Illiquidity Premium and Crypto Option Returns

Christina Atanasova[1,*], Terrel Miao[1], Ignacio Segarra[1], Tony (Tong) Sha[1], Frederick Willeboordse[1]

Abstract

We examine the economic drivers of illiquidity in cryptocurrency options markets and its effect on crypto option returns. Using transaction-level data for bitcoin (BTC) options on Deribit from January 2020 to July 2024, we compute intraday measures of option illiquidity. Our results show that when market makers hold net-long positions, they demand a positive illiquidity premium to compensate for hedging and rebalancing costs associated with their risk exposure. Our regression results show that one standard deviation increase in option illiquidity increases the daily delta-hedged returns by about 0.07% for calls and 0.06% for puts. We estimate a factor model based on latent instruments derived from option characteristics and show that illiquidity is a distinct pricing factor in the cross-section of option returns. These findings highlight the importance of market liquidity, offering valuable insights for traders and market makers in nascent financial markets.

Keywords: Cryptocurrency Option Markets, Net Order Imbalances, Relative Spread, Factor Models

[*]Corresponding author

Email addresses: cva3@sfu.ca (Christina Atanasova), terrel_miao@sfu.ca (Terrel Miao), isegarra@comillas.edu (Ignacio Segarra), tong_sha@sfu.ca (Tony (Tong) Sha), frederick_willeboordse@sfu.ca (Frederick Willeboordse)

[1]Beedie School of Business, Simon Fraser University

1. Introduction

Cryptocurrencies offer new ways to transfer value, invest, and raise capital outside the traditional financial system. Many of these decentralized assets have become important innovations with values tied to their utility and the problems they solve.[2] In May 2024, the global cryptocurrency market crossed the $2.5 trillion threshold, with daily trading volumes surpassing $90 billion. The crypto derivatives markets have also gained momentum. As early as December 2017, the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) introduced bitcoin (BTC) futures contracts (see Halle *et al.*, 2018). While unregulated exchanges such as Deribit, Binance, and OKX have offered cryptocurrency options trading for several years, the introduction of BTC futures options by the CME in January 2020 marked a significant development as the CME is the only U.S.-regulated platform focused on institutional investors.[3]

Using detailed transaction-level data from Deribit for European BTC options between January 2020 and July 2024, this paper examines how the illiquidity of crypto options affects their returns. Deribit has established itself as a leading platform in cryptocurrency derivatives, especially in Bitcoin and Ethereum options, offering contracts with diverse strike prices and expiration dates. By May 2024, Deribit's monthly trading volume exceeded US$50 billion—over sixteen times greater than that of the regulated CME. Deribit's appeal is further strengthened by offering higher leverage (up to 1:20), smaller contract sizes (BTC 1), and a lower minimum order size (0.1 contracts) compared to CME's 5 BTC-sized futures options that do not permit fractional trading. For these reasons, Deribit has successfully developed deeper and more liquid trading, attracting a broader scope of market participants, including retail and institutional clients. The exchange operates 24/7, specializing in options while also offering perpetual and calendar futures,

[2] Crypto assets form a diverse universe with varied features and economic roles. Cryptocurrencies like Ethereum derive value from powering DApps and smart contracts. Some coins are used for fundraising, while social trends and influential figures drive meme coins like Dogecoin and Shiba Inu.

[3] Additionally, Nasdaq has recently filed with the SEC to list and trade bitcoin index options. The planned Nasdaq Bitcoin Index Options (XBTX) will be based on the CME CF Bitcoin Real-Time Index.

primarily used for delta hedging.

Markets with a positive net supply, like bonds and stocks, are typically associated with a positive illiquidity premium (see Amihud and Mendelson, 1986, and subsequent studies). However, Christoffersen *et al.* (2017) argue that in zero net supply derivatives markets, where market makers balance buying and selling pressures, the direction of the illiquidity premium—whether positive or negative—depends on net demand. Market makers hedge these positions, and these hedging costs and risks affect illiquidity measures and, therefore, the cross-section of expected option returns.

Using intraday option trades, we construct measures of option illiquidity. Our findings show that when the net demand pressure in crypto option markets like Deribit is negative, implying that market makers hold a net long position, a positive illiquidity premium is required for the risks and costs of making a market for these options.

Figures 1 to 3 depict the dynamics of net order imbalances for both call and put options traded on Deribit. In general, both call and put options exhibit positive net order imbalances. However, there is considerable heterogeneity, with DOTM calls and puts, as well as call options involving small trades (less than one BTC), showing negative net order imbalances. Additionally, significant time variation is observed, corresponding to movements in the BTC price. This finding aligns with previous research suggesting that the BTC options market is influenced by crypto market sentiment.

We examine the economic drivers of options trading spreads. We follow Christoffersen *et al.* (2017) and analyze observable proxies for the illiquidity risks and costs that the market makers face when trading these assets. We show that proxies for hedging and rebalancing costs explain almost 60% of the spread variation. We also show that proxies for asymmetric information and inventory risk are important determinants of option illiquidity.

We also estimate panel OLS regression of daily delta-hedged returns. When we split option contracts by their net order imbalance, our results show that the illiquid options with negative order imbalances exhibit a higher return. In particular, one standard deviation increase in option illiquidity corresponds to an approximate 0.07% increase in the daily delta-hedged return for calls and 0.06% for puts. This is economically very large when compared to the daily average delta-hedged return of 0.24%.

Our regression analysis is also based on a factor pricing model for crypto delta-hedged option returns. The factor structure in the cryptocurrency options market is not well understood. In this context, using a factor model can shed light on what drives option return predictability in the cryptocurrency markets. Building on Büchner and Kelly (2022) work, we estimate an Instrumented Principal Component Analysis (IPCA) model for portfolios of options sorted by their illiquidity. This factor model prices option contracts in terms of their relevant characteristics via time-varying latent factor loadings. Our empirical findings indicate that a model with three latent factors prices the cross-section of option returns and explains most of the variation in a panel of daily BTC option returns. The daily risk-adjusted returns (alpha) of call option contracts is 0.17% (illiquidity premium), which is economically large and statistically significant, indicating that illiquidity is a distinct pricing factor.

Understanding the factors that account for differences in asset returns across various securities is crucial in asset pricing research. Previous studies have proposed various factor models for stock returns, such as the five-factor model by Fama and French (2015), the q-factor model by Hou *et al.* (2014), the mispricing factors by Stambaugh and Yuan (2016), and the behavioral factors by Daniel *et al.* (2019). Recent research has extended these factor models to other asset classes, including currencies (Lustig *et al.*, 2011), commodity futures (Szymanowska *et al.*, 2014), and cryptocurrencies (Liu *et al.*, 2022).[4]

A new line of research has also applied factor models to explain the cross-section of equity option returns. Unlike equity markets, options markets are characterized by informed trading, volatility-related trading, speculation, and hedging. Delta-hedged option positions, which have minimal exposure

[4]Several studies examine if stock pricing factors apply to cryptocurrency. Liu *et al.* (2022) find that a three-factor model—cryptocurrency market, size, and momentum—explains expected returns well. However, recent studies highlight the importance of news and investor sentiment. Sockin and Xiong (2023) emphasize sentiment's role in price appreciation, while Canayaz *et al.* (2023) show social media sentiment predicts crypto returns, unlike news media sentiment.

to stock market movements, further differentiate options markets. Many studies challenge Black and Scholes (1973) notion that options are redundant assets. For instance, Goyal and Saretto (2009), Cao and Han (2013), An *et al.* (2014), and Zhan *et al.* (2021) show that options provide valuable information for predicting returns. Building on these findings, Bali *et al.* (2023) and Büchner and Kelly (2022) demonstrate that option-specific information, such as implied volatility and option Greeks, significantly influences option returns.

Factors such as illiquidity and momentum, well-studied in equity markets, also play a role in pricing equity options (see Christoffersen *et al.*, 2017; Heston and Li, 2020). Other important predictors include embedded leverage, the structure of volatility term, and volatility of volatility (Vasquez, 2017; Cao *et al.*, 2022). Bally et al. (2022), for example, propose a five-factor model to explain option returns, which includes factors such as option illiquidity, option price, option-implied kurtosis, the difference between realized and option-implied volatility, and the general option market factor.

