Are Bitcoin Futures Options a Cheaper Way to Play the Bitcoin Lottery?

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Abstract

This is the first paper to analyze trading patterns in Bitcoin futures option contracts traded on the Chicago Mercantile Exchange (CME) using Bitcoin options implied volatility levels. Using two years of daily Bitcoin futures option prices ranging from Jan 13th, 2020 to Dec 31st, 2021, we uncover strong evidence of market participants using Bitcoin options to 'play the Bitcoin lottery'. We find that the speculative demand for Bitcoin call options increases with Bitcoin returns as indicated by the positive relationship between the ATM (at-the-money) call options' implied volatility and Bitcoin returns, in sharp contrast with what is observed in S&P 500 option contracts. This lottery-like demand leads to a symmetric volatility smile and a positive term structure for OTM (out-of-the-money) options. We also find that these dynamics cause call options to be more expensive than put options, particularly for longer-dated contracts, indicating a higher demand for a relatively less expensive long position in the Bitcoin cryptocurrency.

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1 Introduction

The Chicago Mercantile Exchange (CME) launched futures contracts on the Bitcoin cryptocurrency in 2017 and subsequently expanded its offering to include futures options contracts in 2020 (Corbet et al. (2018)). Prior to this development, cryptocurrency options trading had been limited to specialized cryptocurrency exchanges such as Deribit. The introduction of options on the CME has brought these contracts within the reach of many more traders, institutional and retail ones alike. In this paper we analyze the trading dynamics of Bitcoin Futures Options on the CME in order to investigate whether market participants behave differently in this arena relative to the more traditional S&P 500 options market. To the best of our knowledge, no study has yet analyzed the trading patterns of CME-traded Bitcoin options using their implied volatility levels. We aim to fill this gap by analyzing Bitcoin futures options from January of 2020 to December of 2021 and comparing their dynamics against those of S&P 500 options. Out analysis takes a two-tier approach: first, we focus on static comparisons between the two option contract types' dynamics by using the volatility smile, volatility surface, and risk-neutral moments. Then, we examine how the dynamics of at-the-money (ATM) implied volatility and the implied volatility curve respond to a variety of variables.

The most important finding of our analysis is the disparity in how market participants use options in these two markets. In the S&P 500 equity options market, we conclude, in line with past findings, that options are used primarily for hedging. In contrast, we find that in the Bitcoin options market, participants use options as a less expensive way to play the 'Bitcoin lottery'. The term 'Bitcoin lottery' refers to market participants using options to bet that Bitcoin prices will rally. Three observations support our conclusions. First, when we examine order volume, we find that the call volume greatly exceeds the put volume. The put-to-call volume ratio for Bitcoin futures options during this period is close to 0.5

whereas it is around 2 for S&P 500 options. This is despite the fact that the dynamics of the underlying returns are similar in this period. Second, when we compare volatility smiles, we find that S&P 500 options exhibit the well-known negative implied volatility skew with out-of-the-money (OTM) puts displaying a higher implied volatility level than the rest of the options, indicating a higher degree of risk aversion or fear of a crash. In contrast, Bitcoin futures options display an almost symmetric smile indicating a much lower level of risk aversion. Finally and most significantly is the contrasting relationship between ATM implied volatility levels and returns. Using Bollen and Whaley (2004)'s methodology, we find that ATM calls' implied volatility levels have a positive relationship with Bitcoin returns. This indicates that when Bitcoin prices are rising, investors demand more call options, a result consistent with the lottery hypothesis. When we compare this result with that of S&P 500 options, we find that the S&P 500 index has a negative relationship with both ATM calls and put options' implied volatility, a result consistent with past findings. Black (1976) attributed this phenomenon to a leverage effect, however other studies such as Hasanhodzic and Lo (2011) have pointed to the risk aversion amongst participants being the culprit, while Hibbert et al. (2008) conclude that this result is due to the feedback effect.

Our investigation also reveals that in addition to using Bitcoin call options to speculate, market participants also appear to use these options to mimic holding Bitcoin in the long term. Our analysis of the volatility surface reveals a positive term structure for OTM options. Further examination shows that this effect is especially true for OTM call options. This result appears to reflect an attempt by market participants to mimic holding Bitcoin at a fraction of the cost. Similarly, using a methodology akin to Cremers and Weinbaum (2010), we find that call options are more expensive than put options, a result more pronounced for longer-dated options and deep-out-of-the-money (DOTM) call options.

Given this preference for call options amongst market participants, we also find that the risk-neutral skewness of the returns distribution inferred from Bitcoin options is higher than that obtained from S&P 500 index options, a result consistent with the said finding above. Positive skewness indicates a high frequency of small positive and negative returns along with a few very large positive returns ("winning the lottery") and is thus consistent with call options being in higher demand as a way to capitalize on the chance of a large payoff. Conversely, negative skewness indicates a higher frequency of positive returns but a few extremely large negative returns (inducing the fear of a crash) and is therefore consistent with put options being in more demand than calls as a way to hedge the downside. Using a method inspired by Bakshi and Madan (2000), Bakshi et al. (2003), and Bali and Murray (2013), we find the overall risk-neutral skewness for Bitcoin options to be -0.1 and -0.3 for the S&P 500 index, indicating a higher preference for call options in the Bitcoin market and a higher preference for put options in the more traditional equity markets.

Another unique result we uncover is the contagion of fear between Bitcoin and equity markets. In our analysis of ATM implied volatility, we find that the VIX volatility index (sometimes referred to as the "fear gauge") has a positive relationship with ATM Bitcoin futures put options' implied volatility levels. This indicates that when fear - proxied for by the VIX - increases in the equity market, Bitcoin put options' implied volatility levels also increase. This suggests a higher demand for downside protection, indicating that fear and hedging activity can occur simultaneously in equity and Bitcoin markets

The limited prior work on Bitcoin options has usually focused on the Deribit Exchange, a platform mostly used by cryptocurrency enthusiasts. Examples of such work include Zulfiqar and Gulzar (2021) and Alexander et al. (2022). Additionally, the analysis of Bitcoin options has mostly targeted pricing models and the underlying stochastic process as in Hou et al. (2020), Pagnottoni (2019), or Cao and Celik (2021). Our paper is, to the best of our knowledge, the first study using Bitcoin futures options traded on the CME and their implied volatility levels to analyze their dynamics and trading patterns. The rest of the article is structured as follows: section 2 provides a description of the data and its summary statistics, section 3 describes the methodology and the various tests employed, section 4 reports the results, and section 5 concludes.

2 Data Sample and Summary Statistics

2.1 Data Description

Bitcoin Futures options data are obtained from the Chicago Mercantile Exchange (CME). The sample spans from Jan 13th, 2020 (the first day Bitcoin futures options began trading) to Dec 31st, 2021, providing about two years of daily prices. The dataset contains 8,033 option data points covering both put and call options of various strikes. The data purchased from the CME contains implied volatilities and deltas computed for each option.

For each option, we calculate the moneyness as the futures price divided by the strike price. As mentioned, the data from the CME include the delta of each option. Consistent with the methodology of Bollen and Whaley (2004), we sort options into 5 groups based on the delta of each option. A detailed description of the methodology used to sort options into groups is provided in the next section. Consistent with past studies, we calculate Bitcoin returns as the log difference between the Bitcoin futures price at time t and the price at time *t-1*. The data collected for S&P 500 options come from OptionMetrics. Not surprisingly, our S&P 500 dataset is significantly larger than our Bitcoin one, with a total of 8,475,999 records. Finally, we simply obtain VIX levels from Yahoo Finance.

2.2 Summary Statistics

We begin by reporting in Table 1 the summary statistics for the main variables used in our analysis and tests. Part A describes the summary statistics for Bitcoin futures options, while Part B pertains to the S&P 500 index options. The first column indicates the variable's name, and the remaining columns report the minimum, maximum, mean, median and standard deviation of each variable.

[Table 1 about here.]

The summary statistics for Bitcoin options indicate that the contracts display a fair amount of range. The options deltas span from -1 for deep-in-the-money (DITM) put options to 1 for deep-in-the-money (DITM) call options. Option deltas have a positive mean and median value of 0.065 and 0.082 respectively, a reflection of the fact that there are more call options in our data than put options. Option moneyness has a mean value of 1, indicating a fairly even distribution around the at-the-money range. However, we find that there is also a significant amount of variation in moneyness as indicated by a maximum value of 9.4 and a minimum value of 0.1. Bitcoin implied volatility has a mean value of 0.78, which as expected, is significantly larger than that of the S&P 500 index (0.36). However, as with the rest of the data, there is a significant amount of deviation from the mean with a minimum value of 0.153 and a maximum value of 2.022. A look at the time to maturity reveals that most of the options tend to be of the lower maturity kind, as indicated by a mean of 0.102 translating into about 37 days. However, some options exhibit much longer maturities, as evidenced by a maximum value of over two years.

During the Jan 13th 2020 to Dec 31st 2021 period, Bitcoin experienced strong returns, with a daily log mean return of 0.00275. However, it is important to note that the minimum value of -0.25697 is greater in magnitude than the maximum of 0.20199. For comparison purposes, Figures 1-3 illustrate the evolution of Bitcoin prices, S&P 500 levels, and their returns over time.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

Part B of Table 1 reports summary statistics for S&P 500 options. As one would expect, there are more data points in the S&P 500 options sample than in the Bitcoin one, with a total of 8,475,899 option records in the S&P 500 dataset. As with the Bitcoin dataset, there is a good amount of spread or range in the variables. The option delta spans from -1 for deep-in-the-money put (DITM) option to 1 for deep out-of-the-money (DOTM) call options. The S&P 500 options' moneyness also shows a wide range extending even further both deep in-and-out-of-the-money compared to the moneyness of Bitcoin options. Implied volatility, as expected, is much lower than that of Bitcoin options with a mean value of 0.36 and a median of 0.29.

