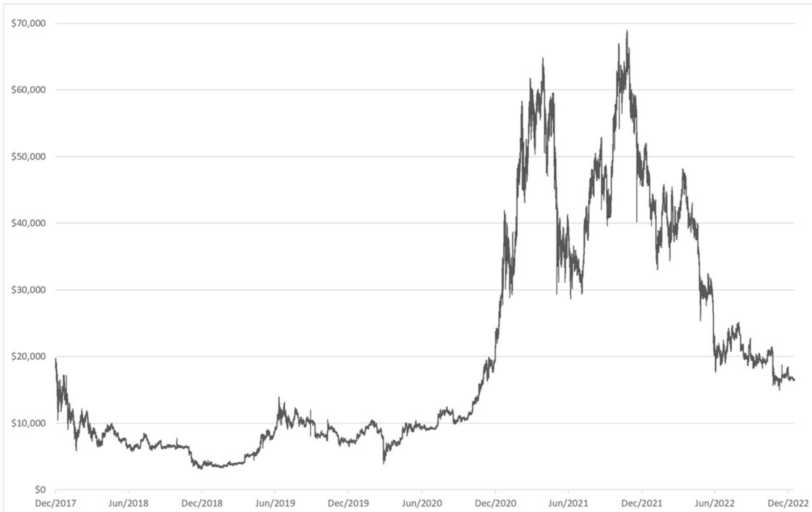
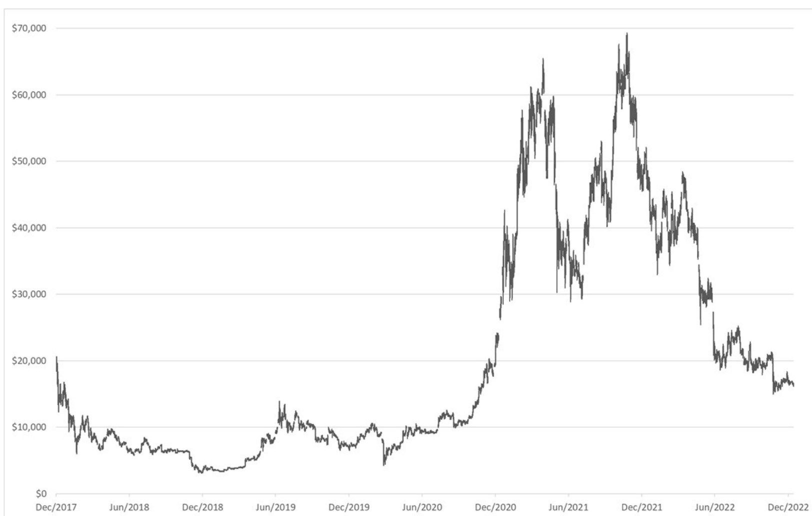
Figure 1: Bitcoin price performance, spot and futures markets

(a) Bitcoin Spot Market Price



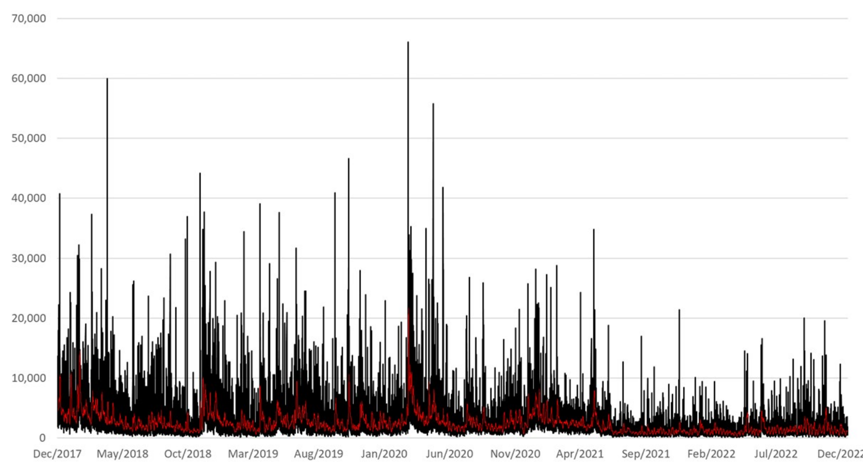
(b) Bitcoin Future Market Price



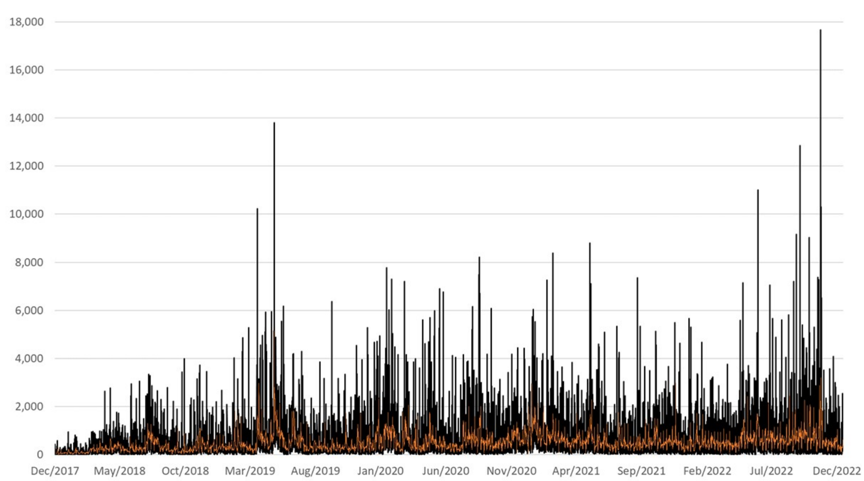
Note: The above figures represent the hourly price performance of both Bitcoin spot and futures markets.

Figure 2: Bitcoin liquidity conditions, spot and futures markets

(a) Bitcoin Spot Market Volumes Trades

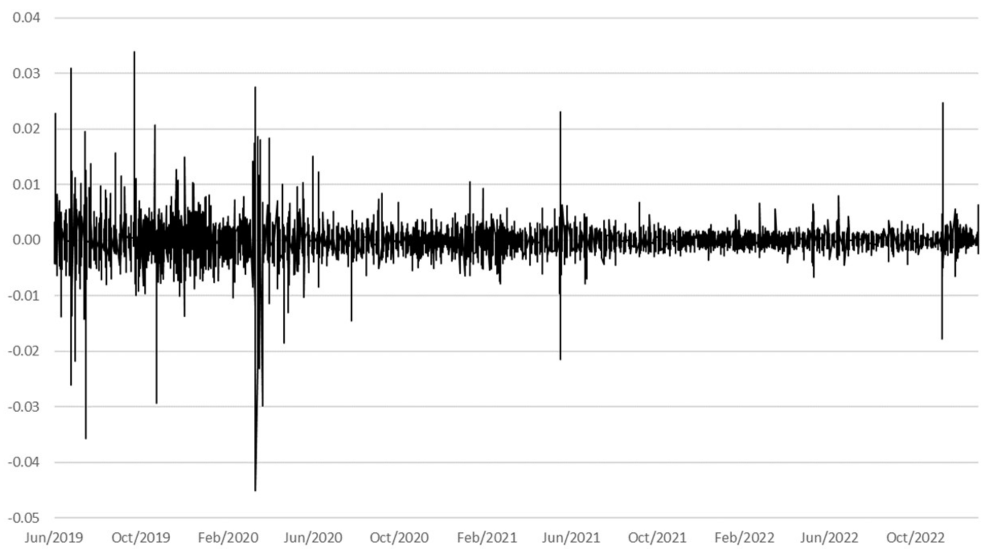


(b) Bitcoin Future Market Volumes Traded



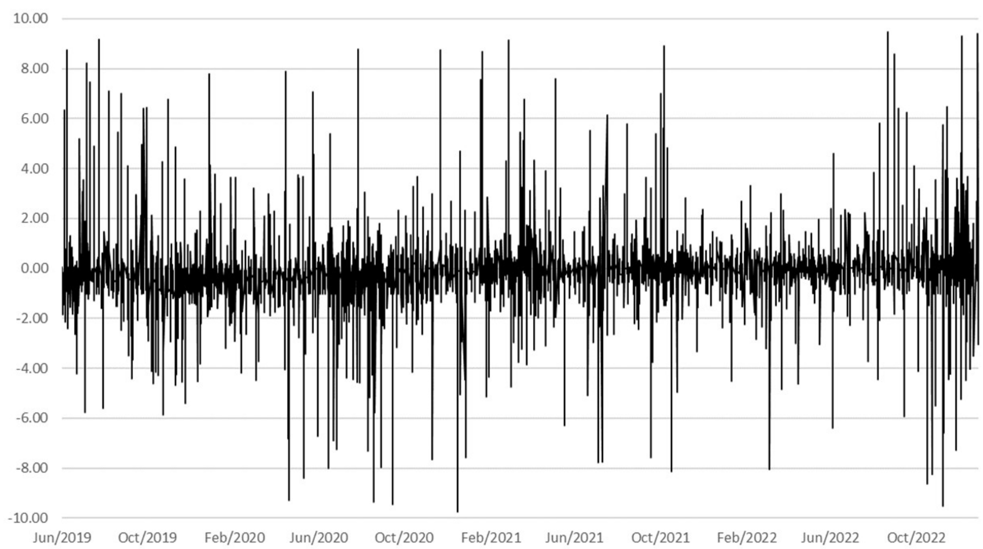
Note: The above figures represent the hourly volumes traded of Bitcoin spot and futures markets. The dashed red line within each respective figure presents the twenty-four-hour moving average of hourly volumes traded.