More directly relevant to our work, Wang *et al.* (2022) highlight liquidity challenges and the impact of high-frequency trading in cryptocurrency markets. These challenges stem from comparatively low market capitalization, concentrated ownership structures, and a fragmented, multi-platform market setup. Makarov and Schoar (2021) argue that these characteristics often render cryptocurrency markets less liquid than traditional asset classes. In addition, papers that document significant mispricings and arbitrage opportunities, implying that there is excess volatility not explicable by usual constructs of "fundamentals" (e.g., Borri and Shakhnov, 2018; Hautsch et al., 2018; Makarov and Schoar, 2020). For example, Biais *et al.* (2023) show that measures of transactional costs and benefits (proxies for "fundamentals" in their model) explain only 5% of the variation in bitcoin return.

Our paper contributes to several strands of the literature. First, we add to the growing literature on cryptocurrencies and cryptocurrency options. At the time of this writing, research on Bitcoin options remains limited. Siu and Elliott (2021), Akanksha Jalan and Urquhart (2021), and Chen and Huang (2024) explore empirical applications of stochastic volatility pricing models, though none delve into the hedging performance of these models. Hou *et al.* (2020) examine various stochastic volatility models to price bitcoin options, emphasizing the significance of jumps and proposing stochastic volatility with a correlated jump (SVCJ) model, particularly useful for pricing exotic options like cliquet or ratchet options.

Alexander et al. (2022) investigate the implied volatility smiles of bitcoin options to discern whether demand pressures on market makers stem from directional or volatility traders. Matic *et al.* (2023) present one of the few detailed studies on hedging bitcoin options, employing a distinct methodology. They utilize implied volatilities quoted by the Deribit exchange to calibrate a parametric stochastic-volatility-inspired implied volatility surface, comparing hedging performance across different stochastic volatility jump-diffusion models.

In a related study, Alexander *et al.* (2023) assess the valuation of crypto inverse options in the Black-Scholes model, while Alexander *et al.* (2023) and Matic *et al.* (2023) analyze the hedging of Bitcoin inverse options, employing various stochastic volatility and jump models. Sepp and Lucic (2024) offer critical insights into the valuation and delta-hedging of inverse options, clarifying misconceptions presented in previous working papers. Moreover, the cryptocurrency investment landscape is delineated between USD-focused and crypto-focused investors, necessitating distinct accounting rules for P&L of systematic option strategies. Sepp and Lucic (2024) introduce USD and Coin-based accounting rules to address this dichotomy and contribute to empirical studies on volatility risk-premia observed in options on Bitcoin and Ethereum.

Our paper also relates to the existing literature that empirically studies illiquidity premia in equity option markets. The existing empirical evidence on illiquidity premia and discounts in derivatives markets is limited. Li and Zhang (2011) find that buying pressure and illiquidity result in price premiums for more liquid warrants than illiquid options on the Hang Seng index. Deuskar *et al.* (2011) identify a liquidity price discount in the market for interest rate caps and floors, where market makers hold net short positions. Brenner *et al.* (2001) report a 21% illiquidity discount for non-tradable central bank-issued options compared to exchange-traded ones. Christoffersen *et al.* (2017) show that selling pressures and illiquidity in equity options on S&P 500 stocks create a positive illiquidity premium in expected returns. Market makers, who absorb net negative demand from end-users, hold long positions and demand higher compensation for illiquid options, leading to lower current prices and higher expected returns.

Our paper also adds to the growing literature on option predictability. Several key findings from related research highlight different aspects of option predictability. Goyal and Saretto (2009) find that options with high implied volatility relative to historical volatility earn lower returns. Bali and Murray (2013) observe a strong negative relationship between risk-neutral skewness and the skewness of asset returns constructed from a pair of options and a position in the underlying stock. Karakaya (2013) reports that selling options with high embedded leverage yields lower returns than selling those with low embedded leverage after controlling for moneyness-maturity. Cao and Han (2013) show that the idiosyncratic volatility of the underlying stock negatively predicts the cross-section of delta-hedged option returns. Vasquez (2017) finds a positive relationship between the slope of the implied volatility term structure and straddle returns in the cross-section. Büchner and Kelly (2022) identify option characteristics such as implied volatility and option Greeks as most relevant for capturing option returns under the instrumented principal component analysis framework. Ramachandran and Tayal (2021) report a monotonic relationship between various measures of short-sale constraints and delta-hedged returns of put options on overpriced stocks. Zhan *et al.* (2021) uncover the predictability of delta-hedged option returns using stock characteristics such as cash flow variance, analyst forecast dispersion, and profitability.

The structure of this paper is as follows. Section 2 details the data, outlines the construction of variables for our empirical analysis, and reviews key summary statistics. Section 3 covers our research methodology, with Subsection 3.1 exploring the economic factors influencing BTC options trading spreads, and Subsection 3.2 introducing the return OLS regressions and IPCA factor model. Section 4 presents the model estimations and discusses the results of various tests. Section 5 concludes the paper and suggests directions for future research.

2. Data, Variables and Summary Statistics

2.1. Deribit Exchange and the Sample Data

Over the past few years, options on crypto assets have seen significant growth, expanding across traditional exchanges like the CME and centralized (CEX) and decentralized (DEX) exchanges.[5] Among the centralized exchanges (CEX) offering digital asset options, Deribit has over 80% of the volume of BTC options and around 90% share of BTC options open interest.[6] Apart from regulatory oversight, the main factor that differentiates the centralized crypto derivatives platforms is the type of products that they offer. For example, CME and Robinhood run order books in standard European put and calls with a contract size in BTC or ETH, and all contracts margined and settled in USD. Deribit, on the other hand, only runs order books in so-called inverse options. An inverse option contract is quoted and traded in the units of the underlying cryptocurrency. The main economic reason for the popularity of inverse contracts in crypto exchanges such as Deribit is that inverse contracts enable traders to operate without maintaining fiat cash accounts. Sepp and Lucic (2024) show that inverse options are just regular vanilla options considered under the martingale measure using the forward of the underlying as the numeraire, thus requiring an adjustment to the option delta.

Alexander *et al.* (2023) point out that the unregulated and less mature bitcoin options market differs from the well-established S&P 500 Index options market in three key ways. First, the bitcoin options market predominantly trades short-term options (less than seven days), which carry higher market risk and are more sensitive to volatility than longer-term options. Moreover, the call–put ratio for bitcoin options is approximately 9:7, in contrast to about 4:6 for S&P 500 options. Second, bitcoin options exhibit a more

[5] The most common type of platform for trading exchange-rate crypto pairs is the order book of an off-chain centralized exchange such as Binance or OKX. By contrast, most asset-swap crypto pairs are traded in liquidity pools of an on-chain decentralized exchange, such as Uniswap or Pancakeswap. Most crypto–crypto asset swaps are traded in on-chain liquidity pools. Trading volumes in all these markets have exploded over recent years.

[6] According to `https://www.theblock.co/data/crypto-markets/options`

symmetric volatility smile, and the bitcoin volatility risk premium (implied minus realized volatility) is consistently negative and significantly larger than that of S&P 500 options. This indicates that bitcoin options market makers face greater challenges in hedging their inventory risk due to price jump risk and lower liquidity, leading them to charge a higher risk premium.

We collect tick-level trade data on options from the Debirit platform from Jan 2018 to July 2024. The exchange lists a wide variety of standard European calls and puts with expiry dates ranging from one-day and 2-day options, as well as 1-week, 2-week, and (more recently) 3-week options to a maximum of 12 months. All listed options are of European style. The nominal value of each option is 1 BTC, and settlement is at 8:00 UTC time (coordinated universal time). Each trade (observation) contains a trading price, amount, timestamp, and direction. Deribit also provides options greeks, implied volatility, underlying index price, and options mark price. The underlying index price is calculated from eight BTC exchanges, including Bitfinex, Bitstamp, Bittrex, Coinbase, Gemini, ItBit, Kraken, and LMAX Digital. It serves as a reference price to calculate option moneyness. The mark price is typically computed as the average of the best bid and best ask price.[7] Options of different strikes and maturities are classified by their Black–Scholes deltas. These are calculated as $\Delta_t^C = \Phi\left[\frac{ln(F_t/K)+0.5\sigma^2\tau}{\sigma\sqrt{\tau}}\right]$, where Φ is the standard cumulative normal distribution function, B_t is the underlying price (USD), $F_t = B_t exp(r\tau)$ is the forward price (USD), K is the strike price (USD), σ is the annualized volatility, τ is the residual time to maturity in years. Deribit also has a proprietary model to fit implied Black-Scholes volatilities from bid-ask prices of inverse options using $V_t^{USD} = F_t^M V_t^{BTC}$, where F_t^M is the marked price of the underlying futures to convert their prices to prices of regular options and to compute the deltas.