2.3 Implied Volatility Time Series Comparison

Figure 4 plots the average implied volatility of Bitcoin ATM call options over time. Bitcoin implied volatility spikes at the beginning of 2020 and again at the beginning of 2021. The first spike of about 120% coincides with the onset of COVID fear in the markets and coincides in timing with the one found in the S&P 500 (Figure 5). The second spike, considerably larger than the first one at around 140%, happens when bitcoin prices start to rise extremely rapidly. Although not a statistical test per say (those are conducted next), at first glance this second spike at least appears to be consistent with the lottery-like demand theory for bitcoin options in the sense that, when bitcoin prices are rallying quickly, market participants are buying more call options hoping to participate in the upside.

Focusing now on S&P 500 call options ATM implied volatility instead, we see that there is only one considerable spike in implied volatility, and it is when COVID fear was impacting the markets the most, with volatility levels reaching 70%. After that, implied volatility remains at more "normal" levels, between 20% to 30%, keeping in mind however, that these levels are still significantly higher than the pre-COVID ones when implied volatility hovers around 15%.

[Figure 4 about here.]

[Figure 5 about here.]

3 Methodology

Our goal in this paper is to analyze the trading dynamics of Bitcoin futures options on the Chicago Mercantile Exchange (CME) and to compare them with those of S&P 500 index options. For this purpose, we take a two-tier approach. In a first step, we perform static comparisons between the two by analyzing the volatility smile, volatility surface, and the risk-neutral moments. In a second step, we compare the dynamics of ATM implied volatility, the volatility slope, and the implied volatility spread.

3.1 Volatility Smile

We begin our analysis by computing the volatility smile for both Bitcoin futures options and S&P 500 index options, first giving us an overall view of how the two compare. We compute the volatility smile using the delta group methodology of Bollen and Whaley (2004). The reason for using delta as opposed to the moneyness for the volatility smile is that moneyness fails to account for the time to maturity. In line with the original methodology, we classify options according to the delta group in which they fall, creating five delta groups for both puts and calls. For example, options that have a delta between 0.375 (-0.375) and 0.625(-0.625) for calls (puts) are placed in delta group 3. We eliminate any options with an absolute delta value greater than 0.98 and less than 0.02. Table 2 describes the full classification of the options based on the delta methodology.

[Table 2 about here.]

After classifying the options into these five groups, we calculate the average implied volatility of the options falling into each groups. We then plot the volatility smile as the average implied volatility against the five delta groups. This implies that delta group 1 will contain deep-in-the-money (DITM) calls and deep-out-of-the-money (DOTM) puts. Similarly, delta group 5 will contain DITM puts and DOTM calls. We additionally repeat this procedure for calls and puts separately in order to later highlight any differences in demand between these option groups.

3.2 Volatility Surface

We follow our preliminary volatility smile analysis by examining the volatility surface in more detail, helping us further our comparison between Bitcoin options and S&P 500 options by including a term structure component. There are several ways to build a volatility surface, with Homescu (2011) highlighting different techniques and their respective advantages and disadvantages, as well as when they can appropriately be used. Given the magnitude of the number of observations, we deem the cubic spline technique to be the most fitting here.

Cont and Da Fonseca (2002) highlight how differences in implied volatilities on different days caused by factors not related to moneyness or time to maturity can violate the no-arbitrage condition. For this reason, only as an example, we first generate the volatility surface using a cubic spline interpolation for a particular random day (August 2nd, 2021). This allows us to depict the volatility surface without being affected by daily changes. However, a one-day snapshot does not give a complete picture of the volatility surface and we must therefore also generate the volatility surface for the entire sample. For the whole period, we thus use a variation of the cubic spline, the thin plate spline, and use moneyness defined as the futures price divided by the strike price.

3.3 Risk Neutral Density

In this next portion of the analysis, we then examine the risk-neutral moments of the returns' distribution. The risk-neutral skewness and kurtosis measure the skewness and kurtosis of the underlying asset's risk-neutral probability distribution of returns implied by the asset's option prices. As previously mentioned, positive skewness indicates a high frequency of small positive and negative returns along with a few large positive returns ("winning the lottery") and is thus consistent with call options being in more demand as a way to capitalize on the chance of a large payoff. Conversely, negative skewness indicates a higher frequency of positive returns but a few large negative returns (inducing the fear of a crash) and is thus consistent with put options being in more demand than calls as a way to hedge the downside. We estimate the risk-neutral skewness and kurtosis using a combination of the methods derived in Bakshi et al. (2003) and Bali and Murray (2013). Bakshi et al. (2003) show that risk-neutral skewness can be calculated as

$$RNSskew = \frac{e^{rt}(W - 3uv) + 2u^3}{(e^{rt}V - u^2)^{3/2}} \tag{1}$$

where

$$u = e^{rt} - 1 - (e^{rt}/2)V - (e^{rt}/6)W - (e^{rt}/24)X$$

We use the methodology of Bali and Murray (2013) to discretize the risk-neutral skewness. Formally

$$V = \sum_{i=1}^{n^c} \frac{2(1 - ln(\frac{K_i^c}{Futures})CallK_i^c \Delta K_i^c}{K_i^{c2}} + \sum_{i=1}^{n^c} \frac{2(1 + ln(\frac{K_i^p}{Futures})PutK_i^p \Delta K_i^p}{K_i^{p2}}$$

$$W = \sum_{i=1}^{n^c} \frac{6ln(\frac{K_i^c}{Futures}) - 3ln(\frac{K_i^c}{Futures})}{K_i^{c2}} CallK_i^c \Delta K_i^c + \sum_{i=1}^{n^p} \frac{6(ln\frac{K_i^p}{Futures}) - 3ln(\frac{K_i^p}{Futures})}{K_i^{p2}} PutK_i^p \Delta K_i^p$$

$$X = \sum_{i=1}^{n^c} \frac{12(ln\frac{K_i^c}{Futures})^2 - 4ln(\frac{K_i^c}{Futures})^3}{K_i^{c2}} CallK_i^c \Delta K_i^c + \sum_{i=1}^{n^p} \frac{12(ln\frac{K_i^c}{Futures})^2 - 4ln(\frac{K_i^c}{Futures})^3}{K_i^{c2}} PutK_i^c \Delta K_i^c$$

In the above equation, we use the variable name *Futures* somewhat loosely as both the closing price of the Bitcoin futures price and of the spot S&P 500 index level, so as not to repeat the formulas twice. K_i^p is the strike of the i^{th} OTM put option when strikes are sorted in decreasing order. $\text{Put}(K_i^P)$ is the price of a put option with strike K_i^p. We require each option to have a minimum of two calls and two puts for a specific maturity. ΔK_i^p is the difference in strike between two options of the same maturity. For the first option in the series, ΔK_i^p is the difference between the strike and the futures price.

We similarly calculate the kurtosis of the returns distribution using the equation below:

$$RNkurtosis = \frac{e^{rt}X - 4ue^{rt}W + 6e^{rt}u^2V - 3u^4}{(e^{rt}V - u^2)^2} \tag{2}$$

3.4 At-The-Money Implied Volatility

In the next section, we subsequently examine the dynamics of ATM options' implied volatilities. We apply the methodology of Bollen and Whaley (2004) and examine the determinants of both calls and puts' ATM implied volatilities separately, using the options' deltas to determine whether the options are at-the-money. As before, we classify all calls (puts) options with a delta between 0.375 (-0.375) and 0.625 (-0.625) as at-the-money options, the third delta group. We then calculate the average implied volatility for each day, and examine which factors influence ATM implied volatility, employing the following time-series regression:

$$\Delta\sigma_t = \alpha_0 + \alpha_1 R_t^{\text{BTC}} + \beta \text{Controls}_t + \epsilon \tag{3}$$

Our dependent variable is the change in ATM implied volatility, while the independent variables are Bitcoin returns and various other independent variables: futures volume, normalized call open interest, normalized put open interest, VIX, and lagged ATM implied volatility. The full form of this regression is similar in essence to Bollen and Whaley (2004). However, due to data constraints, we use open interest instead of option volume as an indicator of information flow. We also add the VIX in the original equation to analyze if there is contagion between the S&P 500 and the Bitcoin market. We use various different combinations of the independent variables to eliminate any data mining biases. We then perform the above analysis for S&P 500 index options, naturally excluding the VIX from the controls.

3.5 Dynamics of Calls and Puts Volatility Slopes

In this analysis, we examine the dynamics of the volatility slope. In previous studies, the implied slope has been calculated in a variety of ways. However, the idea has always been to examine how expensive out-of-the-money options are compared to at-the-money options and what factors lead to changes in relative prices. As an example, Cremers et al. (2008) estimate the implied volatility slope as the difference between the implied volatility of put options with a strike-to-spot ratio of 0.92 and the implied volatility of ATM put options divided by the difference in the strike-to-spot ratio. Duan and Wei (2009) use regressions to calculate the slope of the implied volatility surface. We take advantage of the delta group we created and calculate the volatility slope as the difference between the out-of-the-money options and at-the-money options. For call options, this is the difference in implied volatility between the fourth delta group and the third delta group. For put options, this is the difference between the second delta group and the third delta group. After computing the put/call volatility slope, we examine what causes this slope to change. Analyzing the slope allows us to get some insight as to what causes the relative demand for options to be affected. For this purpose, we run the following regression:

$$\Delta VolatilitySlope_t = \alpha_0 + \alpha_1 R_t^{\text{BTC}} + \alpha_2 \Delta \text{VolatilitySlope}_{t-1} + \beta \text{Volume}_t + \epsilon \tag{4}$$

Our dependent variable is the change in the implied volatility slope, and our independent variables are Bitcoin returns, the lagged change in implied volatility slope, and Bitcoin futures volume. We additionally perform the same analysis for S&P 500 index options.

