Returns from Liquidity Provision in Cryptocurrency Markets

Abstract

We examine the liquidity provision premium in cryptocurrency markets using the returns from the short reversal strategy. We show that returns from liquidity provision can be predicted using the volatility index, realized variance, risk aversion, crash risk, tail risk, and innovations of Tether liquidity. We also find that an increase in the liquidity provision premium is associated with a decline in liquidity, trading volume, and transaction count, as well as more withdrawals, higher fees, and greater impermanent loss on Uniswap. This suggests potential competition between centralized and decentralized exchanges. Further, the liquidity provision premium of stock markets in the US, Canada, and the UK positively predicts the premium of cryptocurrency markets (effect of a common shock), while that of stock markets in China and Japan negatively predicts the premium of cryptocurrency markets (effect of substitution).

1 Introduction

Considerable focus has been placed on the volatility, speculation, lack of regulations, novel microstructure, and leverage of cryptocurrency markets (Makarov and Schoar, 2020; Sockin and Xiong, 2023); however, the dynamics of liquidity provision remain unclear. The microstructure of cryptocurrency markets fundamentally differs from that of the traditional financial markets owing to the underlying blockchain technology, which provides reduced trading costs, transparency, efficiency, and speed in addition to its improved ownership traceability (Yermack, 2017). Market-maker, high-frequency, and algorithmic traders operating in centralized exchanges (CEXs) are all identified as liquidity providers (Çötelioğlu et al., 2021). Moreover, automated market makers (AMMs) can provide liquidity through decentralized exchanges (DEXs) such as Uniswap (Malamud and Rostek, 2017; Lehar and Parlour, 2021; Aoyagi and Ito, 2022). Further, compared with traditional financial markets, cryptocurrency markets are less regulated, experience greater microstructure noise and reduced market depth, and are more susceptible to market manipulation (Dimpfl and Peter, 2021; Harris et al., 2024). This may make them more exposed to liquidity risk (Griffin and Shams, 2020).[1]

Given these distinctive features, we examine whether uncertainty affects the returns on the liquidity provision of cryptocurrencies. We measure the liquidity provision premium of cryptocurrencies as the returns on the reversal strategy following Nagel (2012). Specifically,

[1]For example, regulatory and policy changes that limit or prohibit cryptocurrency trading expose investors to liquidity risk.

using over 100 high-frequency cryptocurrencies from 2017 to 2022, we find empirical evidence that the spot volatility (SPOTVOL) and left tail (LTV) index (Andersen et al., 2024), realized variance (RV) of equally-weighted cryptocurrency market returns, investor risk aversion (RA) of Bekaert et al. (2022) and Bekaert and Hoerova (2016), crash risk (NCSKEW), tail risk (Tail), and Tether liquidity ($\text{DV}_{Tether}^{INNOV}$) are key factors in predicting the reversal strategy. This suggests that market makers are compensated for providing liquidity during market turmoil. Our results are consistent with the findings of Nagel (2012) based on US equity markets.

Next, we examine the effect of impermanent loss (IL), fees, changes in liquidity, trading volume, transaction count, and withdrawals from Uniswap on the liquidity provision premiums in cryptocurrency markets. Uniswap is one of the largest decentralized exchanges that uses automated liquidity pools of tokens locked into smart contracts on the Ethereum blockchain (Capponi and Jia, 2021; Han et al., 2021). A unique characteristic of Uniswap is that it enables its users to become liquidity providers by adding tokens to these pools of tokens. Our analysis reveals that improvements in liquidity, trading volume, and transaction count on Uniswap lower the liquidity provision premium in centralized cryptocurrency markets. This implies that greater liquidity on Uniswap reduces the compensation needed for liquidity provision in centralized markets. Conversely, more withdrawals, higher fees, and greater IL on Uniswap result in a higher liquidity provision premium in centralized markets. This indicates that more withdrawals and higher costs on Uniswap elevate the compensation required for liquidity provision in centralized markets. Overall, our findings indicate potential competition between centralized and decentralized exchanges, with decentralized exchanges potentially being used for trading traditional assets (Barbon and Ranaldo, 2021; Aoyagi and Ito, 2022).

Prior research has documented the diversification benefits of cryptocurrencies in international financial markets (Briere et al., 2015; Dyhrberg, 2016; Bouri et al., 2017; Anyfantaki et al., 2021). Hackethal et al. (2022) have highlighted the potential co-movement between the cryptocurrency and global stock markets and shown that cryptocurrency investors typically purchase stocks with high media sentiment and tend to place greater emphasis on riskier stocks after investing in cryptocurrencies. Therefore, we investigate whether liquidity provision varies between cryptocurrency and global stock markets. We show that the liquidity provision premium of stock markets in the US and Canada positively predicts the premium of cryptocurrency markets, while the premium in China and Japan negatively predicts the premium of cryptocurrency markets. This suggests common shocks for market makers in the cryptocurrency market and the US and Canada stock markets. However, the Chinese and Japanese stock markets seem to act as substitutes for cryptocurrency markets from the perspective of market makers. Overall, our results show the interconnectedness of liquidity provisions among market makers across both cryptocurrency and traditional stock markets.

We conduct several robustness tests and find that our results are consistent throughout. For instance, we examine the predictability of key variables by (1) considering the time-varying risk exposure; (2) controlling for liquidity supply; (3) controlling for the network effect[2]; (4) accounting for the cryptocurrency factor model including market, size, and momentum

[2]Recent studies (Sauer, 2015; Bakos and Halaburda, 2018; Catalini and Gans, 2018; Li and Mann, 2018; Pagnotta and Buraschi, 2018; Biais et al., 2020; Howell et al., 2020; Sockin and Xiong, 2020; Cong et al., 2021) have highlighted the importance of the network effect in cryptocurrency.