We applied several filters to refine our dataset. First, we excluded all observations with missing values for transaction prices, mark prices, and order sizes. We keep only observations with positive implied volatility, ensuring the option price adheres to basic no-arbitrage conditions. We exclude observations with extreme embedded leverage following Karakaya (2013) and Buchner and

[7] According to https://www.deribit.com/kb/options, the mark price is the option's current "fair" value as calculated by the Deribit risk management system.

Kelly (2022). The embedded leverage is defined as $\Omega = \left|\Delta \times \frac{B}{C^T}\right|$, where B is the underlying BTC price, C is the call price and Ω is the embedded leverage. We drop option observations with extreme embedded leverage, removing observations in the 1% tail quantile.

Further, we filtered out sell transactions where the trade price exceeded the mid-point and buy transactions where the trade price fell below the mid-point. We retained only those options with more than seven days to expiration, a minimum of three trading days, and at least ten 10-minute trading intervals per day. This filtering process ensures we can accurately compute the intraday volatility of order imbalances.[8]

2.2. Variables Construction

2.2.1. Option returns

Deribit lists only inverse options, which feature a contract size of one bitcoin and follow the USD value of the coin. Even though these contracts are margined and settled in BTC, their strike prices are in USD. An inverse contract specifies a notional number N of coins multiplied by a so-called "point value" to obtain a payoff expressed as a number of coins. Currently, all exchanges that list inverse options use a notional of exactly one coin. That is, the payoff is in the coin units, and the terminal payoff is transferred to the trader in cryptocurrency (not in USD). The payoff can be written as:

$$V_T^B = N \frac{(B_T^{\$} - K^{\$})^+}{B_T^{\$}}$$

where the second term is a dimensionless quantity called the point value.

For a USD-denominated trader, the payoff can be converted into USD by multiplying V_T^B by the price of the underlying asset at the time of settlement, $\tilde{B_T}$. It is important to note that this price is distinct from the settlement

[8] Unlike equity options, where the most liquid maturity is typically one month, Deribit's most traded instruments have significantly shorter maturities, so we cannot follow previous studies and remove options with less than 30 days to expiration.

price, which is the average price over the 30 minutes preceding the settlement time. Given the extreme volatility in crypto markets, there can be a significant difference between these prices. Therefore, we can express the payoff to a USD-denominated trader as follows:

$$V_T^{\$} = \tilde{B_T} V_T^B = \tilde{B_T} \frac{(B_T^{\$} - K^{\$})^+}{B_T^{\$}} \approx (B_T^{\$} - K^{\$})^+$$

This shows that the inverse option payoff is equivalent to a standard FX option, except that the payoff is denominated in crypto rather than foreign fiat currency (see Lucic, 2022 for more details). There is a large body of academic research on FX options, their pricing, hedging, volatility dynamics, and so forth, see Levy (1992), Carr and Wu (2007), Demeterfi (1998), and many others.

We can use Coval and Shumway (2001) derivation for the expected instantaneous return on an option $E[R^C]$, given by:

$$E[R^C] = \left(r + (E[R^B] - r) \frac{B}{C} \frac{\partial C}{\partial B} \right) dt$$

where $E[R^B]$ is the expected return from BTC and the sensitivity of the call price to the underlying BTC price (the option delta) is $\frac{\partial C}{\partial B}$ or Δ. Crucially, this simple pricing approach relies on the assumptions that both markets denominated in USD and in BTC are complete, and there are no restrictions on exchanging wealth from one to the other.[9]

The presence of $E[R^B]$ and Δ on the righthand side of the option expected return equation shows how important it is to control for the return of the underlying when regressing option returns on illiquidity measures. To disentangle the effect of the underlying price movements, we do not use option returns in our empirical analysis but instead, compute the daily returns to

[9] Most decentralized and centralized crypto exchanges (such as Deribit) assume a zero discount rate when valuing their listed options. In our context, r represents a low-risk opportunity cost available in DeFi, accounting for the risk of blockchain technology hacks, where deposited and staked assets could be lost. Currently, staking high-quality stablecoins in leading DeFi protocols yields 1% to 2%, significantly lower than the 4% to 5% rates offered by short-term government bonds in traditional markets.

delta-neutral call strategy according to common practice (e.g., see Büchner and Kelly, 2022).

$$R_{i,t+1}^{delta-hedged} = \frac{\left(C_{i,t+1}^{\$} - C_{it}^{\$}\right) - \Delta_{it}(B_{t+1} - B_{it})}{C_{it}^{\$} - \Delta_{it} \times B_{it}}$$

where $C_{i,t+1}^{\$} - C_{it}^{\$}$ is the raw profit or loss (P&L) of the option trade from time t to $t+1$ and $\Delta_{it}(B_{t+1} - B_{it})$ is the P&L of the underlying in the same time period that adjusts for the delta-hedging. The denominator measures the cost of the initial investment.

2.2.2. Illiquidity Measures

Deribit relies entirely on third-party market makers, as it does not have an internal trading desk. A downside of non-regulated exchanges is the potential for opaque practices, where specific traders or desks might gain undue advantages. Market makers might secure customized fee arrangements and setup assistance depending on their trading volume. In exchange, they must comply with regulations such as maintaining a minimum quoting time, covering specific instruments, adhering to maximum bid/ask spreads, and ensuring minimum quote sizes. Notably, Deribit market makers are not privy to insider information, do not benefit from preferential order queuing, and lack access to exclusive features. The market makers on Deribit include QCP Capital, Magpie Capital, and XBTO, all of which are crypto trading firms, with QCP also managing an OTC desk handling spot, forwards, and options. Market makers continuously post buy (bid) and sell (ask) quotes on the order book for various options contracts with different sizes. Deribit provides several protections for market makers, including strict margin requirements, partial liquidation processes, and an insurance fund to cover potential losses from counterparty defaults. Additionally, market makers benefit from reduced trading fees, advanced order types, and priority in order matching, all of which help them manage risk and maintain liquidity efficiently.

Our main measure of option illiquidity is the daily volume weighted relative option spread defined as:

$$Spread_{it} = \frac{1}{Vol_{it}^{\$}} \sum_{n=1}^{\#trades} 2 \times \frac{\left|C_{in,t}^{M} - C_{in,t}^{T}\right| \times Vol_{in,t}^{\$}}{C_{in,t}^{M}}$$

where $Spread_{it}$ is the day t relative spread of option contract i, $C^M_{in,t}$ and $C^T_{in,t}$ are the mark price and the transaction price for trade n for contract i on day t whereas $Vol^{\$}_{in,t}$ is the dollar value of transaction n for instrument i on day t.[10]

In a series of robustness tests, we also construct a transaction-based Amihud's illiquidity measure (see Amihud, 2002; Acharya and Pedersen, 2005) and use it to replicate all our regression analysis. Our results remain qualitatively the same.[11] The Amihud measure is computed as follows:

$$Amihud_{it} = \frac{1}{\#trades - 1} \sum_{n=1}^{\#trades} \frac{\left|R^C_{in,t}\right|}{Vol^{\$}_{in,t}}$$

where $Amihud_{it}$ is the adjusted Amihud's percentage illiquidity measure for contract i on day t and $\left|R^C_{in,t}\right|$ is the absolute return of the option i on day t between trades $n-1$ and n.

2.2.3. Illiquidity Determinants

Bid-ask spreads in the options market are closely tied to the costs of market making, originating from three main sources: fixed costs, inventory holding, and information asymmetry. Previous research (e.g., Cao and Wei 2010; Wei and Zheng 2010; Engle and Neri 2010; Goyenko, Ornthanalai, and Tang 2015; Huh, Lin, and Melon 2015; Christoffersen, Goyenko, Jacobs, Karoui 2018) have examined their effects on spreads within the equity options market. However, the literature on the microstructure of the crypto options market is limited due to the nascent nature of the underlying asset.