Figure 3: Estimated Bitcoin Basis



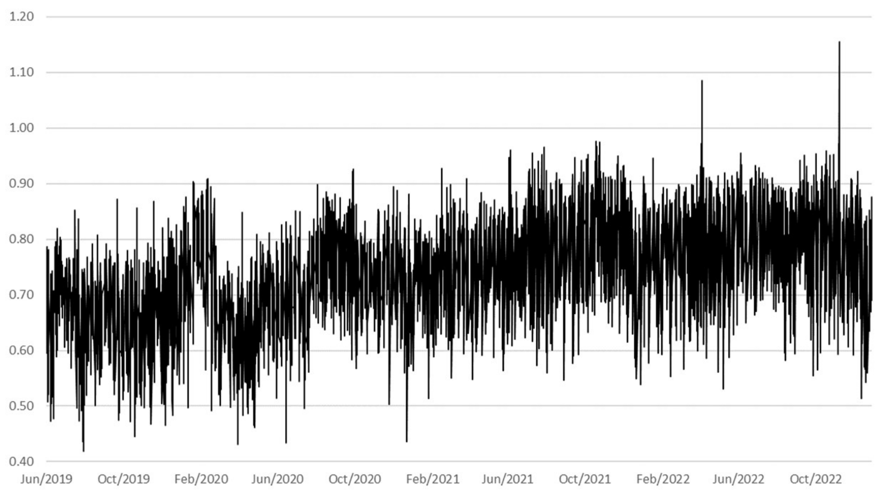
Note: The above Bitcoin basis is estimated as Bitcoin futures less Bitcoin spot prices. Basis, in the context of futures contracts, is the difference between the spot price of an asset and its futures price. It represents the cost of carry or the cost associated with holding the asset until the contract's delivery date. The spot price is the current market price of the asset, while the futures price is predetermined and reflects the anticipated value of the asset at a future date. Investors often use the basis to identify potential profits from delivering the underlying asset or cash upon the futures contract's expiration. It also serves as a tool for spotting arbitrage opportunities, as well as guiding the timing of buying or selling an asset based on whether the basis is strengthening or weakening. The basis is not static; it can either strengthen or weaken. If it strengthens, that means its value has increased. Conversely, a decrease in value indicates a weakening basis. Key factors influencing these changes typically include shifts in short-term demand and supply. For example, if demand outweighs available supply, spot prices may rise relative to futures prices, thus strengthening the basis. The reverse situation—where supply exceeds demand—can cause the basis to weaken. A key concept related to basis is basis risk, which arises from unexpected changes in the differential between the spot and futures prices. This dynamic underscores that hedging protects against outright price risk but still exposes the investor to basis risk. Although the basis can fluctuate, it tends to be less volatile than the spot or futures prices. Regardless, changes in the basis can significantly impact the profitability of hedging strategies, particularly when it comes to closing out positions. If the basis is lower than anticipated when the transaction concludes, the hedger may lose money on the hedge. Conversely, a higher-than-expected basis could yield profits.

Figure 4: The Estimated Relative Basis of Bitcoin



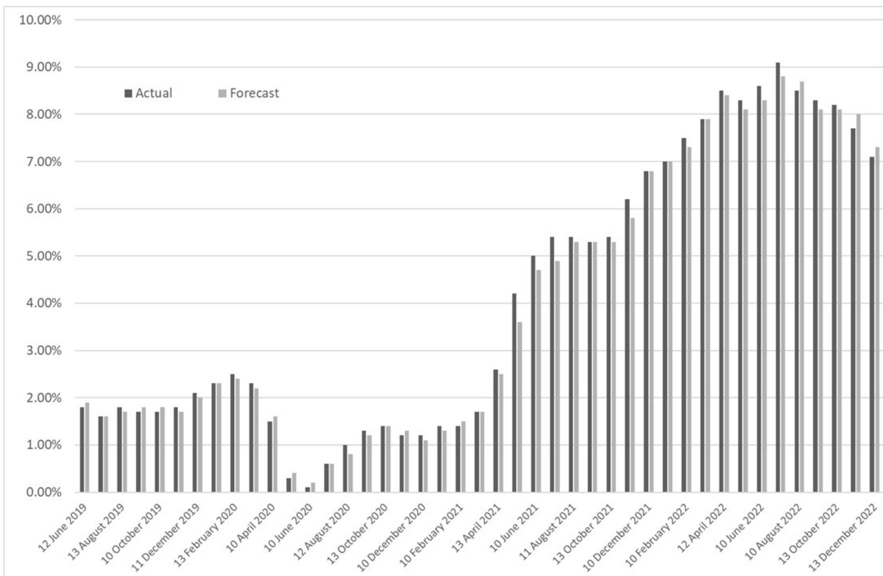
Note: Relative basis refers to the basis, the difference between the futures price and the spot price of Bitcoin, normalised to the futures price expressed as a percentage, allowing for a more standardised comparison across different assets or the same asset at different price levels. The relative basis provides a measure of the annualised return an investor can earn from a cash-and-carry arbitrage strategy price converge at contract expiration. Further, relative basis allows for more meaningful comparisons over time and across different assets. It allows traders to assess whether the basis is high or low, not just in absolute terms9 but in relation to the price level of the underlying asset. It's particularly useful in markets where prices can be highly volatile, such as in the case of cryptocurrencies such as Bitcoin.

Figure 5: Estimated Relative Volume of Bitcoin



Note: The relative volume of Bitcoin provides insights into the liquidity and activity level of a particular asset and helps traders identify periods of unusual market activity. In the context of spot and futures markets, relative volume can help traders to understand where the bulk of trading activity is taking place. For instance, if the relative volume of a Bitcoin futures contract is significantly higher than the relative volume of Bitcoin on the spot market, it could suggest increased speculative interest or hedging activity in the futures market. Conversely, a higher relative volume on the spot market might indicate stronger buying or selling activity at the current price. It is important to note that relative volume is a context-dependent metric, providing information about trading activity that can be combined with other indicators and market analysis to inform trading strategies. High relative volume often accompanies significant price movements.

Figure 6: Comparison of United States Actual and Expected Inflation



Note: The above figure presents the differential behaviour between expected inflation and actual inflation in the United States. Data is obtained from the US Bureau of Labor Statistics Consumer Price Index, the FRED database made available by the St Louis Federal Reserve, and the inflation expectations database made available by the Federal Research Bank of Cleveland.