This analysis is important as the shape of the volatility slope has a lot of information embedded in it. For example, Dennis and Mayhew (2000) finds that riskier stocks as indicated by beta, as well as small-cap stocks, tend to have a steeper implied volatility slope. Similarly, Yan (2011) finds that stock with the steepest implied volatility slope underperform stocks with the least steep volatility slope.

3.6 Call and Put Options Implied Volatility Spreads

As a final step, we examine whether call options are generally more expensive than put options, all else being constant. There could be a few reasons for differences in puts and calls volatility smiles. First, due to the disparity in the trading of Bitcoin calls and puts on different days, their differing volatility smiles could reflect a difference in the volume on those days. Second, it is also possible some of the variations stem from end-of-day transactions. Battalio and Schultz (2006) conclude that when intraday transactions are used, the discrepancy between puts and calls implied volatility disappears. Nonetheless, since we posit that calls might be more expensive than puts, we extend the analysis to examine if this possible extra demand for calls leads them to be more expensive than puts. We examine this issue by taking an approach inspired by Cremers and Weinbaum (2010). Similar in spirit to the creation of delta groups, we create five groups based on time to maturity. Time group 1 has the lowest time-to-maturity, while time group 5 has the highest time-to-maturity. We then sort options based on these 25 groups of delta and time-to-maturity. For each group, we then calculate the average implied volatility of calls and puts. We then calculate the volatility spread as the difference between the implied volatility of calls and puts. We then plot the volatility spread as a function of the delta group and of the time-to-maturity group.

4 Results

4.1 Volatility Smile

Figure 6 plots the volatility smile of bitcoin options as a function of the delta groups. We can see that Bitcoin options exhibit an almost symmetrical smile. This means that the implied volatility of ATM options is lower than others in general, while the implied volatility of OTM put and call options is higher and approximately the same at both ends. This pattern of volatility smile is consistent with a lower level of risk aversion by market participants and can be indicative of speculative behavior. We further investigate implied volatility smiles in more detail by examining the differences between call and put options smiles separately (figure 7). We find that Bitcoin put options display a reverse skew while Bitcoin call options exhibit an almost symmetric smile, a result consistent with speculative demand for Bitcoin call options, keeping in mind that the reason why call options do not display a forward skew (with DOTM calls being more expensive than DITM calls) is because of some pressure from the negative skew puts and the somewhat adherence to the put-call parity condition despite the somewhat low liquidity leading to high spreads.

[Figure 6 about here.]

[Figure 7 about here.]

We finally apply the same approach to S&P 500 index options, with their resulting implied volatility smile displayed in figure 8. We can here observe the well-known reverse implied volatility skew, with OTM puts having the highest implied volatility and OTM calls having the lowest implied volatility. This result is not surprising as it has been documented extensively and particularly given the rampant volatility present during COVID where stocks were sharply falling and rising, creating an increased demand for protective put options.

[Figure 8 about here.]

4.2 Volatility Surface

As an illustration, figure 9 reports the volatility surface of Bitcoin options on Aug 2nd, 2021 where we can see a U-shape pattern and a somewhat positive term structure. The benefit of using a single day to calculate the volatility surface is that it eliminates the daily changes in implied volatility caused by external factors. The obvious drawback of a one-day chart is it does not provide a complete picture of the entire sample. In that spirit, figure 10 subsequently reports the volatility surface for the full sample period, where, consistent with the smile found earlier, we first observe that Bitcoin OTM options have a greater implied volatility than ATM options. Interestingly, we also observe a positive term structure for OTM calls (ITM puts). This result is consistent with an attempt by market participants to mimic holding Bitcoin at a lower cost where, rather than buying Bitcoin directly, market participants can buy longer-dated OTM call options in an attempt to replicate holding Bitcoin. We examine this further by focusing on the volatility surface of call options only (figure 11) and find that this is indeed appears to be the case. The reason why this phenomenon is in line with a mimicking strategy has to do with the kurtosis of the physical distribution: we find the daily and monthly kurtosis are much greater than the yearly kurtosis. Das and Sundaram (1999) find that when such a situation exists, the implied volatility of long-term options should be lower than that of short-dated options. However, as we can see, this is not the case here, providing additional evidence for the mimicking/lottery theory and the resulting increased buying pressure for longer-dated OTM call options.

[Figure 9 about here.]

[Figure 10 about here.]

[Figure 11 about here.]

4.3 Risk-Neutral Moments

In the next analysis, we examine and compare the risk-neutral moments implied by options written on Bitcoin futures and the S&P 500 index. Figure 12 depicts the risk-neutral skewness over time for options on Bitcoin and the S&P 500. The figure shows that Bitcoin displays a higher level of risk-neutral skewness than the S&P 500 index, with Bitcoin also showing a relatively smoother risk-neutral skewness and several bursts of positive skewness. A positive skewness indicates that demand for out-of-the-money calls is higher than for in-the-money puts. Meanwhile, the S&P 500 index displays a considerable negative risk-neutral skewness, especially at the beginning of COVID when the stock market was experiencing a correction. Since a negative risk-neutral skewness indicates that the demand for out-of-the-money puts is higher than for out-of-the-money calls, this result is consistent with the correction that the market was experiencing during COVID where one would expect to see more demand for puts than for calls. In a similar manner, figure 13 depicts the risk-neutral kurtosis for Bitcoin Futures and the S&P500 index. The results are more mixed in this instance, as the S&P 500 index originally displays lower kurtosis levels in the first half of the sample but subsequently higher levels in the second half.

[Figure 12 about here.]

[Figure 13 about here.]

4.4 At-The-Money Implied Volatility

In this section, applying the methodology described in Section 3.4, we examine the relationship between call and put options' ATM implied volatility and the return of the corresponding underlying asset (Bitcoin futures or S&P 500 index), with results for three models each time reported in tables 3-6. In every table, the dependent variable is the change in ATM implied volatility, while the independent variables are Bitcoin futures or S&P 500 index returns and a mix of control variables (varying depending on which of the three models is being run): volume, normalized call open interest, normalized put open interest, lagged ATM implied volatility, and the VIX (for Bitcoin options only). Table 3 shows that Bitcoin returns have a positively statistically significant relationship with ATM call implied volatility, indicating that as Bitcoin value increases, market participants demand more call options. This result is consistent with the lottery-like hypothesis whereby speculation activity increases with the positive performance of the underlying asset (Bitcoin) and is robust across all three models being run. However, when we perform the above analysis for the S&P 500, we find a negative relationship between returns for both puts and calls (Table 5 and Table 6), a result consistent with Black (1976) and his leverage effect theory, with further studies attributing it to hedging and risk aversion effects. (Hasanhodzic and Lo (2011) and Hibbert et al. (2008)). The hedging effect can be seen in table 6 where for S&P 500 index put options we observe a consistent negative relationship between ATM implied volatility and S&P 500 returns, in significant contrast with how participants behave in the Bitcoin sphere. In the case of the S&P 500 index, participants buy put options when the stock market is falling as a way to hedge against a possible further correction. And owing to high liquidity and the holding of the put-call parity condition, we find this negative relationship to be present in call options as well (table 5). This is in contrast with the Bitcoin futures arena where investors buy call options when Bitcoin value is increasing as a way to speculate on future possible additional positive returns, as an attempt to capitalize on possible momentum. This increased demand for Bitcoin call options causes their relative prices to go up, leading to a positive relationship between ATM implied volatility and Bitcoin returns. Another noticeable observation is that due to lower liquidity levels creating higher spreads which serve as an impediment to put-call parity, we do not observe the same relationship between Bitcoin returns and put options' implied volatility levels (Table 4). The nonexistent relation between ATM implied volatility for Bitcoin put options and returns gives additional support to the lottery hypothesis as it indicates that when the Bitcoin market is rallying, most of the trading activity takes place with call options.

[Table 3 about here.]

[Table 4 about here.]

[Table 5 about here.]

[Table 6 about here.]

In addition to our main finding, we also find that Bitcoin lagged ATM implied volatility has a significant inverse relationship with current ATM implied volatility. This is similar to what Bollen and Whaley (2004) find in their analysis of equity markets. We moreover find that Bitcoin futures volume has a significant positive relationship with Bitcoin call ATM implied volatility. This result indicates that the informational effect of volume is very much relevant, consistent with the findings of Alexander et al. (2022).

Finally, in addition to the overall nonexistent relationship between Bitcoin returns and put options ATM implied volatility established in table 4, we find a moderate positive relationship between put options ATM implied volatility levels and the VIX (column 3), an indication of some contagion between the S&P 500 index and Bitcoin markets. This would seem to indicate that when there is a sense of fear on the equities side, with market participants feeling that a correction in one asset class is likely to spread to another, investors using protection across multi-asset classes also buy Bitcoin put options.

4.5 Implied Volatility Slope

As an additional exercise, we also examine the dynamics of the volatility slope, namely, what affects its changes over time. We define the volatility slope as the difference between out-of-the-money (OTM) options and at-the-money (ATM) options. For the put implied volatility slope, this is the difference between the average implied volatility of puts in the delta group 2 and in the delta group 3. For the call implied volatility slope, this is the difference between the implied volatility of calls in the delta group 4 and in the delta group 3.

The results of this analysis are reported in table 7, with all coefficients/estimates highly statistically significant. The put implied volatility slope flattens when Bitcoin prices are rallying, indicating that the demand for OTM puts decreases relative to that of ATM puts. This finding is consistent with market participants being less worried about the downside during or after a good performance and thus with decreasing their demand for OTM puts usually purchased for downside protection. When examining the call implied volatility slope, we also observe that the slope flattens, indicating that ATM calls become more expensive relative to OTM calls. While at first this result might not appear to fully support the speculative "inexpensive long shot strategy/lottery" hypothesis whereby more OTM calls would theoretically be purchased, ATM options have higher liquidity and volume and therefore more of the purchasing activity could be taking place in this group when Bitcoin prices are rallying. One major reason for this is the fact that as long as the call option's maturity is not extremely long, an ATM call option does not cost significantly much more than an OTM one given the fact that most of the option pricing function below the strike price is fairly flat; thus, by buying call options that are closer to being at-the-money, one does not pay significantly more of a premium and yet can enjoy the potential upside much sooner since it is precisely around the strike price that the Gamma or curvature is at its highest, with the option value rising significantly and quickly past that point. When we perform the above analysis for the S&P 500 (Table 8), although the levels of significance are more mixed for put options, we find that the put implied volatility slope overall also flattens when the S&P 500 index is rising, indicating that the demand for OTM puts decreases relative to that of ATM puts, a phenomenon once again consistent with traders being less worried about downside protection during positive returns or news. OTM calls, on the other hand, become relatively more expensive than ATM ones, as evidenced by a steepening of their implied volatility curve.