In our regression analysis, we examine several economic drivers of illiquidity. We begin by computing measures of the (fixed) costs of trading. We measure the initial delta hedging cost (DHC) following Cho and Engle (1999). The hedging cost is simply the dollar volume-weighted embedded leverage for

[10] Mark price is an exchange metric estimate of the fair value of the option. All user positions are valued against it to calculate their equity and to check if any open positions are at risk of possible liquidation.

[11] These results are available from the authors on request.

instrument i on day t and can be calculated as:

$$Hedging\ Cost_{it} = \frac{1}{Vol^{\$}_{it}} \sum_{n=1}^{\#trades} |\Delta_{in,t}| \times \frac{B_{nt}}{C^{\$}_{in,t}} \times Vol^{\$}_{in,t}$$

where Δ_{it} is the dollar volume-weighted delta of option i on day t.

We compute rebalancing costs proposed by Leland (1985) and scale them by option price following Goyenko, Ornthanalai ,and Tang 2015. The percentage rebalancing cost is defined as:

$$Rebalancing\ Cost_{it} = \text{vega}_{it} \times \frac{\text{Spread}^{B}_{t}}{C^{\$}_{i,t}}$$

where $vega_{it}$ is the option i dollar volume-weighted vega on day t. $Spread^{B}_{t}$ is the daily spread of BTC calculated by the average of spread data on Bitfinex, Bitstamp, and Gemini, which are brokers with the fewest non-missing data points.

Next, we turn to our measures of inventory risk and asymmetric information. The net position of the market maker is inferred from the opposite of the order imbalance from liquidity-taking investors (net demand pressure from end users). For a specific instrument i, order imbalance on day t is calculated as follows:

$$Imbalance_{it} = \frac{\sum_{n=1}^{\#trades} Buy_{in,t}|\Delta_{in,t}| - \sum_{n=1}^{\#trades} Sell_{in,t}|\Delta_{in,t}|}{\sum_{n=1}^{\#trades} Buy_{in,t} + \sum_{n=1}^{\#trades} Sell_{in,t}}$$

where $Buy_{in,t}$ denotes the number of contracts with the n_{th} buy order, and $Sell_{in,t}$ is the number of contracts with the n_{th} sell order for instrument i on the day t. Using the index reference price, we also compute the dollar volume of the notional amount where contracts are converted from BTC coins to a dollar value. We aggregate delta-weighted order imbalances for all instruments traded on day t to construct a measure for market-wide the order imbalance.

Bogousslavsky and Collin-Dufresne (2023) argue that much of the literature focusing on daily and lower-frequency order imbalance to measure adverse selection risk is overlooking a key aspect. They suggest that high-frequency order imbalance volatility (HFOIV) is more likely to capture inventory risk. Longer-horizon imbalances, on the other hand, reflect different factors, offering complementary insights. For example, suppose an asset sees increased buy imbalances in the morning and sell imbalances in the afternoon. In that case, the daily imbalance remains unchanged, but HFOIV reflects the heightened inventory risk for liquidity providers, such as high-frequency market makers, throughout the trading day.

Following Bogousslavsky and Collin-Dufresne (2023), we compute a high-frequency measure of order imbalance volatility to approximate the inventory risk faced by liquidity providers. This measure, HFOIV, is defined as the standard deviation of the ten-minute option imbalance. However, using same-day order imbalance can introduce bias due to endogeneity and the presence of informed trading (Shleifer 1986). The authors also suggest that asymmetric information may influence liquidity through the idiosyncratic component of volume and order imbalance volatility. To address this, we regress an option's ten-minute order imbalance on the market-wide share imbalance, weighted by dollar trading volume. To minimize estimation errors, we require that an option have at least ten ten-minute trading intervals. The standard deviation of the residuals from this regression serves as a proxy for adverse selection costs.

In addition to the idiosyncratic component of HFOIB, we propose the proportion of the delta-weighted amount of large orders as another proxy, which is calculated as:

$$\%\ of\ Large\ Amount_{it} = \frac{\sum_{1}^{\#trades} |\Delta_{int}| I_{int}\{large\ trade = 1\} \times Size_{in,t}}{\sum_{n=1}^{\#trades} Size_{in,t}}$$

where a large trade is defined as a trade with a transaction size bigger than one option contract. The intuition for including this proxy for asymmetric information is that investors who trade in large amounts may be more sophisticated, and those who trade in tiny amounts are likely to be retail investors. This notion is further supported in Figure 3, which shows the distinct trading patterns observed between orders smaller than one and those greater than one option contracts.

2.3. Descriptive Statistics

This subsection provides descriptive statistics for our sample data, focusing on the number of transactions, trading volume (in BTC and USD), and total order imbalance (OIB). Table 1 summarizes the activity for call and put options traded on Deribit between January 1, 2020, and July 31, 2024. For call options, the average transaction size is 1.86 BTC, with significant variability as indicated by a standard deviation of 4.78 BTC. The average trading volume in USD is $36,170, with order imbalances averaging -0.21%. On average, call options are traded over 24.77 days with an average time to maturity (TTM) of 93.23 days and a delta of 0.2547. Put options, in comparison, have an average transaction size of 1.80 BTC and a USD trading volume of $28,243. The average OIB for put options is at -1.41%. These options typically trade over 23.48 days with an average TTM of 80.21 days and a delta of -0.2320.

Table 2 further details the distribution of trades based on moneyness, time to maturity, and trade size. Call options are more actively traded, especially in deep out-of-the-money (DOTM), out-of-the-money (OTM), and at-the-money (ATM) categories, with larger trades dominating the market despite their smaller numbers. When examining trades by time to maturity, short-term options (less than 14 days) account for the majority of activity but exhibit high OIB compared to longer-term options, which have lower OIB values. Additionally, the data show that smaller trades tend to have a negative OIB, while larger trades are characterized by positive OIB, suggesting a general buy-side bias in the informed flow and sell-side bias in the uninformed flow.

Table 3 provides summary statistics for call and put option contracts for illiquidity analysis, along with the performance of the underlying BTC market. Panel A presents the results for the call options in our sample. The average relative spread for call options is 5.52%, with considerable variability (SD = 6.26%). Embedded leverage averages 11.57, while rebalancing costs are 6.90% on average. The High-Frequency Order Imbalance Volatility (HFOIV) calculated under two methods shows mean values of 11.63% for the systematic and 21.45% for the idiosyncratic component. Large orders constitute 20.73% of the trading volume, and the log of dollar volume averages 10.51.

Panel B of Table 3 shows the results for the put options in our sample. For put options, the average relative spread is slightly higher at 5.94%, with embedded leverage averaging 11.41. Rebalancing costs are 6.65% on average. HFOIV values are 11.28% and 19.23% for the systematic and idiosyncratic components, respectively. Large orders make up 18.85% of the trading volume, and the log of dollar volume averages 10.32.

Finally Panel C shows the summary statistics for the BTC Market Performance. The underlying BTC market shows an average daily return of 0.17%, with a standard deviation of 2.75%. The daily realized volatility, calculated from 10-minute index price movements, averages 2.60%, reflecting the market's overall price fluctuations during the sample period.

3. Research Design

3.1. Model Specifications for Option Spreads

If illiquidity significantly impacts expected returns, identifying its underlying determinants is essential for understanding its role in asset pricing. Market makers, who absorb the order imbalances resulting from investors trading, incur fixed costs primarily due to the need to hedge inventory risks. These fixed costs include expenses related to initial hedging (Cho and Engle, 1999) and subsequent position rebalancing (Leland, 1985; Boyle and Vorst, 1992; Kaul, Nimalendran, and Zhang, 2004). Engle and Neri (2010) find that initial hedging and rebalancing costs are key determinants of option spreads, suggesting that market makers take these costs into account when setting bid and ask quotes.

In practice, market makers cannot fully hedge or replicate options through trading in the underlying assets, which leads to inventory risks when their positions deviate from optimal levels. Garleanu et al. (2009) demonstrated that a net demand shock increases option prices proportionally with the unhedged portion. Similarly, Muravyev (2015) found that inventory risks significantly affect option prices, indicating that a demand shock can widen spreads even after accounting for the fixed costs of hedging.