Table 1: Description of the Variables Analysed

Variable Name	Ticker	Description
Bitcoin Spot	BTC	Bitcoin is a decentralised digital currency created in 2009 by an unknown person named Satoshi Nakamoto. It operates on a peer-to-peer network without the need for a central authority. Bitcoin transactions are recorded on a public ledger called the blockchain. BTC is the ticker symbol used to represent Bitcoin in cryptocurrency exchanges.
Bitcoin Future	XBT	Bitcoin futures contracts allow traders to speculate on the future price of Bitcoin. These contracts represent an agreement to buy or sell Bitcoin at a predetermined price on a specific date in the future. XBT is a commonly used ticker symbol for Bitcoin futures.
Cboe Vol. Index	VIX	The Cboe Volatility Index (VIX) measures market expectations for near-term volatility conveyed by S&P 500 index option prices. Also known as the "fear index," the VIX reflects the market's sentiment and uncertainty. It is commonly used as a gauge of investor fear or complacency and is often utilized to assess the level of risk in the market.
VIX Volatility Index	VVIX	The VIX Volatility Index (VVIX) measures the expected volatility of the Cboe Volatility Index (VIX). It provides insights into the market's expectations for future volatility levels in the VIX. Traders and investors use the VVIX to analyze and monitor the sentiment and behaviour of the VIX.
Cboe DJIA Vol. Index	VXD	The Cboe DJIA Volatility Index (VXD) measures market expectations for near-term volatility in the Dow Jones Industrial Average (DJIA). It represents the market's perception of the future volatility of the DJIA index. The VXD is used as an indicator of market sentiment and can be helpful in assessing the level of risk in the Dow Jones Industrial Average.
Cboe Crude Oil Vol. Index	OVX	The Cboe Crude Oil Volatility Index (OVX) measures the market's expectation of future volatility in crude oil prices. It tracks the implied volatility of options on crude oil futures contracts and is often used by traders and investors to assess the market's perception of oil price volatility.
Cboe Gold Vol. Index	GVZ	The Cboe Gold Volatility Index (GVZ) measures the market's expectation of future volatility in gold prices. It tracks the implied volatility of options on gold futures contracts and provides insights into the market's perception of gold price volatility. Traders and investors can utilise the GVZ to evaluate the level of risk and uncertainty in the gold market.
Cboe S&P 500 Risk Rev. Index	RXM	The Cboe S&P 500 Risk Reversal Index (RXM) measures the sentiment and positioning of options traders in the S&P 500 index. It reflects the market's expectations for potential changes in the S&P 500 index and helps gauge the balance between bullish and bearish options activity. Market participants use the RXM to assess market sentiment and sentiment shifts in the S&P 500.
Cboe NASDAQ Vol. Index	VXN	The Cboe NASDAQ Volatility Index (VXN) measures the market's expectation of future volatility in the NASDAQ-100 Index. It reflects the market's perception of volatility in technology and growth stocks listed on the NASDAQ exchange. The VXN can indicate sentiment and risk in the technology sector.
Cboe SPX Far-term VIX In.	VIF	The Cboe SPX Far-term VIX Index (VIF) measures the market's expectation of future volatility in the S&P 500 index over a longer time horizon. It tracks the implied volatility of options on the S&P 500 index with a longer expiration date, providing insights into the market's outlook on longer-term volatility in the S&P 500.
Cboe SPX Near-term VIX In.	VIN	The Cboe SPX Near-term VIX Index (VIN) measures the market's expectation of future volatility in the S&P 500 index over a shorter time horizon. It tracks the implied volatility of options on the S&P 500 index with a shorter expiration date, providing insights into the market's outlook on short-term volatility in the S&P 500.

Note: The respective CBOE volatility indices that are analysed are presented in the Table above. A complete list of available Cboe Volatility products is available at the following link.

Table 2: Summary Statistics of Selected Analysed Variables

	Mean	Var	Skew	Kurt	Min	Max	Obs	Percentile 1%	5%	10%	25%	50%	75%	90%	95%	99%
								Bitcoin Products								
BTC Spot	0.0000	0.0001	-0.5622	43.20	-0.1867	0.1963	21,233	-0.0273	-0.0127	-0.0080	-0.0033	0.0000	0.0035	0.0082	0.0125	0.0264
BTC Futures	0.0000	0.0001	-0.3002	23.40	-0.1119	0.1217	21,233	-0.0241	-0.0112	-0.0069	-0.0028	0.0000	0.0029	0.0072	0.0110	0.0232
								Volatility Indices								
VIX	0.0000	0.0006	1.6276	20.08	-0.1668	0.3822	12,640	-0.0632	-0.0314	-0.0216	-0.0097	-0.0010	0.0077	0.0222	0.0364	0.0750
VVIX	0.0000	0.0003	0.7486	10.12	-0.1670	0.1603	7,211	-0.0439	-0.0237	-0.0162	-0.0076	-0.0007	0.0060	0.0168	0.0269	0.0542
VXD	0.0000	0.0012	1.9834	102.53	-0.6294	0.8855	7,224	-0.0911	-0.0360	-0.0216	-0.0084	0.0000	0.0056	0.0216	0.0392	0.1032
OVX	0.0000	0.0012	1.9834	102.53	-0.6294	0.8855	7,224	-0.0911	-0.0360	-0.0216	-0.0084	0.0000	0.0056	0.0216	0.0392	0.1032
GVZ	0.0001	0.0005	0.6541	30.10	-0.3459	0.2615	7,224	-0.0600	-0.0270	-0.0167	-0.0060	0.0000	0.0050	0.0162	0.0285	0.0685
RXM	0.0001	0.0000	-3.3598	1,487.37	-0.3329	0.2943	7,004	-0.0095	-0.0035	-0.0020	-0.0006	0.0000	0.0008	0.0021	0.0037	0.0090
VXN	0.0000	0.0006	0.8890	11.87	-0.2274	0.2541	7,224	-0.0660	-0.0325	-0.0224	-0.0107	-0.0014	0.0083	0.0239	0.0401	0.0790
VIF	0.0000	0.0005	1.4770	18.50	-0.1612	0.3504	12,653	-0.0591	-0.0297	-0.0203	-0.0092	-0.0011	0.0072	0.0213	0.0345	0.0692
VIN	0.0000	0.0019	8.3754	432.77	-0.8424	1.7624	7,224	-0.0981	-0.0379	-0.0241	-0.0107	-0.0015	0.0081	0.0267	0.0444	0.1197

Note: At the top of the above Table, we present the summary statistics of the analysed Bitcoin spot and futures products, while in the lower half of the Table, we present the summary statistics for the analysed Cboe Volatility products. Dependent on the CBOE volatility futures contract analysed, there are between 7,004 and 12,653 comparable observations through which the selected methodological processes can be analysed. A complete list of available Cboe Volatility products is available at the following link. The selected series include the CBOE Volatility Index (VIX), the VIX Volatility Index (VVIX), the CBOE DJIA Volatility Index (VXD), the CBOE Crude Oil Volatility Index (OVX), the CBOE Gold Volatility Index (GVZ), the CBOE S&P500 Risk Reversal Volatility Index (RXM), the Cboe NASDAQ Volatility Index (VXN), the CBOE SPX Far-term VIX Index (VIF), and the CBOE SPX Near-term VIX Index (VIN). Each respective volatility index included accounts for a dynamic examination of multiple differentials of financial market behaviour sourced from various implied volatility conditions within major international traditional financial markets.

Table 3: Bitcoin Basis response to Exceptional Volatility Index Volatility

	$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
			Differential of Basis			
GVZ	0.0005***	0.0004***	0.0003***	-0.0001***	-0.0007***	-0.0008***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
OVX	0.0001	0.0000	0.0001	0.0000	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
RXM	0.0003**	0.0002***	0.0001***	0.0001*	0.0001	-0.0001
	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0002)
VIF	0.0007***	0.0003**	0.0001	-0.0004***	-0.0005***	-0.0012***
	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
VIN	0.0002	0.0001	0.0002***	-0.0001	-0.0002	-0.0002
	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0002)
VIX	0.0003*	0.0003***	0.0001	-0.0004***	-0.0005***	-0.0014***
	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
VVIX	0.0002	0.0002	-0.0001	-0.0003***	-0.0008***	-0.0016***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
VXD	0.0001	0.0000	0.0001	0.0000	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
VXN	0.0005	0.0003**	0.0002**	-0.0003***	-0.0005***	0.0003
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)
			Volatility of Basis			
GVZ	0.0005***	0.0004***	0.0003***	-0.0001***	-0.0007***	-0.0008***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
OVX	0.0001	0.0000	0.0001	0.0000	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
RXM	0.0092	0.2240***	0.0038	0.1150***	0.1790***	1.1280***
	(0.1100)	(0.0258)	(0.0179)	(0.0187)	(0.0445)	(0.0845)
VIF	0.2820***	0.0132	0.0410*	0.1490***	0.2790***	0.4168***
	(0.0570)	(0.0275)	(0.0175)	(0.0194)	(0.0240)	(0.0163)
VIN	0.1460	0.2510***	0.1670***	0.0170	0.1700***	0.2570*
	(0.1010)	(0.0376)	(0.0213)	(0.0271)	(0.0513)	(0.1130)
VIX	0.5382***	0.0969***	0.0536**	0.1490***	0.6410***	1.5360***
	(0.0619)	(0.0252)	(0.0174)	(0.0194)	(0.0253)	(0.0809)
VVIX	0.6090***	0.0418	0.0152	0.0290	0.5320***	1.3000***
	(0.0566)	(0.0240)	(0.0171)	(0.0249)	(0.0350)	(0.0889)
VXD	0.2390***	0.4000***	0.3250***	0.1370***	0.3870***	0.4230***
	(0.0710)	(0.0390)	(0.0203)	(0.0215)	(0.0223)	(0.1010)
VXN	0.0267	0.1590***	0.1760***	0.1430***	0.1770***	0.2720
	(0.1510)	(0.0283)	(0.0184)	(0.0221)	(0.0461)	(0.1910)