[Table 7 about here.]

[Table 8 about here.]

4.6 Call-Put Implied Volatility Spread

Finally, after having established the differences in smiles between Bitcoin put and call options, we examine whether there is a difference in their call-put volatility spread. Having already demonstrated that the implied volatility of out-of-the-money calls is significantly higher than in-the-money puts - particularly true for the delta group 5 (deep-out-of-the-money calls and deep-in-the-money puts), we now examine this further by following Cremers and Weinbaum (2010) and create five groups based on time to maturity. Time group 1 has the lowest time to maturity, while time group 5 has the highest time-to-maturity. We then sort options based on these 25 groups of delta and time-to-maturity. For each group, we then calculate the average implied volatility of calls and puts. We then calculate the volatility spread as the difference between the implied volatility of calls and puts.

[Figure 14 about here.]

Figure 14 shows the results of this analysis, revealing that OTM Bitcoin call options are more expensive than ITM put options. We also observe that longer maturity calls are relatively more expensive than longer maturity puts, another indication of market participants trying to mimic holding Bitcoin as a cheaper long-term speculative strategy.

5 Conclusion

We analyze the trading patterns of options on Bitcoin futures and compare them with those of options on the S&P 500 index, investigating whether Bitcoin futures options are used as a way to play the "Bitcoin lottery", a less expensive way to have a chance at participating in a Bitcoin currency rally in the long term. We uncover two important results that highlight how market participants act differently in the Bitcoin options sphere compared to those in the S&P 500 options market. Examining the Bitcoin volatility smile, we find that Bitcoin options reveal a symmetric smile while S&P 500 options displays the well-known negative skew. This result indicates how participants in the S&P 500 options market use put options as a way to hedge while those in the Bitcoin options market do not. Our second result which cements our lottery hypothesis is the relationship between call options at-the-money implied volatility and returns in both these markets. While this analysis in S&P 500 options leads to the established negative relationship between returns and at-the-money implied volatility levels (an indication of risk aversion and hedging behavior in this market), we find the opposite relationship in the case of Bitcoin futures options. This indicates that when Bitcoin prices are rallying, market participants demand more Bitcoin call options in the hope of capitalizing on further increases in the currency.

[Table 9 about here.]

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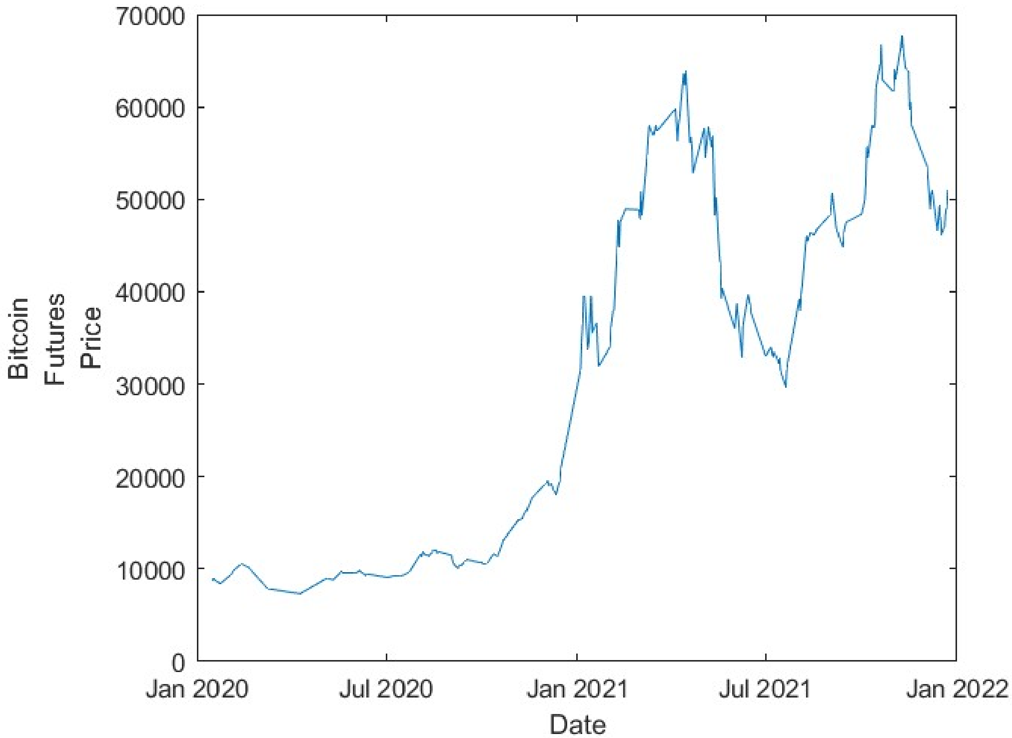
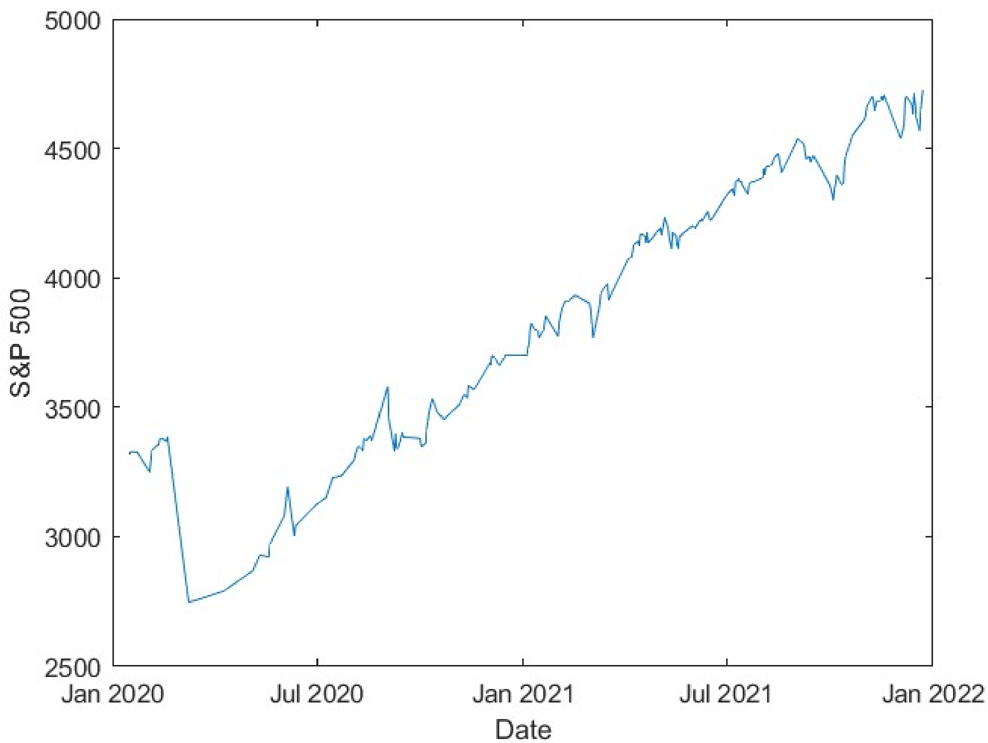
List of Figures

Figure 1: Bitcoin Prices



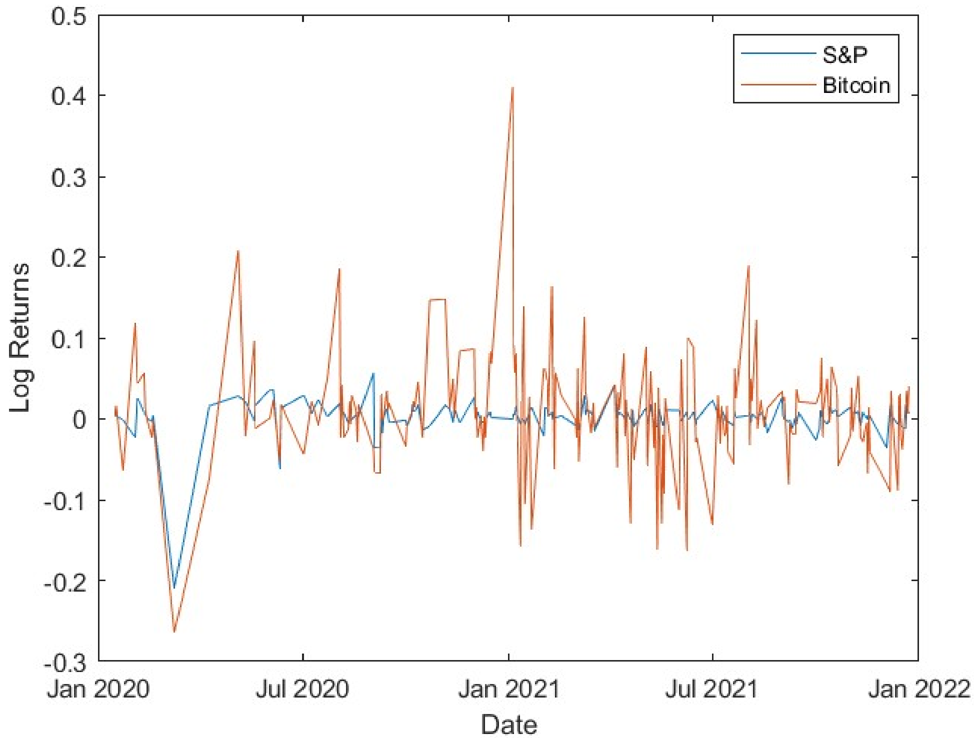
The figure depicts daily Bitcoin Futures Prices from Jan 13th 2020 to Dec 31st 2021.