Beyond inventory management, option market makers must also consider the risks posed by informed traders. To mitigate potential losses from trading with these informed investors, market makers set spreads wide enough to absorb the risks. Huh, Lin, and Mello (2015) developed a sequential trading model to explore the impact of adverse selection in the options market, confirming that wider call spreads are closely associated with hedging activities driven by information risks.

Drawing on theoretical models and empirical evidence, we test whether fixed costs, inventory shocks, and information risks influence relative bid-ask spreads in crypto option markets.

To examine the impact of the illiquidity determinants discussed in the previous section on the option spreads, we use the Fama-MacBeth (1973) cross-sectional regression approach. The Fama-MacBeth procedure involves running a series of cross-sectional regressions at a daily frequency, where each day's cross-section includes all options that meet our data requirements. Specifically, we estimate the following regression model:

$$\begin{aligned} Spread_i = & a_0 + a_1 DHC_i + a_2 RBC_i + a_3 HFOIB_i^C + a_4 HFOIB_i^I \\ & + a_5 \% \text{ of Large Order}_i + Volume_i \end{aligned}$$

where $Spread_i$ is the mean spread for option contract i, DHC_i and RBC_i are the mean delta-hedging and rebalancing costs associated with contract i. $HFOIB_i^C$ and $HFOIB_i^I$ are the systematic and idiosyncratic components of the high-frequency measure of the volatility of order imbalances for option contract i.

3.2. Model Specification for Option Returns

Having documented the illiquid nature of bitcoin options, the next step is to examine how such friction affects the bitcoin options pricing and return. In Table 3, we reported summary statistics for the daily delta-hedged options returns. The delta-hedged return averages are small and positive for call options and negative for put options. We test whether illiquidity influences subsequent delta-hedged returns by estimating the following OLS panel regression:

$$r_{i,t+1} = a_0 + a_1 Spread_{it} + a_2 DHC_{it} + RBC_{it} + Controls$$

where $r_{i,t+1}$ is the daily delta-hedged return for option contract i on day $t+$. The rest of the explanatory variables are the same as in the spread model specification. The vector of control variables includes the number of days to expiration, delta, and log dollar volume.

To investigate the effect of illiquidity on the cross-section of option returns, we also follow Bruckner and Kelly (2022) and estimate a factor model specifically tailored to explain the cross-section of option returns. Their model addresses the unique characteristics of options markets, where traditional asset pricing models often fall short. By incorporating factors from the options market, their approach captures the dynamics that drive option returns. The model incorporates option-specific factors, providing a more comprehensive explanation of option return dynamics. Bruckner and Kelly use an instrumented principle component model (IPCA) of Kelly et al. (2019) to estimate the factor loadings and returns. The IPCA approach accounts for the high-dimensional nature of options data, efficiently extracting the factors that drive the cross-section of returns.

The model for excess delta-hedge option returns is:

$$\begin{aligned} r_{i,t+1} &= \alpha_{it} + \beta_{it}\mathbf{f}_{t+1} + \epsilon_{i,t+1} \\ \alpha_{it} &= z_{it}'\Gamma_\alpha + \nu_{\alpha,it}, \text{ and } \beta_{it} = z_{it}'\Gamma_\beta + \nu_{\beta,it} \end{aligned}$$

where the system is estimated over a total of N option contracts and T periods. The loadings, β_{it}, are time-varying and partially depend on an $L \times 1$ vector of (option) characteristics z_{it}. We assume that z_{it} includes a constant. The vector of factors, $\mathbf{f}_{t+1}$, is dimension $K \times 1$, i.e the number of factors. Following Kelly et al. (2019), the IPCA model can be estimated by means of an alternating least squares procedure that iterates between the first order conditions of Γ and $\mathbf{f}_{t+1}$.

We analyze a set of option-level variables, including BMS delta (delta), time-to-maturity (ttm), embedded leverage ($embed_lev$), BMS implied volatility (impvol), BMS theta (theta), BMS gamma (gamma), and BMS vega (vega).

These variables are crucial in capturing the option-specific characteristics that might influence returns.

We employ a standard panel regression framework to analyze the option span, using delta-adjusted returns as the dependent variable and the option characteristics as predictors. Recognizing the potential influence of unobserved factors and temporal dynamics, we incorporate time-fixed effects into the model for robustness. This approach helps control for variations that may occur over calendar time, ensuring that our results are not driven by temporal anomalies.

We do not include contract-specific fixed effects for several reasons. Options, particularly in cryptocurrency markets, tend to have short lifespans. Including a fixed intercept for each option could lead to overfitting, compromising the generalizability of the model. Introducing option-specific fixed effects may also absorb much of the variation between contracts, making it difficult to interpret the results meaningfully. The absorption of differences could obscure the actual effects of the variables of interest. The next section discusses the results of our empirical analysis.

4. Empirical Results

4.1. Illiquidity Drivers

Before testing the effect of illiquidity on option returns, we first examine the factors that determine illiquidity. We present the results of cross-sectional Fama-MacBeth regressions conducted on 7,720 option contracts from January 1, 2020, to July 31, 2024. These options are traded for at least ten 10-min interval per day for high frequency imbalance estimation. Relative spread greater than 0.4 are excluded to rule out the effect of outliers. The analysis distinguishes between call and put options, with the dependent variable being the daily relative spread.

The results show that Embedded Leverage has a positive and highly significant impact on relative spreads across all specifications. Options with higher embedded leverage tend to have wider relative spreads. Specifically, the coefficient for embedded leverage is 0.0033 for call options and increases to 0.0058 for put options in the basic model, indicating both strong statistical and economic significance.

The Rebalancing Costs variable also exhibits a significant positive relationship with relative spreads. The coefficient is 1.1745 for call options and 0.9532 for put options in the base model. When additional factors are included, these coefficients rise to 1.9250 for call options and 1.3124 for put options, further confirming the significant association between higher rebalancing costs and wider spreads.

Regarding Inventory Risks, the variable HFOIV(c) is included in models (2) and (4) for both call and put options. The results indicate a positive and significant effect on relative spreads, with coefficients of 0.0334 for calls and 0.0305 for puts, both of which are statistically significant.

The Information Risks category includes HFOIV(i) and the percentage of large orders. HFOIV(i) is significant only for call options in model (2), with a coefficient of 0.0663 and a highly significant p-value. However, this variable does not show significance for put options. The percentage of large orders is significant for both call and put options in models (2) and (4), with coefficients of 0.0668 for call options and 0.0377 for put options.

Finally, the control variable Volume was included to account for trading activity. The coefficient for volume is positive but not statistically significant in model (2) for call options, and it is nearly zero for put options in model (4), suggesting that trading volume does not substantially impact relative spreads within this sample.

Overall, these results indicate that hedging costs, inventory risks, and information risks are significant determinants of option relative spreads. These findings are consistent across both call and put options, with the impact of these factors being particularly pronounced for embedded leverage and rebalancing costs.

4.2. Option Returns

After studying the determinants of illiquidity, we now turn to the effect of illiquidity on option returns. We further filter the sample by requiring each option to have at least three days with a one-day ahead delta hedged return. We present the results of Panel OLS regressions conducted on 2,984 option contracts from January 1, 2020, to July 31, 2024. We run the regression with the whole sample as well as sub-sample with positive or negative order imbalance for calls and puts.

Table 5 presents the results from panel OLS regressions analyzing the determinants of delta-hedged returns for 1,650 call and 1,334 put option contracts over the period from January 1, 2020, to July 31, 2024. The dependent variable in each regression is the daily option relative spread, and the models include factors such as delta-hedging costs, rebalancing costs, days to maturity (DtM), delta, and trading volume. For call options, the relative spread is significant only in the subset with negative order imbalance (OIB), showing a positive coefficient. Delta-hedging costs consistently exhibit a negative and highly significant relationship with delta-hedged returns across all specifications, while rebalancing costs also have a significant negative impact on returns. The control variables, including DtM, Delta, and Volume, generally show expected relationships, with DtM and Delta both having significant negative coefficients, and Volume showing a small but significant negative effect in the overall sample and the subset with negative OIB. The adjusted R-squared values for call options are modest, ranging from 2.7% to 3.4%, indicating that the included factors explain a small portion of the variation in delta-hedged returns.