Note: Basis, in the context of futures contracts, is the difference between the spot price of an asset and its futures price. In the above Table, we build upon a GARCH(1,1) volatility process, where the basis is used as a dependent variable and while using a series of dummy variables to represent large upward and downward movements of the respective volatility futures series that are examined, at both the top and bottom 1%, 5% and 10% level of movements as $r_{b,t} = \alpha+\beta_1 r_{b,t-n}+\beta_2^{1\%}V_tQ_1+\beta_3^{5\%}V_tQ_5+\beta_4^{10\%}V_tQ_{10}+\beta_5^{95\%}V_tQ_{90}+\beta_6^{97.5\%}V_tQ_{95}+\beta_7^{99\%}V_tQ_{99}+e_t$, where $r_{b,t}$ represents the basis between Bitcoin spot and futures products. $\beta_2^{1\%}$, $\beta_3^{5\%}$ and $\beta_4^{10\%}$ are dummy variables taking value one if $r_{v,t}$, the respective movement of each of the analysed volatility indices, is below the 1^{st}, 5^{th} and 10^{th} percentile and zero otherwise. Parameters $\beta_5^{90\%}$, $\beta_6^{95\%}$ and $\beta_7^{99\%}$ capture any upwards movements of the analysed volatility indices above the 90^{th}, 95^{th} and 99^{th} percentile and zero otherwise. The total effect is a sum of the relevant coefficients. If the volatility movement exceeds a certain threshold, it also exceeds all smaller thresholds. For example, if returns exceed the 99^{th} percentile, they also exceed the 95^{th} percentile, therefore, representing a comparable estimate of the effects of extreme volatility changes upon Bitcoin. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4: Bitcoin Relative Basis Response to Exceptional Volatility Index Volatility

	$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
			Differential of Relative Basis			
GVZ	-0.1030	-0.1278	-0.1670	-0.1244	-0.1393	-0.1520
	(0.5650)	(0.0938)	(0.1541)	(0.1448)	(0.1589)	(0.5280)
OVX	-0.1590	-0.2050*	-0.1500	-0.2010	-0.2170	-0.2160
	(0.2650)	(0.0916)	(0.0491)	(0.0572)	(0.1120)	(0.2960)
RXM	-0.2900	-0.1410	-0.1310*	-0.1130	-0.1340	-0.2480
	(0.2490)	(0.0750)	(0.0550)	(0.0732)	(0.1090)	(0.3600)
VIF	-0.0398	-0.0346	-0.0804	-0.0913	-0.2108***	-0.3189***
	(0.3420)	(0.0677)	(0.0472)	(0.0507)	(0.0410)	(0.0380)
VIN	-0.0968	-0.1240	-0.1020*	-0.0839	-0.1150	-0.1990
	(0.2210)	(0.0933)	(0.0475)	(0.0708)	(0.1290)	(0.2870)
VIX	-0.0310	-0.0246	-0.0901*	-0.0733	-0.2881***	-0.4163***
	(0.2350)	(0.0696)	(0.0460)	(0.0529)	(0.0411)	(0.0397)
VVIX	-0.0791	-0.0323	-0.0438	-0.1260*	-0.2210***	-0.3958***
	(0.4890)	(0.1050)	(0.0529)	(0.0569)	(0.0210)	(0.0421)
VXD	-0.1590	-0.2050*	-0.1500**	-0.2010***	-0.2170	-0.3160
	(0.2650)	(0.0916)	(0.0491)	(0.0572)	(0.1120)	(0.2960)
VXN	-0.0676	-0.1240	-0.1170*	-0.1040	-0.1080	-0.2360
	(0.3460)	(0.0810)	(0.0547)	(0.0747)	(0.1460)	(0.6140)
			Volatility of Relative Basis			
GVZ	1.8190***	0.8400***	0.2490***	0.1230***	0.5110***	1.4140***
	(0.2320)	(0.0324)	(0.0193)	(0.0167)	(0.0271)	(0.2470)
OVX	0.7830***	0.6990***	0.1520***	0.1600***	0.8280***	0.8930***
	(0.1430)	(0.0272)	(0.0173)	(0.0172)	(0.0228)	(0.1450)
RXM	0.6450***	0.2860***	0.6040***	1.1660***	1.1910***	1.2490***
	(0.1520)	(0.0217)	(0.0173)	(0.0210)	(0.0453)	(0.1440)
VIF	1.8660***	0.0239	0.2210***	0.4500***	1.0930***	2.1970***
	(0.1090)	(0.0238)	(0.0160)	(0.0142)	(0.0298)	(0.1130)
VIN	0.7900***	0.4780***	0.0798***	0.7510***	1.2340***	0.9590***
	(0.1550)	(0.0186)	(0.0151)	(0.0181)	(0.0409)	(0.0967)
VIX	1.3300***	0.0660**	0.1420***	0.4930***	1.2850***	2.1830***
	(0.0698)	(0.0225)	(0.0164)	(0.0139)	(0.0296)	(0.1150)
VVIX	1.5710***	0.9010***	0.0794***	0.4370***	0.4170***	2.1160***
	(0.1720)	(0.0224)	(0.0164)	(0.0150)	(0.0228)	(0.1320)
VXD	0.7830***	0.6990***	0.1520***	0.1600***	0.8280***	0.8930***
	(0.1430)	(0.0272)	(0.0173)	(0.0172)	(0.0228)	(0.1450)
VXN	1.1640***	0.4890***	0.6410***	0.9060***	1.4050***	1.8830***
	(0.1530)	(0.0198)	(0.0139)	(0.0173)	(0.0422)	(0.2430)

Note: Relative basis refers to the basis, the difference between the futures price and the spot price of Bitcoin, normalised to the futures price expressed as a percentage, allowing for a more standardised comparison across different assets or the same asset at different price levels. The relative basis provides a measure of the annualised return an investor can earn from a cash-and-carry arbitrage strategy price converge at contract expiration. Further, relative basis allows for more meaningful comparisons over time and across different assets. In the above Table, we build upon a GARCH(1,1) volatility process, where the relative basis is used as a dependent variable while using a series of dummy variables to represent large upward and downward movements of the respective volatility futures series that are examined, at both the top and bottom 1%, 5% and 10% level of movements as $r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t$, where $r_{b,t}$ represents the relative basis between Bitcoin spot and futures products. $\beta_2^{1\%}$, $\beta_3^{5\%}$ and $\beta_4^{10\%}$ are dummy variables taking value one if $r_{v,t}$, the respective movement of each of the analysed volatility indices, is below the 1^{st}, 5^{th} and 10^{th} percentile and zero otherwise. Parameters $\beta_5^{90\%}$, $\beta_6^{95\%}$ and $\beta_7^{99\%}$ capture any upwards movements of the analysed volatility indices above the 90^{th}, 95^{th} and 99^{th} percentile and zero otherwise. The total effect is a sum of the relevant coefficients. If the volatility movement exceeds a certain threshold, it also exceeds all smaller thresholds. For example, if returns exceed the 99^{th} percentile, they also exceed the 95^{th} percentile, therefore, representing a comparable estimate of the effects of extreme volatility changes upon Bitcoin. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5: Bitcoin Relative Volume Response to Exceptional Volatility Index Volatility