(Liu et al., 2022); (5) controlling for Bitcoin futures contracts; and (6) using high-frequency predictors.

Our study makes several incremental contributions to the literature. First, it contributes to the microstructure literature on cryptocurrencies. Aoyagi (2020), Han et al. (2021), Lehar and Parlour (2021), and Aoyagi and Ito (2022) have examined liquidity provision in decentralized exchanges. Yermack (2017) has argued that blockchain allows market makers to identify informed trading, which helps improve market efficiency. Moreover, Easley et al. (2019) have highlighted the role of structural constraints as microstructure properties in user engagement in cryptocurrencies. This study further contributes to the literature by highlighting the importance of time-varying and predictive features of liquidity provision premiums in cryptocurrency markets. More importantly, it provides novel evidence of Uniswap's influence on the liquidity provision premium in cryptocurrency markets, suggesting potential competition between centralized and decentralized exchanges. Thus, this study extends the works of Capponi and Jia (2021), Han et al. (2021), and Lehar and Parlour (2021).

Second, this study contributes to the literature on the cryptocurrency exposure to common risk factors, by demonstrating that returns from liquidity provision in the cryptocurrency market are exposed to common uncertainty index; see, for instance, the work of Bianchi (2020) and Liu and Tsyvinski (2021). Finally, it extends the works of Griffin and Shams (2020) and Alexander et al. (2021), by showing the impact of Tether liquidity on the profits of cryptocurrency market makers.

Our study is fundamentally different from that of Bianchi et al. (2022), which analyzes the association between the returns of a short-term reversal strategy and de-trended trading volume using a daily cryptocurrency pairs dataset. Bianchi et al. formulated a reversal strategy by lagged returns and volume following Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990), and Jegadeesh and Titman (1995) and showed that the joint effect of previous returns and volume helps predict cryptocurrency returns. However, following Nagel (2012), our paper goes beyond their findings by extending the equity market's reversal strategy and examining whether uncertainty measures predict the cryptocurrency liquidity provision premiums. Unlike equity markets, cryptocurrency markets have small market values, are fragmented owing to undiversified ownership, and operate across various platforms (Makarov and Schoar, 2021). Given the unique market microstructure of cryptocurrency markets, our work provides novel out-of-sample evidence for liquidity provision theories.

Our study has important implications. Our findings that SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}_{TETHER}^{INNOV}$ predict cryptocurrency liquidity provision premiums offer valuable insights for liquidity providers such as Coinbase (which became a publicly traded firm on April 14, 2021), which are key players in liquidity provision in cryptocurrencies. Our results could also have implications for policymakers that could help monitor or regulate cryptocurrency liquidity provision. Firms in Asia, such as BitMEX, allow investors to use up to 100-to-1 leverage in trading cryptocurrencies. Given their high volatility, liquidity provision is critical, particularly during market sell-offs.[3] An increasing number of funds have

[3]See https://www.cnbc.com/2021/05/25/bitcoin-crashes-driven-by-big-margin-bets-new-crypto-banking.html for context.

a growing proclivity toward risk exposure with cryptocurrency.[4] Ben-Rephael (2017) found that mutual funds consume liquidity during market downturns, thereby exacerbating market conditions. Our study shows that a liquidity provision premium is positively related to market downturns, which might help funds to manage liquidity to improve their shortfalls in poor market conditions.

The remainder of the paper is organized as follows. In Section 2, we describe the data and methodology. Section 3 presents the empirical analyses and main findings. Finally, Section 4 concludes the paper.

2 Data and Methodology

We obtain data on the 5-minute cryptocurrency price, market capitalization, and trading volume from Coinpaprika.com for the period between January 1, 2017 and December 31, 2022. Based on market capitalization, we pre-select 1,174 cryptocurrencies out of the approximately 9,000 listed as active on Coinpaprika.com but only include those available on the market since January 1, 2017, which results in 176 cryptocurrencies. We further exclude 54 cryptocurrencies with more than 20% of their observations missing, with 122 cryptocurrencies left. In our sample, 20 cryptocurrencies have 10-20% of missing values, 40 cryptocurrencies have 1-10%, and the remaining 62 have less than 1%. We fill in the missing observations using the forward-fill method.[5] Specifically, if the price is not available for a particular timestamp, we assume

[4]See Cathie Wood's Ark Invest, a Bitcoin exchange-traded fund, at https://fortune.com/2021/06/29/bitcoin-etf-cathie-wood-crypto-btc-ark-invest-arkb/

[5]The forward-fill method assumes that the price from the previous period holds until a new observation appears. In untabulated results, we also conduct our main test using data without forward filling. Our main findings remain robust.

that no trading took place within that timeframe; thus, the price remains at the level set at the last available timestamp.

The cryptocurrency return is the difference between the price at t and that at $t-1$, divided by the price at $t-1$. We exclude observations with less than one million US dollars in market capitalization, following Liu et al. (2022), and returns greater than 1000%.[6] We collect data on daily stock returns from the Center for Research in Security Prices (CRSP), Refinitiv Eikon, and China Stock Market & Accounting Research (CSMAR). The US sample contains NYSE, AMEX, and NASDAQ ordinary common stocks with a CRSP share code of 10 or 11.