For put options, the relative spread is generally not significant but does show a positive and significant coefficient in the subset with negative OIB. Delta-hedging costs, similar to call options, have a consistent and significant positive impact on returns. Rebalancing costs show a strong positive effect on delta-hedged returns across all subsets, indicating that higher rebalancing costs are associated with higher returns. The control variables for put options also follow expected patterns: DtM has a positive and significant relationship with returns, Delta has a negative and significant effect, and Volume is positively correlated with returns across all specifications, suggesting that higher trading activity is associated with higher delta-hedged returns for puts. The adjusted R-squared values for put options are slightly higher than those for calls, ranging from 3.6% to 3.8%, suggesting that the model explains a slightly larger portion of the variation in put option returns. Overall, the results indicate that delta-hedging costs and rebalancing costs are significant determinants of delta-hedged returns, though they explain only a small portion of the variability, highlighting the potential influence of other factors or market dynamics.

Table 6 presents the results for the coefficient estimates from Instrumented Principal Component Analysis (IPCA) three-factor models for portfolios sorted on Illiquidity, Level, Maturity, Delta, and Implied Leverage. The Illiquidity factor is constructed by long options with spread greater than 5% and short options with spread less than 1%. The Level factor is an equally-weighted portfolio with ATM options, and captures fluctuations in the overall level of the implied volatility surface. The Maturity slope factor is constructed by longing options with maturities greater than 90 days and shorting options with less than 14 days. The Delta factor is constructed by longing DOTM options and shorting ATM options. The Implied Leverage factor is constructed by longing options with implied leverage greater than 15 and shorting options with implied leverage smaller than 5. Each portfolio contains at least 10 options to average out the measurement errors.

The analysis focus on a panel data that have least 30 call and put options per day respectively with each instruments traded for at least 5 days, which would facilitate the convergence when estimating IPCA factors .This sample covers 1,660 call and 918 put option contracts over the period from January 1, 2020, to July 31, 2024. The dependent variable is the factor generated by daily delta-hedged return from sorted portfolios.

The IPCA results for call options show that the intercept (alpha) is positive and statistically significant across all factors. This suggests that the sorted portfolios consistently generate excess returns that are not fully explained by the included factors. The intercepts range from 0.0008 for Level to 0.0042 for Maturity, all significant at either the 1% or 5% level. Most importantly, illiquidity factor have a much smaller adjusted R-square compared with other factors, indicating that the risks associated with illiquidity are least effectively captured by IPCA factor model. Therefore, illiquidity factor should be a distinct factor other than option characteristics.

For put options, the results show greater variability and somewhat different dynamics compared to call options. The Illiquidity factor is less consistently significant for put options. It is marginally significant for the intercept (0.0018). For Bitcoin (BTC) options, put options generally do not yield significant positive returns due to their limited upside potential, higher costs associated with volatility and risk aversion, and a positive bias in Bitcoin's price trend over time. The payoff structure of BTC puts, where potential gains are capped, combined with high premiums for protection, reduces their ability to generate strong returns consistently. Additionally, the relatively low number of put contracts in our sample and the BTC options market further diminish the precision of the estimates in the IPCA factor estimation.

5. Conclusions

The Bitcoin options market remains notably illiquid, with significant implications for pricing and expected returns. Our analysis reveals that investors, on average, tend to sell options, though this net sell imbalance has lessened with the growing participation of small retail investors. This illiquid market structure leads to a notable illiquidity premium, where higher illiquidity is associated with increased subsequent delta-hedged returns. Using both panel OLS and IPCA factor models, we find a robust and significantly positive relationship between illiquidity and expected option returns, consistent across various illiquidity proxies and model specifications.

The economic rationale behind these findings suggests that the illiquidity premium compensates market makers for the risks and costs associated with market making. Regression analyses indicate that option relative spreads are influenced by delta-hedging and rebalancing costs, inventory costs, and asymmetric information. Importantly, relative spreads remain a significant determinant of expected returns, particularly for options with negative order imbalances, and delta-hedging costs impact returns across the board, implying the presence of additional contributing factors.

Time-series regression results for the Illiquidity factors based on the IPCA three-factor model further substantiate the illiquidity effect, highlighting its role as a distinct factor separate from option characteristics, given its significant alpha and relatively low adjusted R-square.

These findings carry important policy implications, particularly in enhancing market transparency and regulatory frameworks. Regulators could mandate more detailed trade data reporting, including order imbalance and order book depth. Real-time data would allow investors to gauge liquidity conditions better and adjust their strategies accordingly.

Future research could explore the effects of exogenous shocks on liquidity, the behavior of other options like Ethereum, and the impact of changes in the regulatory environment, such as the transition from proof of work to proof of stake.

Table 1: Summary Statistics: BTC Options Characteristics

The table presents summary statistics for daily data computed from 4,230,878 transactions on 5555 call and 5009 put option contracts on BTC option traded contracts on Deribit from January 1, 2020 to July 31, 2024. Panel A shows the characteristics of the call option contracts in our sample, whereas Panel B reports descriptive statistics for the sample of BTC put options. Variable definitions are in Table A1 in the Appendix.

Panel A: Call Options							
	Mean	Std dev	Median	p5	p25	p75	p95
Option Trading Characteristics							
Transaction size$_{int}$	1.86	4.78	0.3	0.1	0.1	1.2	9.9
Trading volume (BTC)$_{it}$	1.0276	2.4014	0.2547	0.0040	0.0494	1.0229	4.4356
Trading volume ($USD)$_{it}$	$36,170	$89,622	$7,865	$103	$1,444	$33,192	$161,257
Notional value ($USD)$_{it}$	$ 1,090,256	$ 2,328,860	$ 312,127	$ 5,808	$ 66,163	$ 1,110,318	$ 4,709,604
#contracts$_{it}$	31.88	61.97	10.2	0.2	2.1	34.6	135.0
Order imbalance$_{it}$	-0.21%	0.2406	-0.21%	-44.48%	-11.65%	10.71%	45.27%
# of trading days$_i$	24.77	39.41	12	1.7	6	16	100
Total # of trades$_i$	424.53	680.60	185	5	56	476	1871.2
Option Contract Characteristics							
TTM (days)$_{it}$	93.23	94.71	56.15	8.78	18.08	144.77	302.01
Delta$_{it}$	0.2547	0.1816	0.2181	0.0290	0.0880	0.4078	0.5754
Gamma$_{it}$	0.000050	0.000066	0.000029	0.000005	0.000014	0.000059	0.000171
vega$_{it}$	44.27	43.58	29.41	4.02	13.27	60.44	134.30
theta$_{it}$	-103.27	106.22	-65.98	-330.64	-133.85	-32.19	-13.35
Embedded leverage$_{it}$	8.88	6.89	6.96	2.62	4.16	11.93	21.09
Implied volatility$_{it}$	71.93%	0.21	69.08%	44.26%	57.82%	82.40%	109.24%
Panel B: Put Options							
Option Trading Characteristics							
Transaction size$_{int}$	1.80	4.73	0.2	0.1	0.1	1.1	9.1
Trading volume (BTC)$_{it}$	0.8549	2.3504	0.2033	0.0033	0.0384	0.8107	3.6196
Trading volume ($USD)$_{it}$	$28,243	$79,730	$6,410	$105	$1,223	$25,764	$122,218
Notional value ($USD)$_{it}$	$ 937,615	$ 2,163,265	$ 270,018	$ 5,608	$ 58,638	$ 940,984	$ 3,970,409
#contracts$_{it}$	28.60	60.26	8.5	0.1	1.9	30.1	121.4
Order imbalance$_{it}$	-1.41%	0.2226	-1.11%	-41.44%	-12.31%	8.32%	40.04%
# of trading days$_i$	23.48	34.18	13	2	7	16	88
Total # of trades$_i$	373.84	580.91	184	5	66	414	1487.6
Option Contract Characteristics							
TTM (days)$_{it}$	80.21	85.85	46.15	8.58	16.72	111.61	277.18
Delta$_{it}$	-0.2320	0.1685	-0.1943	-0.5417	-0.3661	-0.0801	-0.0280
Gamma$_{it}$	0.000051	0.000067	0.000029	0.000004	0.000013	0.000060	0.000175
vega$_{it}$	39.78	38.36	27.16	3.73	12.25	54.88	116.70
theta$_{it}$	-108.68	107.741	-71.05	-341.85	-141.35	-35.88	-15.08
Embedded leverage$_{it}$	8.69	6.15	7.03	2.04	4.01	11.80	21.00
Implied volatility$_{it}$	73.65%	0.23	70.14%	44.33%	57.56%	85.27%	115.28%

Table 2: Distribution of Call and Put Trades

The table presents summary statistics for the distribution of call and put option contracts and their number of trades, volume, and order imbalance (OIB). Our initial sample consists of 2,358,291 transactions for 5,555 call and 1,872,587 transactions for 5,008 put contracts. Panel A reports the distribution of calls and puts trades by moneyness. Panel B presents the number of trades, volume, and OIB by time to maturity (TTM), whereas Panel C splits the call and put option contracts by trade size. DOTM, OTM, ATM are deep-out-the-money, out-the-money, at-the-money, respectively. Trading volume is the total dollar trading amount in billion USD$. Notional is the dollar amount of the underlying exposure in billion USD$. Variable definitions are in Table A1 in the Appendix.