Figure 2: S&P 500 Index Levels



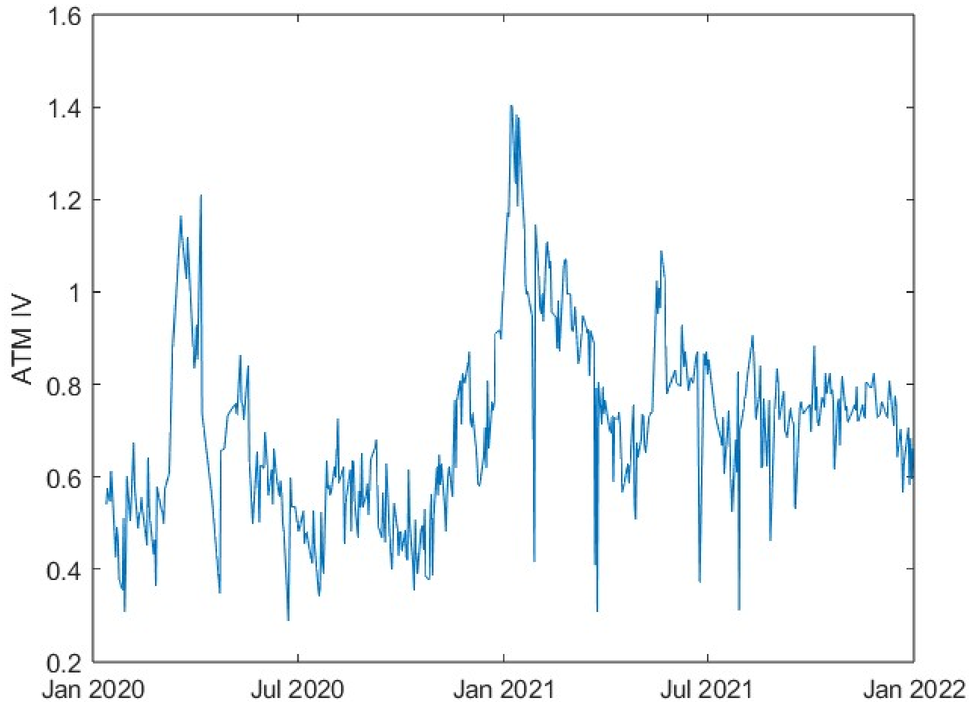
The figure depicts daily S&P 500 index levels from Jan 1st 2020 to Dec 31st 2021.

Figure 3: S&P 500 and Bitcoin Returns



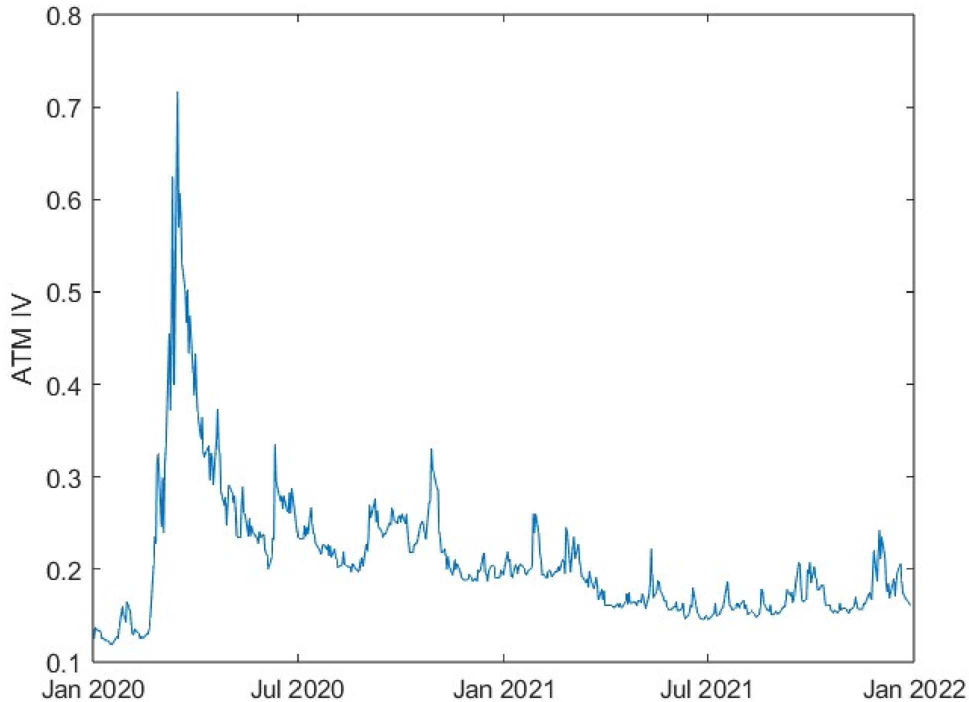
The figure depicts daily returns from Jan 13th 2020 to Dec 31st 2021 for the S&P 500 index and Bitcoin. Returns are calculated as the log difference between prices at time t and t-1

Figure 4: Bitcoin ATM Call Options Implied Volatility



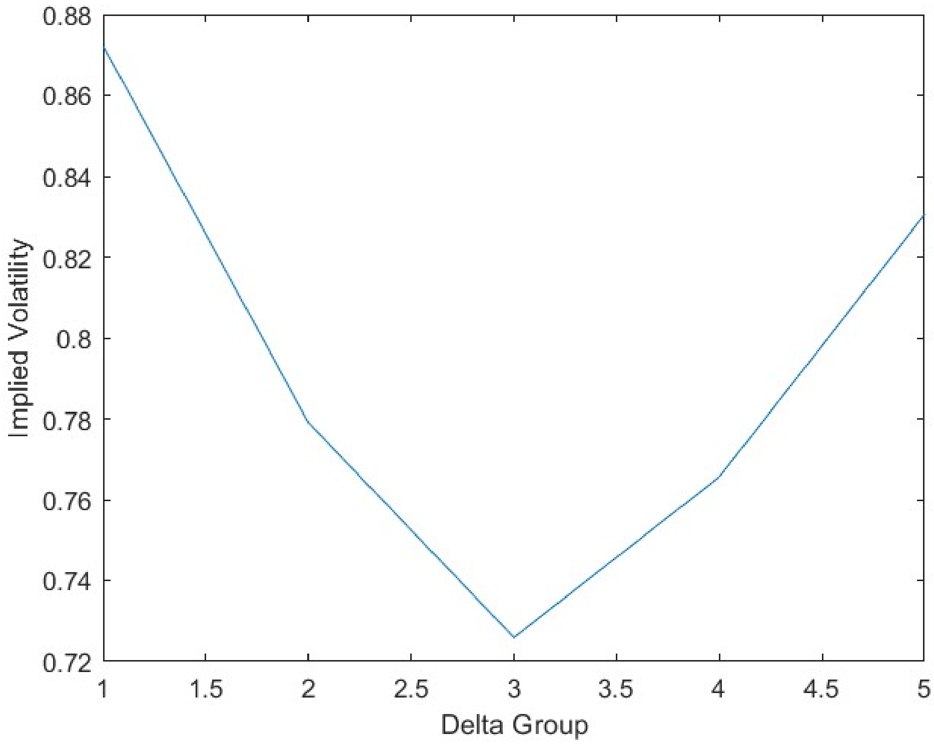
The figure depicts Bitcoin at-the-money call options Implied Volatility levels from Jan 13th 2020 to Dec 31st 2021.

Figure 5: S&P 500 index ATM Call Options Implied Volatility



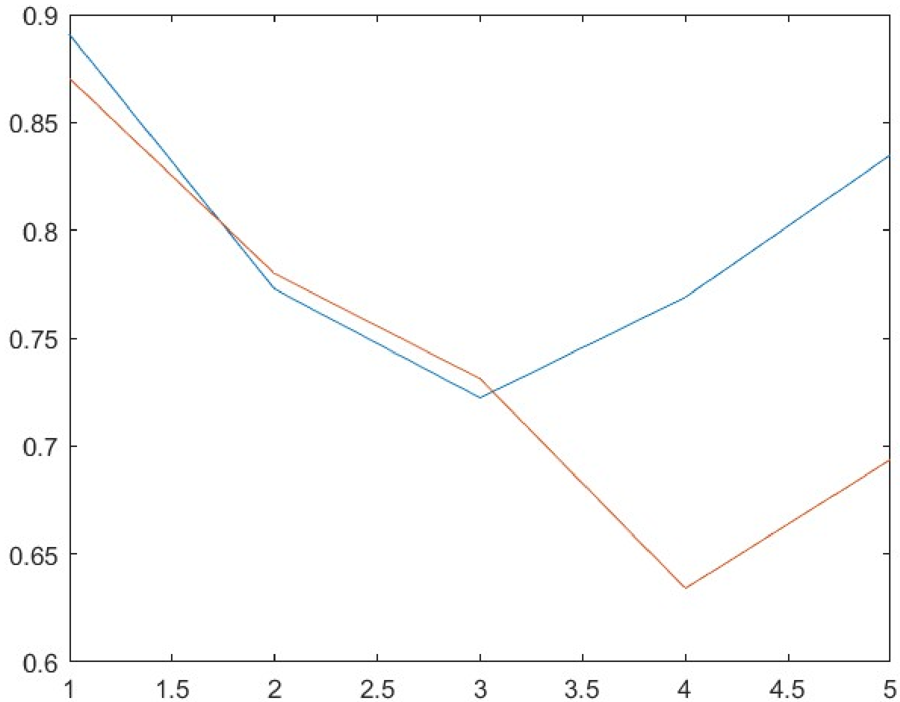
The figure depicts S&P 500 at-the-money call options Implied Volatility levels from Jan 1st 2020 to Dec 31st 2021.