The variable of interest in our study is the profits of the market makers who provide liquidity. Following Nagel (2012), we estimate the liquidity provision premium as in Eq. (1):

$$L_t^R = -\Big(\frac{1}{2}\sum_{i=1}^{N}\big|R_{i,t-1} - R_{m,t-1}\big|\Big)^{-1}\sum_{i=1}^{N}(R_{i,t-1} - R_{m,t-1})R_{i,t}, \tag{1}$$

where $R_{i,t-1}$ is the cryptocurrency i return at time $t-1$, and $R_{m,t-1} = \frac{1}{N}\sum_{i=1}^{N} R_{i,t-1}$ is the equally-weighted cryptocurrency market return at time $t-1$. For example, when the liquidity premium (L_t^R) is estimated at 10:05am, $R_{i,t-1}$ is at 10:00am.

$\omega_{i,t}^R = -\Big(\frac{1}{2}\sum_{i=1}^{N}\big|R_{i,t-1} - R_{m,t-1}\big|\Big)^{-1}\sum_{i=1}^{N}(R_{i,t-1} - R_{m,t-1})$ is the portfolio weight for cryptocurrency i at time t. Past returns $(R_{i,t-1} - R_{m,t-1})$ are used as a proxy for the inventory positions of market makers. Market makers earn a positive liquidity premium in case of a return reversal from time $t-1$ to time t. The scaling factor used in Eq. (1) implies the re-

[6]The results are qualitatively similar with returns winsorized at 1% and 99%.

turn per dollar of capital invested in the 50% margin on both long and short position trading strategies. Eq. (1) shows the return on a one-dollar investment.

The short-run return reversals of winners and losers mimic the immediacy of market makers. Intuitively, a strategy that buys cryptocurrencies whose prices decrease (losers) and shorts cryptocurrencies whose prices increase (winners) in the previous trading days resembles the order imbalance of market makers; that is, market makers provide liquidity to the public by trading in the opposite direction when cryptocurrency prices change. Specifically, market makers sell when investors buy with price increases, and buy when investors sell with price decreases.

While the S&P 500 Volatility Index (VIX) plays an important role in the liquidity provision returns in the US stock market, recent studies (Andersen et al., 2015, 2024) show that the predictive power of VIX for returns stems primarily from its tail component. When this component is removed, the forecasting ability of VIX becomes insignificant, suggesting that tail risk is a crucial factor in asset pricing. Additionally, the tail component provides a more robust and timely warning of volatile market conditions compared to the VIX. Following their work, we use the spot volatility (SPOTVOL) and left tail volatility (LTV), which are the two factors decomposed from VIX, to examine the impact of volatility on liquidity provision premium in the cryptocurrency market.[7] We also use the daily realized variance (RV) of equally-weighted cryptocurrency market returns to measure uncertainty, where RV is the sum

[7]We thank Viktor Todorov for sharing with us the spot volatility (SPOTVOL) and left tail volatility (LTV) data. Prior studies have highlighted the role of volatility in liquidity (Gromb and Vayanos, 2002; Vayanos, 2004; Brunnermeier and Pedersen, 2009; Nagel, 2012).

of the squared 5-minute equally-weighted cryptocurrency market returns in a day (Andersen et al., 2001; Barndorff-Nielsen and Shephard, 2002; Hansen and Lunde, 2006).

Further, the VIX index differs from RV as VIX captures both the underlying return distribution (e.g., crash probabilities), and investor risk aversion (Bekaert and Hoerova, 2016; Bekaert et al., 2022). Risk aversion leads to a desire for protection against potential losses, resulting in relatively higher prices for out-of-the-money put options compared to call options. These elevated put option prices contribute to the consistent presence of a positive variance risk premium (i.e., the difference between the squared VIX index and actual conditional return variance). Thus, we also examine how risk aversion influences the liquidity provision premium of cryptocurrencies. Specifically, we use the daily time-varying aggregate risk aversion (RA) measure of Bekaert et al. (2022) estimated from observable financial information. RA captures the time-varying relative risk aversion of a representative agent in a generalized habit model and preference shocks (Campbell and Cochrane, 1999; Bekaert and Engstrom, 2017).[8]

Following Chen et al. (2001), we calculate the cryptocurrency market crash risk (NCSKEW) on day d as

$$NCSKEW_d = -\frac{n(n-1)^{3/2} \sum {R_M}_d^3}{(n-1)(n-2)(\sum {R_M}_d^2)^{3/2}}, \tag{2}$$

where $n = 365$ days, and R_M is the equally-weighted cryptocurrency market returns.

Eq. (2) indicates that cryptocurrencies with high NCSKEW are more likely to crash as their distribution is more left-skewed than that of cryptocurrencies with low NCSKEW. The

[8]Bekaert et al. (2024) examine the role of risk aversion in the global financial markets.

third moment is scaled so that cryptocurrencies with different variances are more comparable. Earlier studies (Bates, 1991) have also shown that skewness helps capture crash risk.

Following Kelly and Jiang (2014), we compute the time-varying cryptocurrency return tails (λ_d) based on the power law estimate of Hill (1975) using the cross-sectional daily return on day d as

$$\lambda_d^{Hill} = \frac{1}{K_d} \sum_{k=1}^{K_d} ln \frac{R_{k,d}}{u_d}, \tag{3}$$

where $R_{k,d}$ is the k^{th} daily return that falls below an extreme value threshold u_d over the last 30 days; K_d is the total number of observations below u_d over the last 30 days, and u_d is the fifth percentile of the cross-sectional returns over the last 30 days. u_d captures the end of the distribution center and the beginning of the tail and reflects an appropriate extreme bin of distribution where returns lower than the bin threshold follow tail distribution. Eq. (3) uses broad information on tail risk from the cross-section of cryptocurrency returns to alleviate the challenge that tail events rarely occur for an individual asset.