	$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
			Differential of Relative Volume			
GVZ	0.0230	0.0219***	0.0206***	0.0222***	0.0234***	0.0297*
	(0.0152)	(0.0053)	(0.0035)	(0.0031)	(0.0047)	(0.0138)
OVX	0.0124	0.0144**	0.0162***	0.0182***	0.0178***	0.0141
	(0.0097)	(0.0046)	(0.0033)	(0.0034)	(0.0049)	(0.0111)
RXM	0.0142	0.0167***	0.0181***	0.0131***	0.0112*	0.0248*
	(0.0132)	(0.0046)	(0.0031)	(0.0035)	(0.0051)	(0.0115)
VIF	0.0155	0.0134**	0.0167***	0.0198***	0.0220***	0.0324**
	(0.0086)	(0.0042)	(0.0031)	(0.0030)	(0.0040)	(0.0080)
VIN	0.0119***	0.0135***	0.0152***	0.0127***	0.0127**	0.0164***
	(0.0068)	(0.0039)	(0.0030)	(0.0033)	(0.0046)	(0.0030)
VIX	0.0249**	0.0143***	0.0158***	0.0201***	0.0322***	0.0418***
	(0.0081)	(0.0043)	(0.0029)	(0.0030)	(0.0040)	(0.0080)
VVIX	0.0140	0.0160***	0.0161***	0.0215***	0.0218***	0.0522***
	(0.0120)	(0.0047)	(0.0031)	(0.0032)	(0.0049)	(0.0112)
VXD	0.0124	0.0144**	0.0162***	0.0182***	0.0178***	0.0141
	(0.0097)	(0.0046)	(0.0033)	(0.0034)	(0.0049)	(0.0111)
VXN	0.0311**	0.0218***	0.0157***	0.0183***	0.0189***	0.0317**
	(0.0119)	(0.0048)	(0.0031)	(0.0036)	(0.0057)	(0.0122)
			Volatility of Relative Volume			
GVZ	0.3000	0.0990	0.1210*	0.0764	0.0200	0.1040
	(0.2680)	(0.0940)	(0.0598)	(0.0573)	(0.0821)	(0.1870)
OVX	0.0099	0.0959	0.1510**	0.1950**	0.0637	0.0609
	(0.2000)	(0.0794)	(0.0543)	(0.0630)	(0.0971)	(0.2380)
RXM	0.4570	0.2330**	0.1820**	0.3460***	0.2370**	0.2290
	(0.2070)	(0.0747)	(0.0556)	(0.0603)	(0.0862)	(0.2360)
VIF	0.1250	0.2620**	0.1620**	0.1340*	0.4808***	0.4993***
	(0.1750)	(0.0826)	(0.0563)	(0.0538)	(0.0788)	(0.1170)
VIN	0.5580**	0.1920*	0.1110*	0.1770**	0.0383	0.1800
	(0.1850)	(0.0779)	(0.0507)	(0.0627)	(0.0916)	(0.2280)
VIX	0.0338	0.2840***	0.1460**	0.1450**	0.4208***	0.5024***
	(0.1910)	(0.0852)	(0.0549)	(0.0540)	(0.0771)	(0.1172)
VVIX	0.1270	0.0497	0.1340**	0.1500*	0.5238***	0.7107***
	(0.2850)	(0.0840)	(0.0518)	(0.0591)	(0.0886)	(0.1760)
VXD	0.0099	0.0959	0.1510**	0.1950**	0.0637	0.0609
	(0.2000)	(0.0794)	(0.0543)	(0.0630)	(0.0971)	(0.2380)
VXN	0.0113	0.2560**	0.2030***	0.1820**	0.1150	0.2050
	(0.2510)	(0.0928)	(0.0512)	(0.0574)	(0.0987)	(0.3180)

Note: The relative volume of Bitcoin provides insights into the liquidity and activity level of a particular asset and helps traders identify periods of unusual market activity. In the above Table, we build upon a GARCH(1,1) volatility process, where the relative volume is used as a dependent variable while using a series of dummy variables to represent large upward and downward movements of the respective volatility futures series that are examined, at both the top and bottom 1%, 5% and 10% level of movements as $r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t$, where $r_{b,t}$ represents the relative volume between Bitcoin spot and futures products. $\beta_2^{1\%}$, $\beta_3^{5\%}$ and $\beta_4^{10\%}$ are dummy variables taking value one if $r_{v,t}$, the respective movement of each of the analysed volatility indices, is below the 1^{st}, 5^{th} and 10^{th} percentile and zero otherwise. Parameters $\beta_5^{90\%}$, $\beta_6^{95\%}$ and $\beta_7^{99\%}$ capture any upwards movements of the analysed volatility indices above the 90^{th}, 95^{th} and 99^{th} percentile and zero otherwise. The total effect is a sum of the relevant coefficients. If the volatility movement exceeds a certain threshold, it also exceeds all smaller thresholds. For example, if returns exceed the 99^{th} percentile, they also exceed the 95^{th} percentile, therefore, representing a comparable estimate of the effects of extreme volatility changes upon Bitcoin. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Bitcoin Future to Spot Return Differential due to Exceptional Volatility Index Volatility

		Future - Spot Return Differential					
		$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
GVZ	Total Period	0.0017	0.0011	0.0001	0.0004	0.0010	0.0009
	Strong Unexp. Defl.	-0.0003	-0.0005	-0.0005	0.0004	0.0001	0.0004
	Mod. Unexp. Defl.	-0.0007	-0.0033	-0.0025	0.0004	0.0005	0.0005
	No Unexp. Infl.	-0.0009	-0.0001	-0.0005	-0.0003	0.0002	-0.0060
	Mod. Unexp. Infl.	-0.0059	-0.0068	-0.0004	0.0023	0.0002	-0.0062
	Strong Unexp. Infl.	-0.0072	0.0004	0.0001	0.0006	0.0005	0.0004
OVX	Total Period	0.0003	0.0002	-0.0001	-0.0002	0.0001	-0.0002
	Strong Unexp. Defl.	-0.0011	0.0014	0.0001	0.0000	0.0000	-0.0021
	Mod. Unexp. Defl.	0.0016	-0.0021	0.0003	0.0023	-0.0009	0.0001
	No Unexp. Infl.	0.0011	0.0003	-0.0001	0.0002	0.0005	0.0005
	Mod. Unexp. Infl.	0.0002	0.0001	0.0002	0.0004	0.0001	0.0006
	Strong Unexp. Infl.	0.0002	-0.0003	-0.0002	-0.0002	-0.0150	-0.0200
RXM	Total Period	0.0002	-0.0004	-0.0001	0.0003	0.0005	0.0006
	Strong Unexp. Defl.	0.0002	-0.0004	-0.0001	0.0003	0.0005	-0.0006
	Mod. Unexp. Defl.	0.0008	-0.0010	0.0002	-0.0002	-0.0013	-0.0070
	No Unexp. Infl.	0.0004	0.0000	-0.0005	0.0003	0.0004	-0.0012
	Mod. Unexp. Infl.	-0.0003	-0.0004	0.0000	-0.0021	-0.0006	-0.0030
	Strong Unexp. Infl.	0.0004	0.0007	0.0005	-0.0001	-0.0001	-0.0046
VIF	Total Period	-0.0005	-0.0004	0.0005	0.0000	0.0000	-0.0013
	Strong Unexp. Defl.	0.0005	-0.0013	-0.0007	0.0000	0.0002	0.0006
	Mod. Unexp. Defl.	-0.0010	0.0005	0.0011	0.0007	-0.0002	-0.0012
	No Unexp. Infl.	0.0004	0.0005	0.0004	-0.0004	-0.0006	0.0004
	Mod. Unexp. Infl.	0.0011	0.0001	-0.0003	0.0000	0.0001	-0.0004
	Strong Unexp. Infl.	-0.0007	-0.0024	-0.0001	-0.0024	0.0007	0.0016
VIN	Total Period	-0.0001	0.0001	0.0002	-0.0002	0.0008	-0.0144
	Strong Unexp. Defl.	0.0012	0.0000	-0.0004	-0.0001	0.0001	-0.0107
	Mod. Unexp. Defl.	-0.0019	0.0016	-0.0041	0.0004	0.0013	0.0000
	No Unexp. Infl.	0.0009	0.0006	0.0007	-0.0013	-0.0018	-0.0001
	Mod. Unexp. Infl.	0.0001	-0.0005	0.0001	-0.0001	-0.0001	-0.0110
	Strong Unexp. Infl.	-0.0001	0.0013	-0.0001	0.0003	0.0001	-0.0210
VIX	Total Period	-0.0006	0.0003	0.0006	-0.0001	0.0001	-0.0014
	Strong Unexp. Defl.	-0.0005	-0.0012	-0.0014	-0.0050	-0.0160	-0.0216
	Mod. Unexp. Defl.	-0.0071	0.0010	-0.0070	0.0002	-0.0085	-0.0097
	No Unexp. Infl.	0.0007	0.0006	0.0006	-0.0004	-0.0010	-0.0007
	Mod. Unexp. Infl.	0.0002	0.0003	-0.0006	0.0000	-0.0045	-0.0335
	Strong Unexp. Infl.	-0.0168	-0.0124	-0.0080	-0.0054	-0.0286	-0.0315
VVIX	Total Period	-0.0014	0.0006	0.0009	-0.0002	-0.0003	-0.0046
	Strong Unexp. Defl.	-0.0175	-0.0130	0.0005	-0.0001	-0.0124	-0.0196
	Mod. Unexp. Defl.	-0.0010	0.0003	0.0002	0.0000	-0.0067	-0.0085
	No Unexp. Infl.	-0.0019	0.0003	-0.0011	-0.0005	-0.0015	-0.0103
	Mod. Unexp. Infl.	-0.0312	-0.0004	0.0000	0.0003	-0.0138	-0.0136
	Strong Unexp. Infl.	-0.0440	-0.0131	-0.0090	-0.0041	-0.0145	-0.0320
VXD	Total Period	0.0002	0.0003	0.0001	-0.0002	0.0001	-0.0002
	Strong Unexp. Defl.	-0.0013	0.0009	0.0011	0.0001	0.0000	-0.0205
	Mod. Unexp. Defl.	0.0008	0.0004	0.0000	-0.0002	-0.0008	-0.0002
	No Unexp. Infl.	0.0008	0.0005	0.0000	0.0002	0.0005	0.0005
	Mod. Unexp. Infl.	0.0012	0.0001	0.0002	0.0004	0.0001	0.0006
	Strong Unexp. Infl.	-0.0060	-0.0006	0.0000	-0.0002	-0.0003	-0.0072
VXN	Total Period	0.0011	0.0004	0.0004	-0.0003	-0.0003	-0.0001
	Strong Unexp. Defl.	-0.0013	-0.0016	-0.0002	0.0000	-0.0002	0.0002
	Mod. Unexp. Defl.	-0.0022	-0.0003	0.0002	0.0001	0.0005	0.0012
	No Unexp. Infl.	-0.0015	0.0006	0.0006	-0.0005	-0.0013	-0.0003
	Mod. Unexp. Infl.	-0.0006	0.0002	0.0000	0.0000	0.0000	0.0005
	Strong Unexp. Infl.	-0.0004	-0.0003	0.0000	0.0006	0.0006	-0.0004