Figure 6: Volatility Smile of Bitcoin Options



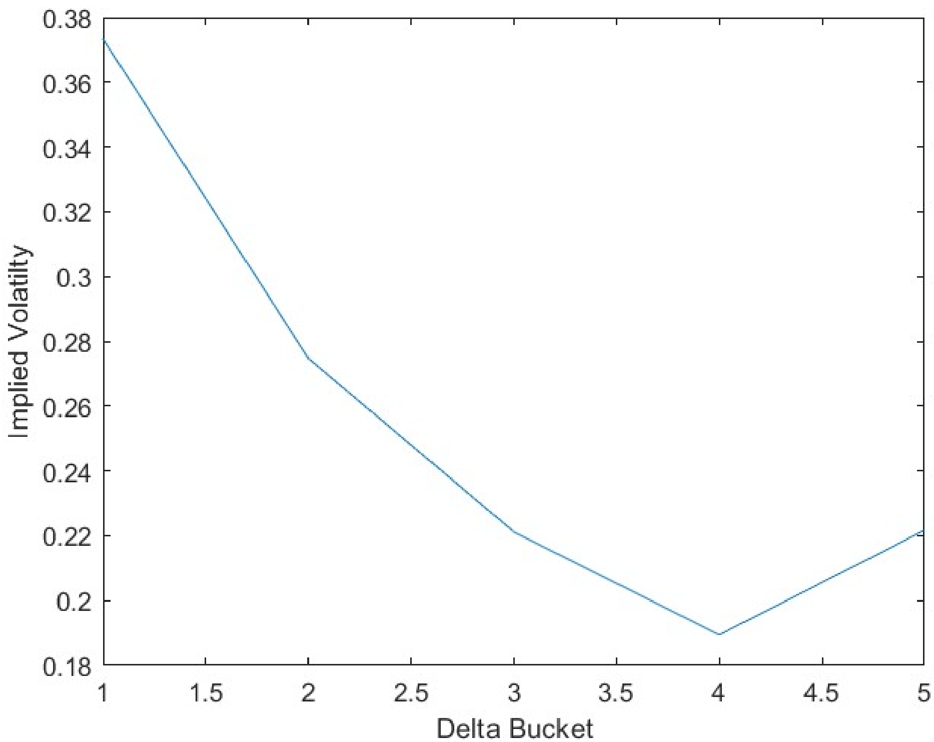
The figure displays the volatility smile of Bitcoin options with calls and puts combined. The volatility smile is calculated using the methodology of Bollen and Whaley (2004). Options are sorted according to their respective Delta groups and the average Implied Volatility of each group is computed. Finally, the average implied volatility is plotted against the Delta Group.

Figure 7: Volatility Smile of Bitcoin Call and Put Options



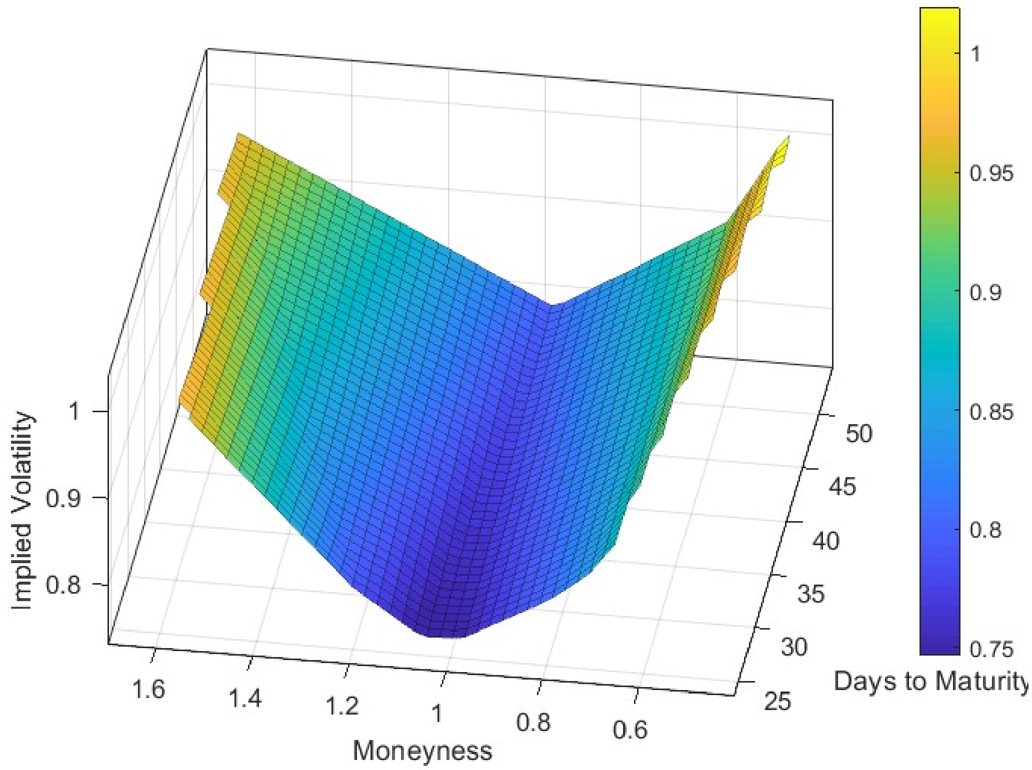
The figure displays the volatility smile of Bitcoin Calls (blue) and Puts (red). The volatility smile is calculated using the methodology of Bollen and Whaley (2004). Options are sorted according to their respective Delta groups and the average Implied Volatility of each group is computed. Finally, the average implied volatility is plotted against the Delta Group.

Figure 8: Volatility Smile of S&P 500 Index Options



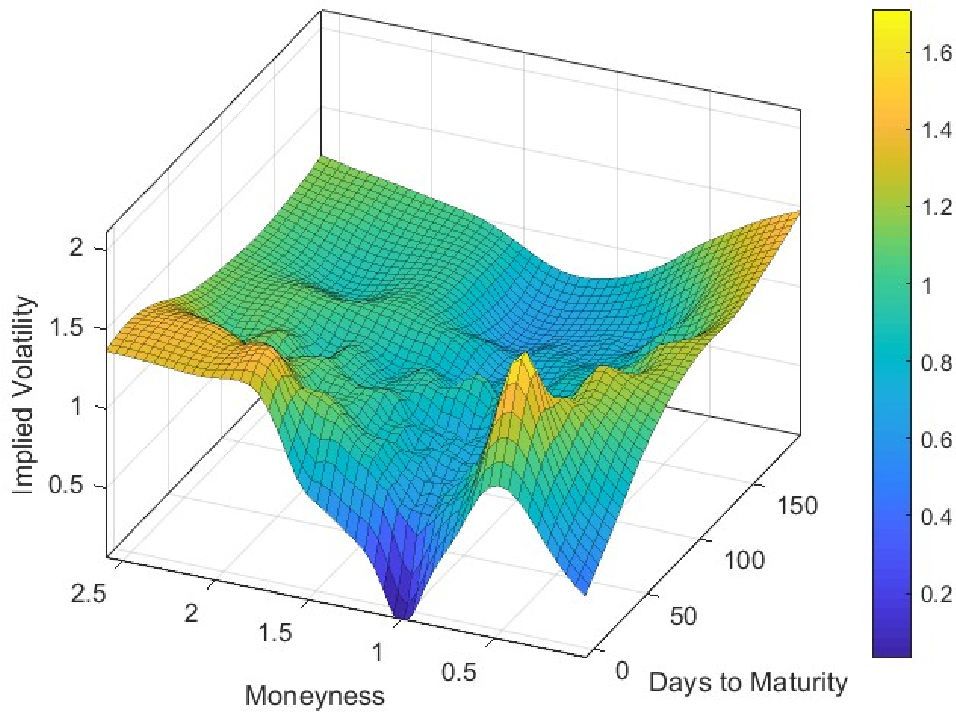
The figure displays the volatility smile of S&P 500 index options. The volatility smile is calculated using the methodology of Bollen and Whaley (2004). Options are sorted according to their respective Delta groups and the average implied volatility of each group is computed. Finally, the average implied volatility is plotted against the Delta Group.

Figure 9: Volatility Surface of Bitcoin Options on August 2nd, 2021



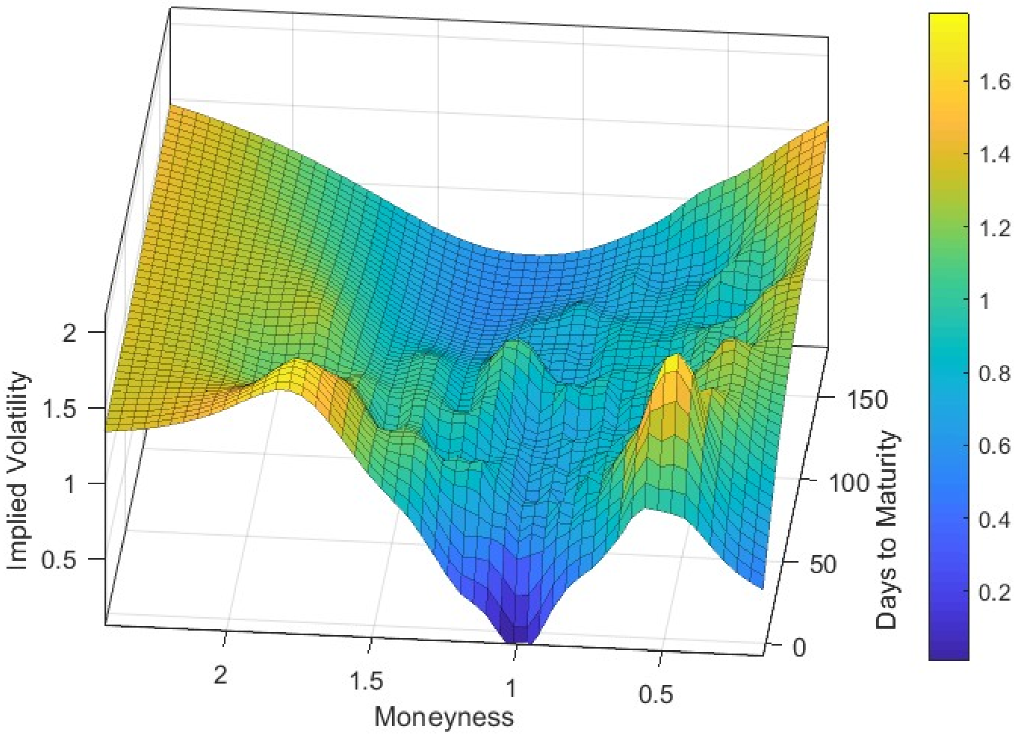
The figure plots the volatility surface of Bitcoin options on August 02, 2021. The volatility surface is estimated using a Cubic Spline approach. The x-axis shows the moneyness, calculated as the futures price divided by the strike price. The y-axis represents the term structure measured as days to maturity and the z-axis reports the implied volatility.