We also examine the effect of Tether liquidity on the premium of liquidity provision. Specifically, we use the trading volume measure of Brennan et al. (1998), DV, defined as the trading volume averaged in a day. Owing to the persistence of liquidity (Pástor and Stambaugh, 2003), in our tests, we use innovation in DV (DV_d^{INNOV}), as estimated from the regression

$$DV_d = \alpha_0 + \alpha_1 DV_{d-1} + DV_d^{INNOV}, \tag{4}$$

where DV_d is the trading volume of Tether in day d. The residuals (DV_d^{INNOV}) capture the liquidity shocks, which tend to coincide with periods of liquidity crisis (Acharya and Pedersen, 2005).

Table 1 provides summary statistics for the main variables used in the empirical analysis. As seen in Panel A, the cryptocurrency reversal strategy has a mean of 0.720% and a standard deviation of 4.526% per five-minute interval, respectively. The reversal strategy is positively skewed, which indicates that the strategy incurs substantial gains during certain periods. SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}_{TETHER}^{INNOV}$ have mean values of 12.263, 10.189, 0.231, 3.025, 0.014, 0.399, 0.136, and 0.544, respectively. Notably, the skewness of RV is 14.857, potentially indicating a heightened likelihood of extreme cryptocurrency volatility events, consistent with the literature (Makarov and Schoar, 2020; Sockin and Xiong, 2023). Panel B of Table 1 reports the correlations. LTV, RV, crash risk, tail risk, and $\mathrm{DV}_{TETHER}^{INNOV}$ exhibit positive associations with the liquidity provision premium in cryptocurrency markets. Additionally, SPOTVOL and LTV, two components of VIX, show a strong positive correlation with crash risk and tail risk, consistent with Bekaert and Hoerova (2016) and Bekaert et al. (2022), who highlight the importance of VIX in capturing crash probabilities.

[Table 1 about here]

3 Empirical Results

3.1 Out-of-sample tests

In this subsection, we examine the out-of-sample forecast power of SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}^{INNOV}_{TETHER}$ in predicting the liquidity provision premium of cryptocurrencies. In-sample predictions may overstate the reliability of predictors (Welch and Goyal, 2008). However, out-of-sample tests help further support predictability as they are less prone to in-sample data mining or biased standard errors. We conduct the out-of-sample test to exclude any variables with no significant predictability. Specifically, assuming that the out-of-sample forecast evaluation begins at time t, we use all available data up to time $t-h$ to estimate the necessary predictive regression parameters to produce the first out-of-sample forecast at time t. Next, we use a recursive forecast procedure for each future time until $T-h$, where T is the sample period.

Our out-of-sample tests follow Welch and Goyal (2008), Rapach et al. (2010), and Rapach and Zhou (2013). Specifically, we use the following equation (5):

$$L_{t,t+h} = \alpha + \beta X_t + \epsilon_{t,t+h}, \tag{5}$$

where $L_{t,t+h} = \frac{1}{h}(L_{t+1} + \cdots + L_{t+h})$, L_t is the returns from the reversal strategy in cryptocurrency markets at time t, and X_t is a predictor variable including SPOTVOL, LTV, RV, RA, NCSKEW, Tail, or $\mathrm{DV}^{INNOV}_{TETHER}$.

The time $(t+1)$ out-of-sample returns forecast of a reversal strategy in cryptocurrency markets is

$$\hat{L}_{t,t+h} = \hat{\alpha} + \hat{\beta} X_t, \tag{6}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the ordinary least-squares (OLS) estimates based on data from the beginning of the sample through to time t. We compare the forecasts based on Eq. (5) with the historical average forecast, which is the average returns of a reversal strategy in cryptocurrency markets from the beginning of the sample through to time t. Following Welch and Goyal (2008), we assume that the returns are unpredictable and use the historical average forecast as the out-of-sample benchmark. Welch and Goyal (2008) show that an individual predictor generally fails to outperform historical average forecasts.

Moreover, we estimate the out-of-sample R^2_{OOS} statistic following Campbell and Thompson (2008), as

$$R^2_{OOS} = 1 - \frac{\sum_{t-m}^{T-h}(L_{t,t+h} - \hat{L}_{t,t+h})}{\sum_{t-m}^{T-h}(L_{t,t+h} - \bar{L}_{t,t+h})}, \tag{7}$$

where $L_{t,t+h}$ is the actual returns of a reversal strategy in cryptocurrency markets; $\hat{L}_{t,t+h}$ is the estimated returns of a reversal strategy based on the results of Eq. (5), and $\bar{L}_{t,t+h}$ is the historical average benchmark.

We specifically compare the reduction in mean squared forecast error (MSFE) at the h-time horizon. This comparison is between a predictive regression forecast of the liquidity provision premium based on the predictor variable and the prevailing mean benchmark forecast. The statistical significance is based on the Clark and West (2007) test of the null hypothesis that the prevailing MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing MSFE is greater than the predictive regression MSFE. The R^2_{OOS} shows the extent to which a forecast variable would have been helpful for investors if used in "real-time" over certain sample periods.

Table 2 reports the results of the out-of-sample tests. Our predictors, namely SPOTVOL, LTV, RV, crash risk, tail risk, and Tether liquidity shocks, all have positive R^2_{OOS}. Further, the Clark and West (2007) test results are statistically significant for all h-time horizons. This suggests that the predictive regression forecasts based on these four predictors generate a smaller MSFE and outperform the benchmark. Overall, SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}^{INNOV}_{TETHER}$ predict the liquidity provision premium in cryptocurrency markets under the out-of-sample tests; therefore, we do not exclude any variables from the following analyses.