Note: In the above Table, we build upon a GARCH(1,1) volatility process, where the differential of price response between Bitcoin futures and Bitcoin spot products is estimated based on the differentials between separate GARCH-based analyses of the form $r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t$,. Where volatility differentials are examined, differentials are based on the inclusion of the dummy variables in the volatility equation rather than the mean equation. The above estimated differential price volatility and liquidity conditions are then partitioned based on quintiles ranked from the strong and moderate deflation through strong and moderate inflation surprise, as separated with a decile representing no unexpected change. To better understand the interactions between Bitcoin spot and futures volatility and liquidity conditions during varying phases of inflation shock in the United States, results are presented as separated by respective quintiles of tiered inflation and deflation surprise.

Table 7: Bitcoin Future to Spot Return Volatility Differential due to Exceptional Volatility Index Volatility

		Future - Spot Return Volatility Differential					
		$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
GVZ	Total Period	0.1900	0.2650	0.0890	0.1836	0.1828	0.4180
	Strong Unexp. Defl.	0.8650	0.4910	0.4320	-0.0880	-0.2030	0.4320
	Mod. Unexp. Defl.	-0.0920	-0.1100	0.1250	-0.0431	-0.0262	-0.1480
	No Unexp. Infl.	0.4270	0.4300	0.3899	0.1748	0.2860	0.6000
	Mod. Unexp. Infl.	1.1168	0.1320	0.0120	0.1000	0.2541	0.2020
	Strong Unexp. Infl.	1.2710	0.2470	0.0080	-0.1169	-0.0940	-0.1030
OVX	Total Period	-0.0290	-0.1138	-0.0758	0.0867	0.0970	0.2163
	Strong Unexp. Defl.	0.4234	0.0243	0.2568	-0.0040	-0.0920	0.2330
	Mod. Unexp. Defl.	-0.0750	0.0350	-0.1020	0.1185	-0.0639	-0.1636
	No Unexp. Infl.	-0.2090	-0.0630	-0.1070	0.1939	0.1761	0.0920
	Mod. Unexp. Infl.	0.5490	-0.0680	-0.0300	0.0470	-0.0270	0.0610
	Strong Unexp. Infl.	-0.0680	-0.0540	-0.0050	0.0260	-0.0166	0.4700
RXM	Total Period	0.1550	0.0320	-0.0230	-0.0278	0.0040	0.2750
	Strong Unexp. Defl.	1.1620	0.1270	-0.0120	0.4721	0.2290	0.3940
	Mod. Unexp. Defl.	0.1460	-0.1690	-0.0820	-0.2040	0.4270	0.6320
	No Unexp. Infl.	0.0570	0.3050	0.1530	0.3184	0.5149	0.1588
	Mod. Unexp. Infl.	-0.0006	0.0340	0.0220	-0.0060	-0.0910	0.1700
	Strong Unexp. Infl.	0.2430	-0.0890	-0.0850	-0.0407	-0.0180	0.7770
VIF	Total Period	-0.0050	-0.0140	0.0254	0.0190	-0.0380	0.1000
	Strong Unexp. Defl.	0.8244	0.0430	0.0102	-0.0530	-0.1160	0.1250
	Mod. Unexp. Defl.	0.7828	-0.0596	-0.2220	-0.0580	-0.1010	0.1930
	No Unexp. Infl.	0.1350	0.1020	0.2041	0.0350	0.0640	0.2750
	Mod. Unexp. Infl.	0.0410	0.0270	0.0010	-0.0180	-0.0020	0.0740
	Strong Unexp. Infl.	0.5155	0.0180	0.0110	-0.1290	-0.1690	0.2210
VIN	Total Period	-0.1550	-0.1416	-0.0428	-0.0070	-0.0540	-0.0030
	Strong Unexp. Defl.	0.0110	0.1970	-0.0141	0.0957	0.3230	0.4840
	Mod. Unexp. Defl.	0.0660	0.1324	0.0707	0.0000	0.4620	0.4530
	No Unexp. Infl.	-0.0050	0.0180	0.0497	-0.0600	-0.0750	0.3046
	Mod. Unexp. Infl.	0.0430	-0.0300	-0.0441	0.1838	-0.0050	-0.0277
	Strong Unexp. Infl.	-0.1200	-0.0545	-0.0447	-0.0450	0.1240	0.1070
VIX	Total Period	-0.0080	-0.0110	0.0050	0.0100	0.0600	0.0750
	Strong Unexp. Defl.	0.6244	0.0450	0.0458	-0.0513	0.1600	0.7154
	Mod. Unexp. Defl.	0.1389	-0.0019	0.0054	-0.0015	0.0839	0.2022
	No Unexp. Infl.	0.0770	0.0970	-0.1221	-0.1130	-0.0970	-0.0390
	Mod. Unexp. Infl.	0.0620	0.0250	0.0080	-0.0120	-0.0060	0.1074
	Strong Unexp. Infl.	0.5155	0.0240	-0.0070	-0.1440	0.1420	0.6242
VVIX	Total Period	0.2158	-0.0730	0.0050	-0.0510	0.0100	0.1310
	Strong Unexp. Defl.	0.7230	-0.1947	0.0407	-0.1029	0.2785	1.1390
	Mod. Unexp. Defl.	0.6200	-0.0498	0.0277	-0.1390	-0.0800	0.8165
	No Unexp. Infl.	0.4460	0.1140	0.0360	-0.0530	0.1141	0.3850
	Mod. Unexp. Infl.	0.2210	-0.0524	-0.0580	0.0155	0.0140	0.7300
	Strong Unexp. Infl.	0.8132	0.0150	0.0290	-0.0950	-0.0960	1.1511
VXD	Total Period	-0.0275	-0.0146	-0.0321	0.0664	0.0172	-0.0267
	Strong Unexp. Defl.	0.4234	-0.1294	-0.0970	-0.0040	-0.0920	0.2330
	Mod. Unexp. Defl.	0.3120	0.0350	-0.1020	0.0427	-0.0639	0.1636
	No Unexp. Infl.	-0.2090	-0.0630	-0.1070	0.1939	0.1761	0.0269
	Mod. Unexp. Infl.	0.5490	-0.0680	-0.0300	0.0470	-0.0270	0.0610
	Strong Unexp. Infl.	0.6800	-0.0540	-0.0050	0.0260	-0.0166	0.4700
VXN	Total Period	0.4040	0.0530	-0.0028	-0.0040	-0.0110	-0.1140
	Strong Unexp. Defl.	0.5105	0.1680	0.0558	0.1142	0.4527	0.2057
	Mod. Unexp. Defl.	0.1211	0.2480	-0.0150	-0.1060	0.1830	0.1595
	No Unexp. Infl.	0.0100	0.1860	0.0879	0.0630	0.0180	-0.0120
	Mod. Unexp. Infl.	0.5480	-0.1520	-0.0510	-0.1300	0.1558	0.0790
	Strong Unexp. Infl.	0.6208	-0.0700	0.0040	-0.1490	0.2360	0.2070