Figure 10: Volatility Surface of Bitcoin Options



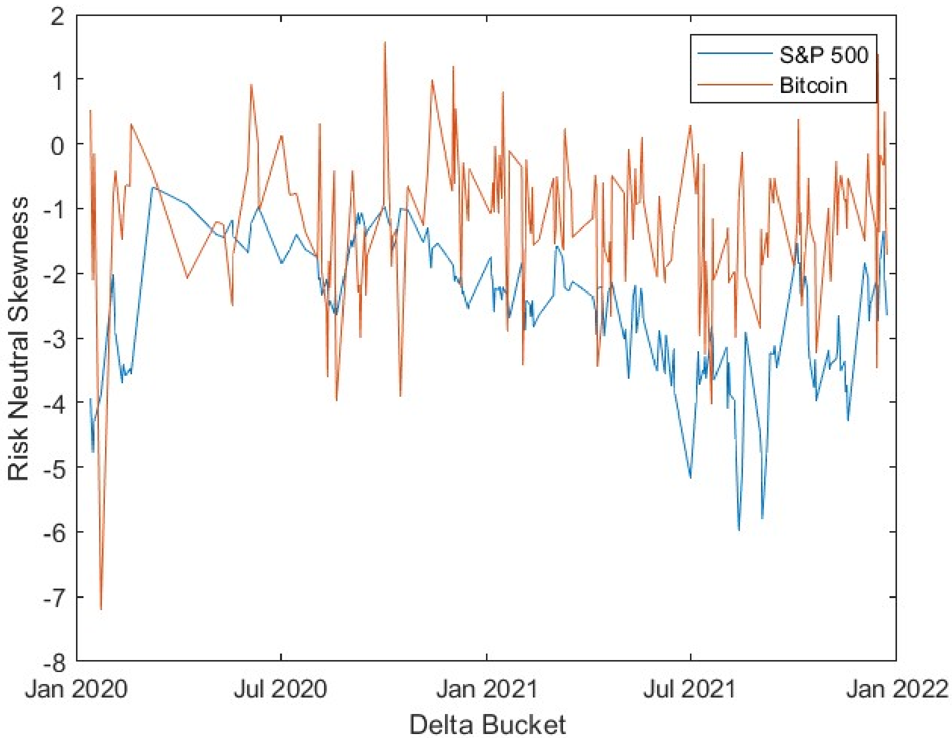
The figure displays the volatility surface of Bitcoin Futures Options for the entire sample. The volatility surface is plotted using a variant of the Cubic Spline - thin plate spline. The x-axis shows the moneyness, calculated as the futures price divided by the strike price. The y-axis represents the term structure measured as days to maturity and the z-axis reports the implied volatility.

Figure 11: Volatility Surface of Bitcoin Call Options



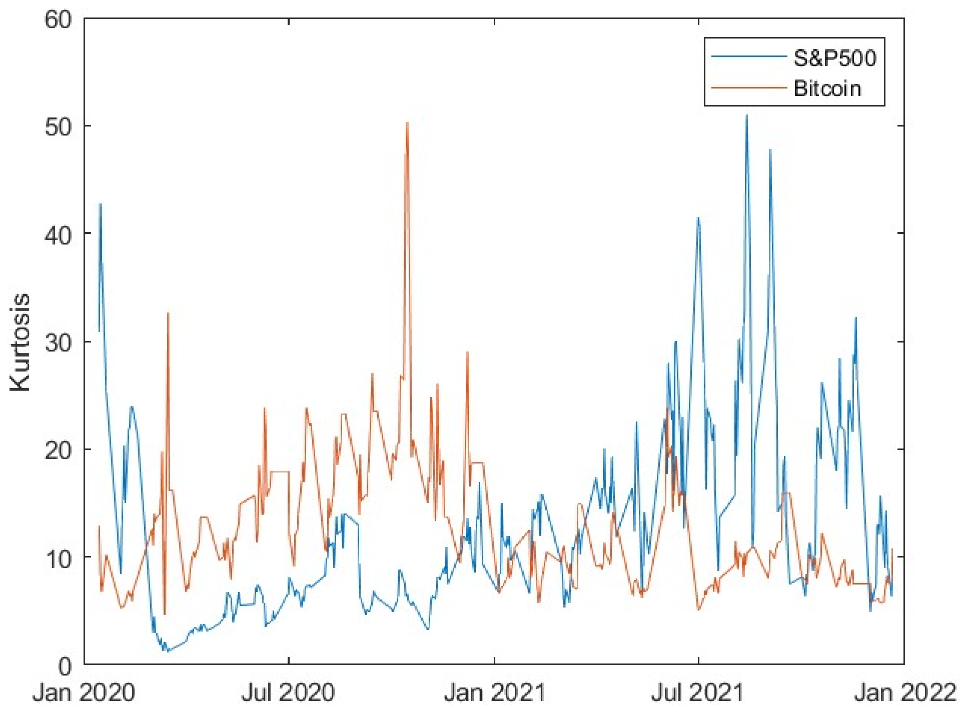
The figure displays the volatility surface of Bitcoin futures call options. The volatility surface is plotted using a variant of the Cubic Spline - thin plate spline. The x-axis shows the moneyness, calculated as the futures price divided by the strike price. The y-axis represents the term structure measured as days to maturity and the z-axis reports the implied volatility.

Figure 12: Risk-Neutral Skewness



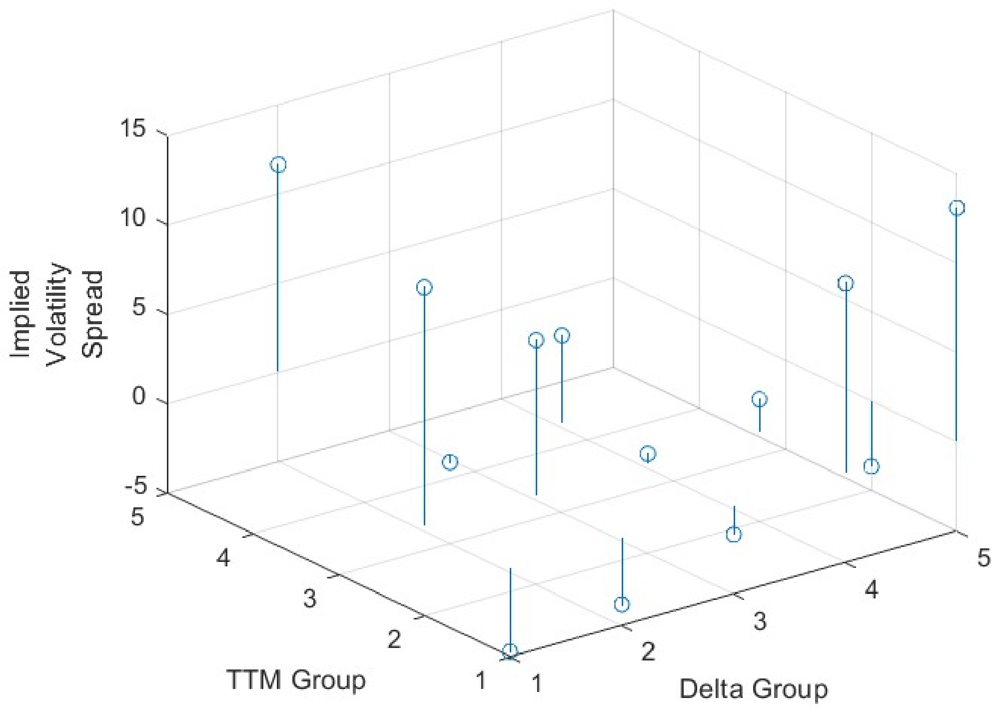
The figure plots the risk-neutral skewness levels derived from Bitcoin futures options and from S&P 500 index options.

Figure 13: Risk-Neutral Kurtosis



The figure plots the risk-neutral kurtosis levels derived from Bitcoin futures options and from S&P 500 index options.

Figure 14: Volatility Spread of Bitcoin



This figure plots the volatility spread of Bitcoin Futures Options. The volatility spread is calculated as the difference between the average implied volatility of Bitcoin calls and puts. The x-axis shows the Delta Group, the y-axis shows the time to maturity, and the z-axis measures the implied volatility spread.

List of Tables

Table 1: Summary Statistics

This table reports summary statistics (minimum, maximum, mean, median, and standard deviation) for all options in our sample. For the period ranging from January 2020 to December 2021, there are 8,033 Bitcoin option observations and 8,475,899 S&P 500 index option observations.