[Table 2 about here]

3.2 Return predictability of liquidity provision

Our main predictive model is

$$L^R_t = a + bX_t + cCR_{M,t} + e_t, \tag{8}$$

where X includes SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$. Following Nagel (2012), we lag these by five days. While the liquidity provision premium (L^R) is measured at a 5-min frequency, other variables (e.g., SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$) are measured on a daily basis only. For example, L^R at any time t on day d is regressed against SPOTVOL, LTV, RV, RA, NCSKEW, Tail, or DV^{INNOV} measured on day $d-5$ (i.e., lagged by five days). Following Hameed et al. (2010), we control for the cumulative equally-weighted cryptocurrency market returns ($CR_{M,t}$) as the premium of the short-term reversal strategy is related to market returns; CR_M is also lagged by five days. To facilitate the interpretation of our results, we standardize SPOTVOL, LTV, RV, RA, NCSKEW, Tail, $\text{DV}_{TETHER}^{INNOV}$, and CR_M so that they all have a mean of 0 and a standard deviation of 1.

Table 3 reports the main results of Eq. (8). Model 1 includes SPOTVOL, LTV, and RV as predictors. In Models 2 through 5, we progressively add RA, NCSKEW, Tail, and $\text{DV}^{INNOV}TETHER$ to the predictor set, respectively. We find that SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$ exhibit significant predictive power for the liquidity provision premium in cryptocurrency markets. Specifically, in Model 5, which includes all predictors, a one standard deviation increase these predictors is associated with a decrease of 0.260% and an increase of 0.100%, 0.056%, 0.085%, 0.031%, 0.019%, and 0.187% in the liquidity provision premium, respectively. These results suggest that the compensation earned by liquidity providers in cryptocurrency markets can be predicted by uncertainty, proxied by SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$.

The contrasting effects of SPOTVOL and LTV on the liquidity provision premium in cryptocurrency markets may arise from their tendency to move in opposite directions during certain periods.[9] For instance, Andersen et al. (2024) show that SPOTVOL has surged sharply in recent years, while the tail risk premium has declined relative to short-term volatility. The role of SPOTVOL and LTV, the two factors decomposed from VIX, in predicting the liquidity provision premium in cryptocurrency markets is similar to what was shown in the US stock market by Nagel (2012). The predictive power of these variables remains significant after controlling for the equally-weighted cryptocurrency market returns as shown in Models 1, 2, 3, 4, and 5 in Table 3. Overall, our main results indicate that a decrease in the ability of market makers to provide liquidity, as signaled by an increase in the liquidity provision premium, significantly contributes to the decline in liquidity during times of heightened uncertainty in cryptocurrency markets. This result is consistent with theories of liquidity provision by financially constrained intermediaries (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009). Additionally, the profitability of reversal strategies in cryptocurrency markets during periods of market turmoil lends further support to Nagel (2012).

[Table 3 about here]

We also conduct the Diebold and Mariano (2002) and West (1996) test (DMW) with an autocovariance adjustment. We find that all models have better forecasting performance than the historical average liquidity provision premium. Specifically, the statistic of the DMW test

[9] In untabulated results, we also observe contrasting effects of SPOTVOL and LTV on the liquidity provision premium in the US stock market.

under the loss function of mean squared error is -9.62 ($p = 0.00$), -9.89 ($p = 0.00$), -10.56 ($p = 0.00$), -11.04 ($p = 0.00$), and -11.78 ($p = 0.00$) for Models 1, 2, 3, 4, and 5, respectively.

3.3 Robustness tests

In this subsection, we conduct several robustness tests. The reversal strategy of Eq. (1) can have time-varying risks from exposure to common factors (Nagel, 2012). To take into account the time-varying risk exposure, we use the following regression, as in Nagel (2012):

$$L_t^R = \alpha + \beta_1 R_{M,t} + \beta_2 (R_{M,t} \times sgn(R_{M,t-1})) + \beta_3 sgn(R_{M,t-1}) + e_t, \tag{9}$$

where $R_{M,t}$ is the equally-weighted cryptocurrency market returns. The time-varying risk exposure is $\beta_{t-1} = \beta_1 + \beta_2 sgn(R_{M,t-1})$. The hedged returns of the reversal strategy are $L_t^R - \beta_{t-1} R_{M,t}$.

Second, liquidity supply factors contribute to the strength of the reversal strategy (Ho and Stoll, 1981; Nagel, 2012; Hendershott and Menkveld, 2014). Following this strand of the literature, we control for idiosyncratic risk. In the spirit of Nagel (2012), we calculate idiosyncratic risk as the cross-sectional standard deviation of cryptocurrency returns.