Note: In the above Table, we build upon a GARCH(1,1) volatility process, where the differential of price response between Bitcoin futures and Bitcoin spot products is estimated based on the differentials between separate GARCH-based analyses of the form $r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t,$. Where volatility differentials are examined, differentials are based on the inclusion of the dummy variables in the volatility equation rather than the mean equation. The above estimated differential price volatility and liquidity conditions are then partitioned based on quintiles ranked from the strong and moderate deflation through strong and moderate inflation surprise, as separated with a decile representing no unexpected change. To better understand the interactions between Bitcoin spot and futures volatility and liquidity conditions during varying phases of inflation shock in the United States, results are presented as separated by respective quintiles of tiered inflation and deflation surprise.

Table 8: Bitcoin Future to Spot Liquidity Differential due to Exceptional Volatility Index Volatility

		Future - Spot Volume Differential					
		$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
GVZ	Total Period	-0.1710	-0.1856	-0.1735	-0.1471	-0.1691	-0.1530
	Strong Unexp. Defl.	-0.2224	-0.220	-0.1228	-0.181	-0.1756	-0.2635
	Mod. Unexp. Defl.	-0.0070	-0.0890	-0.0970	-0.0570	0.0265	-0.2190
	No Unexp. Infl.	-0.1608	-0.2223	-0.2123	-0.1101	-0.1673	-0.1730
	Mod. Unexp. Infl.	-0.1560	0.0768	-0.0684	-0.0110	-0.2210	-0.1290
	Strong Unexp. Infl.	0.2240	-0.1623	-0.0511	-0.1132	-0.0452	-0.1635
OVX	Total Period	-0.0855	-0.0963	-0.1236	-0.1278	-0.1123	-0.1019
	Strong Unexp. Defl.	0.1592	-0.1960	-0.1936	-0.0757	-0.1190	0.2800
	Mod. Unexp. Defl.	0.3330	-0.0300	-0.1016	-0.1087	-0.1134	0.2320
	No Unexp. Infl.	-0.1200	-0.0520	-0.0776	-0.1616	-0.1046	-0.0240
	Mod. Unexp. Infl.	-0.1160	-0.0703	-0.0500	-0.1671	-0.0630	0.2830
	Strong Unexp. Infl.	0.3270	-0.1430	-0.1750	-0.0530	0.0110	0.4132
RXM	Total Period	-0.0102	-0.1160	-0.1173	-0.1145	-0.0984	-0.0195
	Strong Unexp. Defl.	-0.1021	-0.1160	-0.1173	-0.1145	-0.0984	-0.1947
	Mod. Unexp. Defl.	-0.1547	0.1908	-0.0307	-0.1137	0.1334	-0.1570
	No Unexp. Infl.	0.0218	-0.0752	-0.0776	-0.1140	-0.1233	-0.1455
	Mod. Unexp. Infl.	-0.1510	-0.1500	-0.1850	-0.1343	-0.1700	-0.2930
	Strong Unexp. Infl.	0.0218	-0.1370	-0.1230	-0.1174	-0.1200	-0.3574
VIF	Total Period	-0.0157	-0.1084	-0.1255	-0.1340	-0.1410	-0.0313
	Strong Unexp. Defl.	-0.1890	-0.1180	-0.0710	-0.1437	-0.1730	-0.1190
	Mod. Unexp. Defl.	-0.2530	-0.0915	-0.0505	-0.0970	-0.1171	0.0010
	No Unexp. Infl.	-0.1570	-0.1020	-0.1805	-0.0980	-0.1150	-0.1450
	Mod. Unexp. Infl.	-0.2310	-0.1700	-0.1765	-0.1120	-0.1380	-0.1214
	Strong Unexp. Infl.	-0.2966	0.0090	-0.1210	0.0000	-0.0520	-0.2016
VIN	Total Period	0.0191	-0.0124	-0.0463	-0.0850	-0.0750	-0.1242
	Strong Unexp. Defl.	0.1950	-0.1059	-0.1056	-0.1210	-0.0210	0.1390
	Mod. Unexp. Defl.	-0.0946	-0.1386	-0.0620	-0.0070	-0.0500	-0.0826
	No Unexp. Infl.	-0.0041	-0.0990	-0.1112	-0.0720	-0.1340	-0.0046
	Mod. Unexp. Infl.	-0.0823	-0.0910	-0.0616	-0.0560	-0.1131	0.1029
	Strong Unexp. Infl.	-0.1419	0.0093	0.0326	-0.0915	-0.0626	-0.0436
VIX	Total Period	-0.0420	-0.1116	-0.1217	-0.1300	-0.1480	-0.0209
	Strong Unexp. Defl.	-0.2710	-0.1488	-0.1360	-0.1225	-0.1620	-0.2042
	Mod. Unexp. Defl.	0.0196	-0.0237	0.0000	-0.0710	-0.0710	-0.0350
	No Unexp. Infl.	-0.1950	-0.1149	-0.1407	-0.1090	-0.1130	-0.2146
	Mod. Unexp. Infl.	-0.2620	-0.1770	-0.1900	-0.1120	-0.1470	-0.4121
	Strong Unexp. Infl.	-0.3966	-0.1430	-0.0760	-0.1895	-0.2001	-0.4031
VVIX	Total Period	-0.0314	-0.1170	-0.0942	-0.1070	-0.1010	-0.0312
	Strong Unexp. Defl.	-0.2477	-0.1710	-0.1030	-0.0547	-0.1111	-0.0970
	Mod. Unexp. Defl.	-0.0051	-0.1638	-0.1048	-0.1156	-0.0650	-0.1313
	No Unexp. Infl.	-0.1605	-0.0728	-0.0602	-0.0620	-0.0750	-0.2245
	Mod. Unexp. Infl.	-0.0160	-0.0990	-0.1647	-0.1100	-0.0870	-0.4102
	Strong Unexp. Infl.	0.1205	-0.1460	-0.0650	-0.1720	-0.1350	-0.4130
VXD	Total Period	-0.0950	-0.1127	-0.1330	-0.1278	-0.1123	-0.1019
	Strong Unexp. Defl.	0.1582	-0.2270	-0.1975	-0.0515	-0.1190	0.0280
	Mod. Unexp. Defl.	0.1366	-0.0260	-0.0962	-0.0952	-0.1293	-0.2080
	No Unexp. Infl.	-0.1340	-0.0660	-0.0922	-0.1616	-0.1046	-0.0240
	Mod. Unexp. Infl.	0.0635	-0.0703	-0.0390	-0.1671	-0.0630	-0.2830
	Strong Unexp. Infl.	-0.2730	-0.1680	-0.1453	-0.0530	0.0100	-0.3048
VXN	Total Period	-0.1230	-0.1580	-0.1105	-0.1210	-0.0940	-0.1170
	Strong Unexp. Defl.	-0.1240	-0.1470	-0.1065	-0.1330	-0.1790	-0.2543
	Mod. Unexp. Defl.	-0.2310	-0.1720	-0.0335	-0.0914	-0.0240	-0.1313
	No Unexp. Infl.	-0.1890	-0.1581	-0.1340	-0.0920	-0.1090	-0.1322
	Mod. Unexp. Infl.	-0.2375	-0.0900	-0.1090	-0.1210	-0.1120	-0.1970
	Strong Unexp. Infl.	-0.3151	-0.2180	-0.1400	-0.1580	0.0120	-0.3010

Note: In the above Table, we build upon a GARCH(1,1) volatility process, where the differential of price response between Bitcoin futures and Bitcoin spot products is estimated based on the differentials between separate GARCH-based analyses of the form $r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t$,. Where volatility differentials are examined, differentials are based on the inclusion of the dummy variables in the volatility equation rather than the mean equation. The above estimated differential price volatility and liquidity conditions are then partitioned based on quintiles ranked from the strong and moderate deflation through strong and moderate inflation surprise, as separated with a decile representing no unexpected change. To better understand the interactions between Bitcoin spot and futures volatility and liquidity conditions during varying phases of inflation shock in the United States, results are presented as separated by respective quintiles of tiered inflation and deflation surprise.