	Call				Put			
	# Trades	Total Trading Vol	Notional	OIB	# Trades	Total Trading Vol	Notional	OIB
Moneyness								
DOTM	661,676	$0.33	$42.23	-0.12%	593,514	$0.29	$36.84	0.19%
OTM	1,034,129	$2.15	$74.18	0.64%	850,323	$1.70	$53.68	-0.89%
ATM	662,486	$2.50	$33.63	2.76%	428,750	$1.32	$19.75	-0.71%
TTM								
(7, 14]	675,920	$0.78	$42.94	1.28%	589,750	$0.64	$37.31	-0.16%
(14, 30]	654,981	$1.10	$44.63	0.55%	549,688	$0.83	$35.11	-0.72%
greater than 30	1,027,390	$3.10	$62.45%	0.86	733,149	$1.85	$37.85	-0.60%
Transaction Size (BTC)								
(0, 1]	1,746,356	$0.73	$18.76	-1.70%	1,397,660	$0.56	$14.65	-1.08%
(1, 10]	516,078	$2.52	$73.31	1.34%	402,765	$1.66	$52.59	0.19%
greater than 10	95,857	$1.73	$57.97	1.12%	72,162	$1.10	$43.02	-1.03%

Table 3: Summary Statistics: Illiquidity, Returns and Their Determinants

The table presents summary statistics for the filtered dataset for 4,021 call and 3,699 put contracts on BTC option traded contracts on Deribit from January 1, 2020, to July 31, 2024. Panel A shows the characteristics of the call option contracts in our database, whereas Panel B reports descriptive statistics for the sample of BTC put options. Panel C reports summary statistics for the performance of the underlying BTC. Return is the daily percentage of index price. Realized volatility is the daily volatility calculated from 10-min index price movement. Variable definitions are in Table A1 in the Appendix.

	Mean	Std dev	Median	p5	p25	p75	p95
Panel A: Call Options							
Relative spread	5.52%	0.0626	3.64%	0.86%	1.99%	6.81%	15.99%
Embedded leverage	11.57	5.85	10.59	3.79	7.00	15.16	22.79
Rebalancing costs	6.90%	0.0566	5.40%	1.81%	3.39%	8.73%	16.69%
HFOIV^c	11.63%	0.0877	8.77%	0.42%	3.14%	17.92%	31.92%
HFOIV^i	21.45%	0.1261	19.80%	3.93%	10.94%	30.78%	43.81%
% of large order	20.73%	0.1315	19.04%	2.34%	9.85%	30.35%	44.49%
Log dollar volume	10.51	1.4299	10.61	8.02	9.61	11.51	12.67
Delta-hedged return	0.24%	0.0164	0.38%	-2.83%	-0.36%	1.07%	2.60%
Panel B: Put Options							
Relative spread	5.94%	0.0718	3.82%	0.93%	2.06%	7.31%	17.36%
Embedded leverage	11.41	5.80	10.42	3.70	6.99	14.79	22.87
Rebalancing costs	6.65%	0.0435	5.58%	1.96%	3.59%	8.61%	14.70%
HFOIV^c	11.28%	0.0994	8.54%	0.36%	2.92%	17.57%	30.85%
HFOIV^i	19.23%	0.1159	17.53%	3.32%	9.60%	27.86%	39.92%
% of large order	18.85%	0.1208	17.29%	2.05%	8.85%	27.68%	40.43%
Log dollar volume	10.32	1.3798	10.43	7.92	9.44	11.30	12.41
Delta-hedged return	-0.06%	0.0140	-0.21%	-1.93%	-0.78%	0.46%	2.56%
Panel C: BTC Market							
Return	0.17%	0.0275	0.14%	-4.05%	-1.08%	1.35%	4.64%
Realized volatility	2.60%	0.0172	2.23%	0.85%	1.61%	3.14%	5.42%

Table 4: Determinants of Relative Spreads

The table presents coefficient estimates from cross-sectional Fama-Macbeth regressions for 4,021 call and 3,699 put option contracts from January 1, 2020 to July 31, 2024. The dependent variable is the daily option relative spread. Variable definitions are in Table A1 in the Appendix. t-statistics of coefficient mean based on robust standard errors are in brackets. ***,**,* represent 1%, 5% and 10% significance levels.

Option effective spread regressions				
	call options		put options	
	(1)	(2)	(3)	(4)
Hedging Costs				
Embedded leverage	0.0033***	0.0036***	0.0058***	0.0057***
	[14.41]	[13.24]	[9.25]	[8.80]
Rebalancing costs	1.1745***	1.9250***	0.9532***	1.3124***
	[31.41]	[24.33]	[20.88]	[11.00]
Inventory Risks				
HFOIVc		0.0334***		0.0305***
		[5.70]		[2.93]
Information Risks				
HFOIVi		0.0663***		0.0019
		[8.41]		[0.10]
% of Large Order		0.0668***		0.0377***
		[7.92]		[3.33]
Control				
Volume		0.0010		-0.0000
		[1.44]		[-0.02]
# of days	258	258	149	149
Average Observations	47.60	47.60	53.20	53.20
Adjusted R-squared	58.50%	61.38%	53.20%	55.55%

Table 5: Determinants of Delta Hedged Returns

The table presents coefficient estimates from panel OLS regressions for 1,650 call and 1,334 put option contracts from January 1, 2020 to July 31, 2024. The dependent variable is the daily option relative spread. Variable definitions are in Table A1 in the Appendix. *t*-statistics based on robust standard errors are in brackets. ***,**,* represent 1%, 5% and 10% significance levels.

Option delta hedged returns regressions						
	call options			put options		
	All	-OIB	+OIB	All	-OIB	+OIB
Relative spread	-0.0011	0.0171***	-0.0091	0.0056	0.0151**	0.0016
	[-0.21]	[2.60]	[-1.26]	[1.51]	[2.00]	[0.35]
Delta-hedging costs	-0.0007***	-0.0009***	-0.0006***	0.0006***	0.0006***	0.0005***
	[-17.59]	[-14.83]	[-10.78]	[14.53]	[11.41]	[9.12]
Rebalancing costs	-0.0252***	-0.0250***	-0.0264***	0.0609***	0.0590***	0.0591***
	[-5.01]	[-3.80]	[-3.56]	[8.31]	[5.89]	[6.61]
Control						
DtM	-0.0056***	-0.0054***	-0.0055***	0.0047***	0.0049***	0.0046***
	[-17.93]	[-12.51]	[-13.12]	[15.82]	[12.12]	[10.60]
Delta	-0.0124***	-0.0105***	-0.0126***	-0.0115***	-0.0125***	-0.0102***
	[-9.73]	[-12.51]	[-6.82]	[-7.56]	[-5.97]	[-4.82]
Volume	-0.0003**	-0.0003*	-0.0002	0.0008***	0.0007***	0.0008***
	[-2.38]	[-1.80]	[-0.88]	[6.08]	[3.96]	[4.45]
Observations	16534	8309	8225	12054	6195	5859
Adjusted R-squared	2.9%	3.4%	2.7%	3.8%	3.8%	3.6%

Table 6: IPCA Factors v.s. Option Return Factors

The table presents coefficient estimates from time-series regressions for factors generated from 1,660 call and 918 put option contracts from January 1, 2020 to July 31, 2024. The dependent variable is the factors measured by daily portfolio returns. Variable definitions are in Table A1 in the Appendix. Panel A shows the coefficients of the call option characteristic factors in our sample, whereas Panel B reports those for put options factors. Variable definitions are in Table A1 in the Appendix. *t*-statistics based on robust standard errors are in brackets. ***,**,* represent 1%, 5% and 10% significance levels.