Third, the literature shows that cryptocurrencies rely heavily on network effects, with their value and utility strengthening as more individuals and entities join the network.[10] It is therefore easier for users to find transaction counterparties on platforms with more users. Cryptocurrency returns are associated with network growth (Liu and Tsyvinski, 2021). Fol-

[10] See, e.g., (Bakos and Halaburda, 2018; Catalini and Gans, 2018; Li and Mann, 2018; Pagnotta and Buraschi, 2018; Biais et al., 2020; Howell et al., 2020; Sockin and Xiong, 2020; Cong et al., 2021).

lowing this strand of the literature, we control for the network effect to test the robustness of our results; specifically, we use the growth rate of Bitcoin addresses as a proxy for the network effect.[11]

Fourth, we control for the cryptocurrency factor model including market, size, and momentum following the study of Liu et al. (2022).[12]

Fifth, Bitcoin futures contracts were introduced by the Chicago Board Options Exchange (CBOE) on December 10, 2017 and the Chicago Mercantile Exchange (CME) on December 18, 2017. These allow institutional investors to trade Bitcoin futures on the major US exchanges (Corbet et al., 2018; Köchling et al., 2019; Hung et al., 2021; Alexander et al., 2023). Following this literature, we examine the effect of Bitcoin futures volumes on the liquidity provision of cryptocurrency.[13]

Finally, while the liquidity provision premium is estimated at a 5-minute frequency, our predictors, namely VIX, RV, crash risk, tail risk, and Tether liquidity, are measured at a daily frequency. To examine the robustness of our tests, we use 5-minute measures of these predictors; specifically, we use the 5-minute price of the Proshares Short VIX Short-Term Futures ETF as a proxy for VIX (Bialkowski et al., 2016; Bordonado et al., 2017).[14] We construct the 5-minute RV, crash risk, tail risk, and Tether liquidity measures using the rolling estimates over the previous week, in a similar way to their corresponding daily measures.[15]

[11] We obtain the address data from https://www.blockchain.com/.

[12] We obtain the cryptocurrency market, size, and momentum factors from Liu et al. (2022). We thank Yukun Liu for sharing their cryptocurrency market, size, and momentum factors with us.

[13] We use the innovation of Bitcoin futures volumes due to the persistence of liquidity (Pástor and Stambaugh, 2003).

[14] We obtain the 5-minute price of the Proshares Short VIX Short-Term Futures ETF from Refinitiv Datascope.

[15] Prior studies (Liu et al., 2022) have used weekly intervals to analyze cryptocurrency markets.

Table 4 report the results of these robustness tests across various panels, each controlling for different factors that could impact liquidity provision in cryptocurrency markets. Specifically, Panels A through F incorporate risk-adjusted returns, liquidity supply, network effects, cryptocurrency risk factors, Bitcoin futures, and high-frequency predictors, respectively. The findings remain consistent with our baseline regressions, confirming that these predictors significantly forecast returns on a reversal strategy related to liquidity provision in cryptocurrency markets.

For example, after accounting for time-varying risks from exposure to common factors, a one standard deviation increase in SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}_{TETHER}^{INNOV}$ leads to a decrease of 0.259% and an increase of 0.010%, 0.056%, 0.083%, 0.032%, 0.018%, and 0.187%, respectively, in the liquidity provision premium after controlling for equally-weighted cryptocurrency market returns, as presented in Model 5 of Panel A. Thus, these predictors can predict the risk-adjusted premium from liquidity provision in cryptocurrency markets. Overall, the robustness tests suggest that, after considering various factors that might affect liquidity provision, a reduction in liquidity supply, as indicated by an increase in liquidity provision premium, plays a substantial role in the drying up of liquidity observed during periods of volatility in cryptocurrency markets.

[Table 4 about here]

3.4 Liquidity Change in Uniswap

Decentralized finance (DeFi) has grown remarkably since 2020 (Harvey et al., 2021). Decentralized exchanges are one of the most substantial innovations in DeFi, and Uniswap is one of the largest decentralized exchanges (Capponi and Jia, 2021; Han et al., 2021). In contrast to the centralized exchanges based on order books, Uniswap uses automated market maker (AMM) smart contracts on the Ethereum blockchain, and individuals (agents) contribute to the liquidity on the platform by depositing an equal value of two different assets into a liquidity pool; this action facilitates trading for those assets on the platform. By passively adding asset pairs to the existing liquidity pool, anyone can supply liquidity to the exchange (Lehar and Parlour, 2021). Following Capponi and Jia (2021) and Han et al. (2021), we use the Uniswap V2 liquidity data.[16]

Specifically, we examine the impact of impermanent loss (IL), fees, changes in liquidity, trading volume, transaction count, and withdrawals from Uniswap on the liquidity provision premiums in cryptocurrency markets. Uniswap uses a constant product formula to determine market and transaction prices based on the available reserves of a pair (e.g., x tokens of X and y tokens of Y).[17] This implies that regardless of the number of tokens added to or removed from a pair's reserves, the product of the reserves must remain constant; specifically, trades must not alter the product (k) of a pair's reserves (x and y).

[16] We obtain the data from the Graph's Uniswap V2 Subgraph. The Graph is an indexing protocol to retrieve data from blockchains such as Ethereum. Uniswap V2, which enables any ERC 20 token pairs to be traded, started on May 18, 2020. ERC-20, which stands for Ethereum Request for Comment 20, is a widely used standard for creating and deploying fungible tokens on the Ethereum blockchain.

[17] Wrapped Ether (WETH), the ERC-20 representation of Ether (ETH), is the most commonly traded token in Uniswap V2 pools.