Table 9: Bitcoin Future to Spot Liquidity Volatility Differential due to Exceptional Volatility Index Volatility

		Future - Spot Volume Volatility Differential					
		$\beta_2^{1\%}$	$\beta_3^{5\%}$	$\beta_4^{10\%}$	$\beta_5^{90\%}$	$\beta_6^{95\%}$	$\beta_7^{99\%}$
GVZ	Total Period	0.0710	0.0470	0.0140	-0.0110	-0.0470	-0.0830
	Strong Unexp. Defl.	-0.0110	0.0860	0.0700	-0.1510	-0.0830	0.0700
	Mod. Unexp. Defl.	0.1926	-0.0460	0.0470	0.0296	0.1244	0.6770
	No Unexp. Infl.	-0.0069	0.0540	0.0840	-0.0574	-0.1060	0.0970
	Mod. Unexp. Infl.	0.2470	-0.2360	0.1250	-0.0680	-0.0910	0.5820
	Strong Unexp. Infl.	0.6580	0.0060	0.2591	0.0460	-0.2858	0.4458
OVX	Total Period	-0.0320	-0.1696	-0.0837	0.0227	-0.0078	-0.1768
	Strong Unexp. Defl.	0.4240	-0.5470	-0.4449	0.3730	0.1650	-0.0200
	Mod. Unexp. Defl.	0.2720	-0.3510	-0.1262	-0.2602	-0.1019	0.5840
	No Unexp. Infl.	0.2630	0.0160	0.0950	-0.1260	-0.0260	0.2550
	Mod. Unexp. Infl.	-0.3650	-0.2530	0.0093	0.3024	0.4600	0.1470
	Strong Unexp. Infl.	-0.2550	-0.1640	-0.0634	0.1289	0.0539	-0.2950
RXM	Total Period	0.1750	0.0331	-0.0046	0.0730	0.0332	-0.0200
	Strong Unexp. Defl.	0.2680	0.1319	0.0172	0.1560	0.1166	-0.3160
	Mod. Unexp. Defl.	0.3460	-0.0810	0.0293	0.1186	-0.5270	-0.6710
	No Unexp. Infl.	0.4688	0.2238	0.2120	0.1290	0.1526	0.2260
	Mod. Unexp. Infl.	-0.2400	0.0754	0.0334	0.0457	-0.3040	-0.7700
	Strong Unexp. Infl.	-0.2880	0.0240	-0.0010	0.2620	0.1350	-0.2734
VIF	Total Period	0.2728	0.0714	0.1044	0.0037	-0.0090	0.0180
	Strong Unexp. Defl.	1.2590	0.3971	0.4940	-0.1122	-0.3120	0.2350
	Mod. Unexp. Defl.	-0.3139	-0.0207	-0.0108	-0.0050	-0.1253	0.2170
	No Unexp. Infl.	-0.2400	0.1543	0.1829	0.0613	0.1028	0.0090
	Mod. Unexp. Infl.	0.0260	-0.1259	0.1418	-0.0978	0.0600	0.2470
	Strong Unexp. Infl.	1.7318	-0.0884	0.2639	0.0675	-0.0100	-0.2020
VIN	Total Period	-0.4890	-0.1779	0.0390	0.0022	-0.0447	0.0173
	Strong Unexp. Defl.	0.6620	0.0000	0.5670	0.1895	-0.2230	0.6370
	Mod. Unexp. Defl.	-0.2564	-0.0082	0.1273	-0.1187	-0.0300	0.6330
	No Unexp. Infl.	-0.6360	-0.2849	-0.0079	-0.0146	0.0770	-0.0360
	Mod. Unexp. Infl.	0.1676	-0.1685	0.4258	0.0616	0.0132	0.4510
	Strong Unexp. Infl.	0.8860	-0.2040	-0.0707	-0.0720	0.1320	-0.1870
VIX	Total Period	-0.1731	0.0639	0.0837	0.0098	-0.0052	0.1000
	Strong Unexp. Defl.	1.2590	0.3280	0.2850	-0.1057	-0.3890	0.6393
	Mod. Unexp. Defl.	-0.5740	-0.2952	-0.2992	-0.5460	-0.0788	0.4445
	No Unexp. Infl.	-0.3799	0.3587	0.0960	-0.0563	0.0950	0.0170
	Mod. Unexp. Infl.	0.0450	-0.1980	0.0666	-0.1062	0.0837	0.2470
	Strong Unexp. Infl.	1.7318	-0.0540	0.3032	0.0506	0.7010	0.5500
VVIX	Total Period	-0.0734	-0.0764	0.0279	-0.0405	0.0579	0.1182
	Strong Unexp. Defl.	1.0290	-0.1441	-0.0777	-0.1344	-0.1309	1.3840
	Mod. Unexp. Defl.	-0.1920	-0.2300	-0.3100	-0.2338	-0.3898	0.4230
	No Unexp. Infl.	-0.0340	0.0299	0.1754	0.1216	-0.4060	0.5240
	Mod. Unexp. Infl.	1.2610	-0.0020	0.0064	0.0380	0.1460	1.1360
	Strong Unexp. Infl.	1.8540	-0.1469	0.2130	-0.1984	-0.1520	1.6316
VXD	Total Period	0.1280	-0.3701	-0.1302	0.0978	0.0760	-0.1430
	Strong Unexp. Defl.	0.4240	0.0101	-0.0067	0.3730	0.0052	-0.0200
	Mod. Unexp. Defl.	0.0017	-0.3510	-0.1262	0.0000	-0.1019	-0.5840
	No Unexp. Infl.	0.2630	0.0160	0.0950	-0.1260	-0.0260	-0.6170
	Mod. Unexp. Infl.	-0.3650	-0.2530	0.0093	0.3024	0.4600	0.1470
	Strong Unexp. Infl.	-0.2550	-0.1640	-0.0634	0.1289	0.0539	-0.2950
VXN	Total Period	-0.0950	0.0694	0.0628	0.0052	0.0054	-0.2670
	Strong Unexp. Defl.	0.2030	-0.1628	-0.0420	-0.2857	0.0070	1.3420
	Mod. Unexp. Defl.	0.5961	0.5300	-0.1394	-0.1520	-0.0634	0.0070
	No Unexp. Infl.	-0.3850	0.1969	0.0680	0.1654	0.1693	-0.3667
	Mod. Unexp. Infl.	0.1950	-0.1590	0.3830	0.0750	0.2040	0.5770
	Strong Unexp. Infl.	1.0810	-0.2290	0.2750	-0.0620	-0.1480	0.6159

Note: In the above Table, we build upon a GARCH(1,1) volatility process, where the differential of price response between Bitcoin futures and Bitcoin spot products is estimated based on the differentials between separate GARCH-based analyses of the form $r_{b,t} = \alpha + \beta_1 r_{b,t-n} + \beta_2^{1\%} V_t Q_1 + \beta_3^{5\%} V_t Q_5 + \beta_4^{10\%} V_t Q_{10} + \beta_5^{95\%} V_t Q_{90} + \beta_6^{97.5\%} V_t Q_{95} + \beta_7^{99\%} V_t Q_{99} + e_t,$. Where volatility differentials are examined, differentials are based on the inclusion of the dummy variables in the volatility equation rather than the mean equation. The above estimated differential price volatility and liquidity conditions are then partitioned based on quintiles ranked from the strong and moderate deflation through strong and moderate inflation surprise, as separated with a decile representing no unexpected change. To better understand the interactions between Bitcoin spot and futures volatility and liquidity conditions during varying phases of inflation shock in the United States, results are presented as separated by respective quintiles of tiered inflation and deflation surprise.