Panel A: Call Options					
	Illiquidity	Level	Maturity	Delta	Implied leverage
α	0.0017***	0.0008**	0.0042***	0.0017***	0.0033***
	[3.52]	[2.14]	[5.52]	[4.97]	[4.47]
F1	-0.0185***	0.0215***	-0.0066	-0.0268***	-0.440***
	[-4.39]	[5.91]	[-0.88]	[-8.85]	[-5.49]
F2	-0.0507***	-0.0209***	-0.1811***	-0.0382***	-0.2486***
	[-5.45]	[-3.29]	[-13.12]	[-6.31]	[-13.55]
F3	0.2008***	0.2393***	-0.1123***	0.2973***	0.0113
	[9.71]	[16.56]	[-3.68]	[20.57]	[0.31]
# of days	447	309	292	520	261
Adjusted R-squared	26.4%	49.7%	38.4%	53.1%	41.2%

Panel B: Put Options					
	Illiquidity	Level	Maturity	Delta	Implied leverage
α	-0.0018*	-0.0054***	0.0004	-0.0039***	0.0002
	[-1.91]	[-7.51]	[0.17]	[-6.57]	[0.11]
F1	0.0111	0.0115*	0.0952***	0.0521***	-0.0034
	[1.26]	[1.74]	[-0.88]	[9.50]	[-0.25]
F2	0.1410***	0.1531***	-0.0209	0.1411***	0.1538***
	[6.89]	[7.87]	[-0.40]	[12.19]	[3.38]
F3	-0.2122***	0.0174	0.2179***	-1.950***	-0.3190***
	[-8.34]	[0.90]	[4.14]	[-12.27]	[-5.36]
# of days	198	99	76	268	72
Adjusted R-squared	52.6%	38.5%	36.1%	67.4%	48.8%

Figure 1: Call Option Order Imbalances by Moneyness

Weekly order imbalances (OIB) are calculated as the delta-weighted buy volume (number of contracts) minus delta-weighted sell volume as a percentage of total volume. The data covers BTC options traded on Deribit and BTC index reference price. The sample period is January 2020 to July 2024.

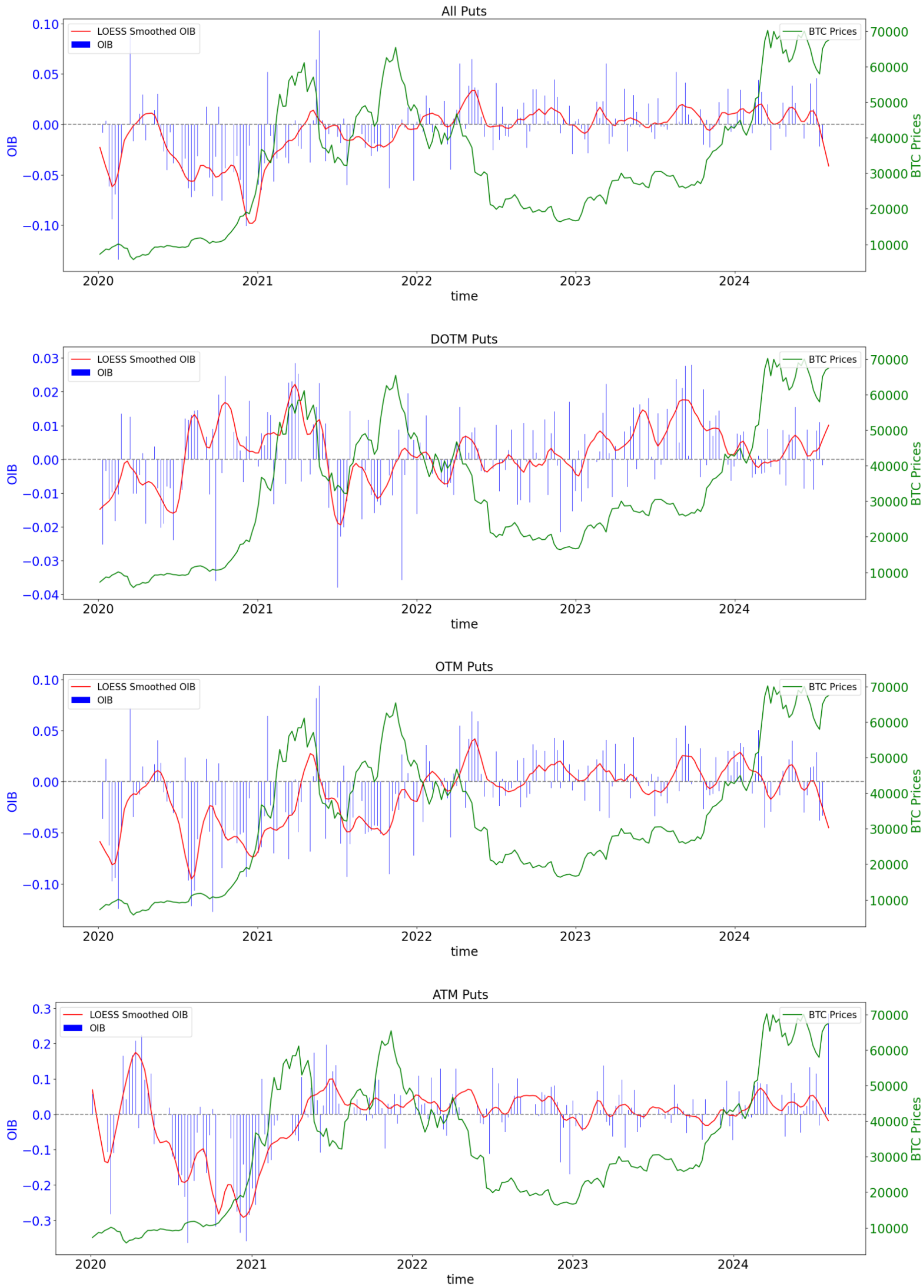

Figure 2: Put Option Order Imbalances by Moneyness

Figure 3: Call and Put Option Order Imbalances by Size

Appendix A1: Variable definitions

Variable	Definition
Panel A: Option Characteristics	
Delta	For a call option is given by: $\Delta_{\text{call}} = \Phi(d_1)$ and for a put option is $\Delta_{\text{put}} = \Phi(d_1) - 1$
Gamma	For call and put options is given by: $\Gamma = \frac{\phi(d_1)}{B\sigma\sqrt{T}}$
Vega	For call and put options is given by: $\nu = B\phi(d_1)\sqrt{T}$
Theta	For a calls is given by: $\Theta_{\text{call}} = -\frac{B\phi(d_1)\sigma}{2\sqrt{T}} - rKe^{-rT}\Phi(d_2)$ for a puts: $\Theta_{\text{put}} = -\frac{B\phi(d_1)\sigma}{2\sqrt{T}} + rKe^{-rT}\Phi(-d_2)$
Implied volatility	Metric reported by Deribit, computed from their proprietary model
Embedded leverage	$\Delta \times B/C$
Panel B: Illiquidity Measures and Its Determinants	
Relative spread	Given by the volume weighted transaction spread: $2 \times \left|C^M_{in,t} - C^T_{in,t}\right| / C^M_{in,t}$
Hedging costs	The dollar volume-weighted embedded leverage
Rebalancing costs	Given by: $\text{vega}_{it} \times Spread^B_t / C^{\$}_{i,t}$
$HFOIV^C$	The systematic component of the high-frequency order imbalance volatility
$HFOIV^I$	The idiosyncratic component of the high-frequency order imbalance volatility
Large Amount	The proportion of large trades given by: $I_{int}\{large\ trade = 1\} \times Size_{in,t}$
Panel C: Delta Hedge Returns	
Daily delta-hedged returns	The daily return from long call (put) option and $\|delta$ units short (long) of the underlying asset

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