	Min	**Max**	**Mean**	**Median**	**SD**
A. Bitcoin options					
Option price	0.1	61,085	18,373	870	2,864
Strike	1,000	150,000	34,581	32,000	22,532
Delta	-1.000	1.000	0.065	0.082	0.347
Moneyness	0.095	9.395	1.000	0.981	0.329
Implied Volatility	0.153	2.022	0.780	0.766	0.233
Time to Maturity	0.0027	1.6521	0.1021	0.0767	0.0919
B. S&P 500 index options					
Option price	0.0	4,630	331	102	535
Strike	100	9,200	3,362	3,375	97,173
Delta	-1.000	1.000	0.164	0.000	0.568
Moneyness	0.021	2.190	0.889	0.918	0.224
Implied Volatility	0.024	3.000	0.360	0.290	0.282
Time to Maturity	0.0027	5.1315	0.3118	0.1589	0.4465

Table 2: Delta Group Classification

The table describes the classification of the options into delta groups using their delta values.

Category	Labels	Range
1	Deep in the Money Calls	0.875 $< \Delta C <$ 0.98
	Deep Out of the Money Puts	-0.125 $< \Delta P < -0.02$
2	In the Money Calls	0.625 $< \Delta C <$ 0.875
	Out of the Money Puts	-0.375 $< \Delta P < -0.125$
3	At the Money Calls	0.375 $< \Delta C <$ 0.625
	At the Money puts	-0.625 $< \Delta P < -0.375$
4	Out of the Money Calls	0.125 $< \Delta C <$ 0.375
	In the money put	-0.875 $< \Delta P < -0.625$
5	Deep out of the Money Calls	0.02 $< \Delta C <$ 0.125
	Deep in the Money puts	-0.98 $< \Delta P < -0.875$

Table 3: ATM Implied Volatility of Bitcoin Call Options

The table reports the results of the regression described in Equation 3. The dependent variable for the regression is the change in ATM IV for Bitcoin futures call options. In Model 1, the independent variables are Bitcoin returns, lagged ATM IV, and Bitcoin futures volume. In Model 2, the independent variables are Bitcoin returns, Bitcoin futures volume, normalized open interest for calls, and normalized open interest for puts. In Model 3, the dependent variables are Bitcoin returns, Bitcoin futures volume, normalized open interest for calls, normalized open interest for puts, and the VIX. t-statistics are reported in parentheses. The number of observations is based on available data for all variables. * $p < .1$; ** $p < .05$; *** $p < .01$.

Dependent variable	**(1)** **ATM Call IV**	**(2)** **ATM Call IV**	**(3)** **ATM Call IV**
Bitcoin Return	0.645***	0.718***	0.732***
	3.70	3.99	3.98
Lagged ATM Implied Volatility	-0.384***	-0.379***	-0.378***
	-9.36	-9.23	-9.21
Bitcoin Futures Volume	4.74e-06***	4.16e-06**	4.10e-06**
	2.55	2.19	2.15
Normalized Call Open Interest		-0.0026	-0.0025
		-0.20	-0.19
Normalized Put Open Interest		0.031**	0.030**
		2.18	2.17
VIX			0.0369
			0.381
Observations	492	492	492
R Squared	0.189	0.197	0.198
F Stat	38	23.9	19.9

Table 4: ATM Implied Volatility of Bitcoin Put Options

The table reports the results of the regression described in Equation 3. The dependent variable for the regression is the change in ATM IV for Bitcoin futures put options. In Model 1, the independent variables are Bitcoin returns, lagged ATM IV, and Bitcoin futures volume. In Model 2, the independent variables are Bitcoin returns, Bitcoin futures volume, normalized open interest for calls, and normalized open interest for puts. In Model 3, the dependent variables are Bitcoin returns, Bitcoin futures volume, normalized open interest for calls, normalized open interest for puts, and the VIX. t-statistics are reported in parentheses. The number of observations is based on available data for all variables. * $p < .1$; ** $p < .05$; *** $p < .01$.

Dependent variable	**(1)** **ATM Put IV**	**(2)** **ATM Put IV**	**(3)** **ATM Put IV**
Independent variables			
Bitcoin Return	0.199	0.262	0.327 *
	1.24	1.58	1.93
Lagged ATM Implied Volatility	-0.246***	-0.247***	-0.248***
	-5.61	-5.64	-5.68
Bitcoin Futures Volume	3.67e-06**	2.83e-06	2.61e-06
	2.14	1.62	1.49
Normalized Put Open Interest		0.034***	0.033***
		2.65	2.59
Normalized Call Open Interest		0.007	0.007
		0.58	0.60
VIX			0.162*
			1.77
Observations	492	492	492
R Squared	0.066	0.081	0.087
F Stat	11.5	8.58	7.7

Table 5: ATM Implied Volatility of S&P 500 Call Options

The table reports the results of the regression described in Equation 3. The dependent variable for the regression is the change in ATM implied volatility for S&P 500 index call options. In Model 1, the independent variables are S&P 500 returns, and lagged ATM implied volatility. In Model 2, the independent variables are S&P 500 returns, lagged ATM implied volatility, and S&P 500 volume. In Model 3, the dependent variables are S&P 500 returns, lagged ATM implied volatility, S&P 500 volume, normalized open interest for calls, and normalized open interest for puts. t-statistics are reported in parentheses. The number of observations is based on available data for all variables. * $p < .1$; ** $p < .05$; *** $p < .01$.

Dependent variable	**(1) ATM Call IV**	**(2) ATM Call IV**	**(3) ATM Call IV**
Independent variables			
S&P 500 Return	-3.953***	-3.921***	-4.032***
	-32.01	-31.41	-31.47
Lagged ATM Implied Volatility	-0.122***	-0.127***	-0.114***
	-4.89	-5.05	-4.50
S&P 500 Volume		2.67e-12	5.73e-12***
		1.61	2.77
Normalized Call Open Interest			0.0118***
			2.68
Normalized Put Open Interest			-0.014***
			-2.51
Observations	502	502	502
R Squared	0.706	0.708	0.714
F Stat	599	402	248

Table 6: ATM Implied Volatility of S&P 500 Put Options

The table reports the results of the regression described in Equation 3. The dependent variable for the regression is the change in ATM implied volatility for S&P 500 index put options. In Model 1, the independent variables are S&P 500 returns, and lagged ATM implied volatility. In Model 2, the independent variables are S&P 500 returns, lagged ATM implied volatility, and S&P 500 volume. In Model 3, the dependent variables are S&P 500 returns, lagged ATM implied volatility, S&P 500 volume, normalized open interest for calls, and normalized open interest for puts. t-statistics are reported in parentheses. The number of observations is based on available data for all variables. * $p < .1$; ** $p < .05$; *** $p < .01$.

Dependent variable	**(1) ATM Put IV**	**(2) ATM Put IV**	**(3) ATM Put IV**
Independent variables			
S&P 500 Return	-3.233***	-3.197***	-3.228***
	-24.02	-23.49	-22.86
Lagged ATM Implied Volatility	-0.0097	-0.0164	-0.0129
	-0.32	-0.53	-0.41
S&P 500 Volume		3.03e-12*	3.40e-12
		1.65	1.48
Normalized Put Open Interest			-0.0019
			-0.30
Normalized Call Open Interest			0.0048
			0.98
Observations	502	502	502
R Squared	0.549	0.552	0.553
F Stat	304	204	123

Table 7: Bitcoin Implied Volatility Slope

This table reports the results of the regression described in Equation 4. The left-hand side of the table reports the results for the Bitcoin call options implied volatility slope while the right-hand side pertains to the put options. The dependent variable for the regression is the change in implied volatility slope. In Model 1, the independent variable is Bitcoin returns. In Model 2, the independent variables are Bitcoin returns and the lagged volatility slope. In Model 3, the independent variables are Bitcoin returns, lagged volatility slope, and Bitcoin futures volume. *t*-statistics are reported in parentheses. The number of observations is based on available data for all variables.

	Call IV Slope			**Put IV Slope**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Return	-0.904***	-0.565***	-0.565***	-0.433***	-0.479***	-0.478***
	-2.92	-2.00	-2.00	-4.34	-5.26	-5.24
LagIVSlope		-0.424***	-0.424***		-0.424***	-0.410***
		-10.38	-10.37		-10.11	-10.10
Volume			8.11e-08***			8.11e-08***
			-0.27			-0.09
Observations	493	492	492	493	492	492
Rsq	0.0171	0.195	0.195	0.037	0.203	0.203
F Stat	8.53	59.1	39.4	18.8	62.4	41.5

Nota: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 8: S&P 500 Implied Volatility Slope

This table reports the results of the regression described in Equation 4. The left-hand side of the table reports the results for the S&P 500 index call options implied volatility slope while the right-hand side pertains to the put options. The dependent variable for the regression is the change in implied volatility slope. In Model 1, the independent variable is S&P 500 returns. In Model 2, the independent variables are S&P 500 returns and the lagged volatility slope. In Model 3, the independent variables are Bitcoin returns, lagged volatility slope, and volume. t-statistics are reported in parentheses. The number of observations is based on available data for all variables.

	Call IV Slope			**Put IV Slope**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Return	0.274***	0.263***	0.262***	-0.012	-0.023*	-0.018 ***
	26.70	25.50	25.20	-0.96	-5.70	-1.47
LagIVSlope		-0.147***	-0.147 ***		-0.190***	-0.196***
		-5.12	-5.11		–4.22	-4.40
Volume			-1.26e-14			5.08e-13**
			- 0.09			- 0.09
Observations	493	492	492	493	492	492
Rsq	0.0171	0.195	0.195	0.037	0.203	0.203
F Stat	8.53	59.1	39.4	18.8	62.4	41.5

Nota: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 9: Appendix : Variable Definition

Variable	Definition and Source
Moneyness	Futures Price divided by Strike Price.
Delta	Sensitivity of underlying option price to changes in underlying price.
Implied Volatility	Implied Volatility calculated using the Black-Scholes model
Time To Maturity	Days to maturity divided by 365
Delta Group	Options are sorted into five groups according to the Delta of the option.