Liquidity provision in Uniswap entails a trade-off between potential profits and the risk of adverse selection. While liquidity providers profit from transaction fees generated by swap trading volumes, they also face the risk of impermanent loss (IL) due to permanent price changes. IL occurs when holding tokens directly proves more profitable than investing them in a liquidity pool (Loesch et al., 2021). Following Heimbach et al. (2021), Barbon and Ranaldo (2021), and Khakhar and Chen (2022), we measure IL as

$$IL = \frac{2\sqrt{\Delta P}}{\Delta P + 1} - 1, \tag{10}$$

where $\Delta P = \frac{P_t}{P_{t-1}}$ is the price change from $t-1$ to t. $P_t = \frac{y_t}{x_t}$ for a liquidity pool containing x tokens of X and y tokens of Y.[18]

Traders on Uniswap also incur costs (gas fees), which determine the order execution priorities on the Ethereum blockchain. Validators process orders based on these gas fees, giving priority to those with higher fees (Capponi et al., 2022). Following Barbon and Ranaldo (2021) and Lehar and Parlour (2021), we measure the gas fees of a swap as the product of the quantity of gas required to execute a swap transaction (Γ = 110000 gas units) and the average gas price on a given day. Gas fees vary depending on market events (Lehar and Parlour, 2021). Further, Capponi et al. (2022) show that trades with high gas fees carry more private information, which may result in losses for liquidity providers on Uniswap (Barbon and Ranaldo, 2021).

[18]IL, fees, and withdraws are calculated using the WETH and USDC pair, which is the pool with the largest total volume (Lehar and Parlour, 2021).

Table 5 reports the results of Uniswap's influence on liquidity provision premiums in the cryptocurrency markets. Positive changes in liquidity, trading volume, and transaction count on Uniswap reduce the liquidity provision premium in centralized cryptocurrency markets; this suggests that increased liquidity on Uniswap decreases the compensation required for liquidity provision in centralized markets. Conversely, increased withdrawals, higher fees, and greater IL on Uniswap lead to a higher liquidity provision premium in centralized markets. This indicates that more withdrawals and higher costs on Uniswap raise the compensation required for liquidity provision in centralized markets. Overall, our findings suggest potential competition between centralized and decentralized exchanges, with the likelihood of decentralized exchanges being used for trading traditional assets (Barbon and Ranaldo, 2021; Aoyagi and Ito, 2022).

[Table 5 about here]

3.5 The liquidity provision premium of stock markets

Cryptocurrencies can provide diversification benefits in international asset allocation (Briere et al., 2015; Dyhrberg, 2016; Bouri et al., 2017; Anyfantaki et al., 2021). Further, Hackethal et al. (2022) show that cryptocurrency investors tend to invest in stocks with high media sentiment, and that their propensity towards riskier stocks increases after their investment in cryptocurrency. Given this potential co-movement between cryptocurrency and global stock markets, we examine the impact of liquidity provision premiums in various stock markets, namely those in the US, Canada, China, and Japan, on the liquidity provision premiums in cryptocurrency markets.

The results reported in Table 6 shows that the liquidity provision premium of stock markets in the US and Canada positively predicts the premium of cryptocurrency markets. This indicates that the inventory of the market makers in the US and Canada is subject to common shocks that influence the liquidity provisions provided by the market makers in these countries (Bekaert et al., 2007; Karolyi et al., 2012). This positive co-movement reflects a shared global liquidity demand, where market makers adjust their positions in response to common shocks. Conversely, the premium in China and Japan negatively predicts that of cryptocurrency markets; thus, the Chinese and Japanese stock markets and cryptocurrency markets are considered by market makers to be substitutes.[19] The substitute relationship could be linked to local regulatory stances or investor preferences that differentiate these markets from those in the US and Cananda (Aggarwal et al., 1989; Pan et al., 2016; Arora, 2020; Borri and Shakhnov, 2020; Titman et al., 2022; Hussain and Su, 2024). Our finding highlights the unique role of regional market characteristics in shaping liquidity flows across traditional and cryptocurrency assets.

Previous studies suggest that liquidity dynamics in major financial markets often extend to alternative asset classes, particularly cryptocurrencies that are viewed as potential diversification tools in international portfolios (Anyfantaki et al., 2021). Our results align with these findings, highlighting a systematic interaction between global and cryptocurrency mar-

[19]In untabulated results, we obtain similar results for the contemporaneous relation of the liquidity provisions for cryptocurrency and stock markets. We thank our anonymous referee for suggesting this.

kets driven by shared liquidity risks (Bekaert et al., 2007). Overall, our findings emphasize the interconnectedness of the liquidity provision across cryptocurrency and traditional stock markets.

[Table 6 about here]

3.6 Cross-sectional variation

In this subsection, we examine the liquidity provision premium of cryptocurrency markets across different cryptocurrency market capitalization groups. Risky assets have higher margin requirements (Brunnermeier and Pedersen, 2009). In case of adverse shocks in financial markets, market makers experience funding constraints and are thus more likely to provide liquidity to assets with lower volatility. Avramov et al. (2006) demonstrate that the returns from reversal strategies exhibit more significant effects in low liquidity stocks than in high liquidity ones. In sum, owing to the "flight to quality" phenomenon, market makers prefer to provide liquidity to more liquid assets with lower volatility (Sadka, 2011; Nagel, 2012).

Following this strand of the literature, we examine the cross-sectional variation in liquidity provision premiums across different cryptocurrency market capitalization categories. Liu et al. (2022) show that cryptocurrency market returns tend to move together with leading cryptocurrencies (e.g., Bitcoin, Ethereum, and Ripple). Additionally, while the liquidity provision premium involves short positions, short selling may be impractical or restricted for small cryptocurrencies. Specifically, we define cryptocurrencies below the 30% of market capitalization as "small-MV", and those above the 70% of market capitalization as "large-MV".

Table 7 reports the estimation results based on size using market capitalization as subsamples. In Panel A, the influence of SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}_{TETHER}^{INNOV}$ on the liquidity provision premium of cryptocurrencies is highly significant for the small-MV subsample. In contrast, SPOTVOL, LTV, RV, and NCSKEW turn out to be insignificance in Model 10 (Panel B the large-MV subsample). Moreover, RA and NCSKEW in Model 8, as well as Tail in Models 9 and 10 reverse their signs. This suggests that the influence of these factors on liquidity provision premium varies across the two subsamples. This result is consistent with (Avramov et al., 2006; Brunnermeier and Pedersen, 2009; Nagel, 2012). Specifically, while these factors positively influence returns on cryptocurrencies with a smaller marketcap, they have a negative impact on those with a larger marketcap, indicating a potential difference in market dynamics based on cryptocurrency market value. Overall, our results highlight how market capitalization moderates the relationship between the effects of key predictors on liquidity provision premium in cryptocurrency markets.

[Table 7 about here]

3.7 Permanent or transitory effect

In this subsection, we investigate whether the effect of predictors on the liquidity provision premium of cryptocurrencies is permanent or transitory. Specifically, we run the following regression:

$$L_{t,t+h}^{R} = a_h + b_h X_t + cCR_{M,t} + e_{t,t+h}, \tag{11}$$

where $L^R_{t,t+h}$ is the cumulative liquidity provision premium of cryptocurrencies from t to $t+h$. If the predictors' effect is persistent, the response coefficient b_h remains constant across horizon h. Conversely, if it is temporary, b_h should diminish to zero.

Panels A, B, C, and D of Appendix Table A.1 report the results for the full sample. Across Models 5, 10, 15, and 20, the impact of SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}^{INNOV}_{TETHER}$ on the liquidity provision premium of cryptocurrencies tends to increases as the time horizon lengthens. For example, the coefficient of RV is 0.114, 0.176, 0.382, and 0.904 at $h = 2$, $h = 3$, $h = 6$, and $h = 12$, respectively. This pattern suggests that the effects of these predictors on the liquidity provision premium persist over time, indicating they are more likely to be permanent than transitory.

[Appendix Table A.1 about here]

Following Hodrick (1992) and Ang and Bekaert (2007), we account for the overlap in liquidity provision over the h period. Our results, presented in Appendix Table A.2, remain consistent when using Hodrick (1992) standard errors, further supporting our findings.

[Appendix Table A.2 about here]

We also examine whether the predictors have a permanent or transitory effect on the liquidity provision premium of cryptocurrencies across different cryptocurrency market capitalization groups. Panels E, F, G, and H of Appendix Table A.1 report the results for the small-MV subsample, while Panels I, J, K, and L present the results for the large-MV subsample. In models where we control for all predictors, we generally observe an increase in coefficient magnitude across both small and large cryptocurrencies as the time horizon extends. However, RV becomes insignificant for large cryptocurrencies in models 45, 50, 55, and 60, while NCSKEW and Tail flip signs between small (models 25, 30, and 35) and large cryptocurrencies (models 45, 50, and 55). The positive coefficients for smaller cryptocurrencies suggest that liquidity providers receive higher compensation for bearing risks associated with smaller assets during periods of heightened volatility, uncertainty, and risk aversion. This is likely due to the risk management constraints associated with fluctuations in financial intermediaries' risk appetite, as well as the funding or liquidity constraints prevalent in these smaller markets (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010; Nagel, 2012). Conversely, the negative coefficients of NCSKEW and Tail for large cryptocurrencies in Panels I, J, K and L may reflect a reduced liquidity provision premium, possibly due to the stability associated with larger assets.

To illustrate these findings, Figure 1 plots the coefficients and 95% confidence intervals of the cryptocurrency liquidity provision premium forecast based on the model with all predictors at various horizons. The figure provides a visual comparison over different horizons and size groups as in Panels A (full sample), B (small-MV), and C (large-MV). The increase in magnitude of regression coefficients associated with longer horizons corroborates the trend shown in Appendix Table A.1, highlighting a more pronounced impact of predictors over longer periods. For small cryptocurrencies' size, the increase in positive coefficients across LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$ suggests a consistent pattern of enhanced liquidity provision premium in response to heightened uncertainty as the forecast time horizon extends, despite exceptions for NCSKEW at the 6- and 12-horizons and Tail at the 12-horizon. In contrast, RV appears to be insignificant, while NCSKEW and Tail negatively impact the liquidity provision premium for large cryptocurrencies. This divergence highlights the role of market capitalization in shaping liquidity provision dynamics.

[Figure 1 about here]

3.8 Sharpe ratio

An increase in return volatility is likely to raise the premium from liquidity provision, though it may not improve the Sharpe Ratio unless market makers face elevated participation costs or greater risk aversion (Grossman and Miller, 1988). Following their work, we examine, in this subsection, the impact of predictors on the Sharpe ratio of the reversal strategy from liquidity provision in cryptocurrency markets. The Sharpe ratio captures market makers' premium per unit of risk. Specifically, we use the full heterogeneous autoregressive model (HARQ-F), which allows RV to vary with realized quarticity (RQ), following Bollerslev et al. (2016).

$$\begin{aligned} RV_t \; &= \; \beta_0 + (\beta_1 + \beta_{1Q} RQ_{t-1}^{1/2}) RV_{t-1} + (\beta_2 + \beta_{2Q} RQ_{t-1|t-7}^{1/2}) RV_{t-1|t-7} \\ &+ \; (\beta_3 + \beta_{3Q} RQ_{t-1|t-30}^{1/2}) RV_{t-1|t-30} + u_t. \end{aligned} \tag{12}$$

The HARQ-F model captures greater average persistence and generates forecasts that more closely match unconditional volatility, especially when the lagged realized volatility is less informative, compared to the standard HAR model.[20] We then use the fitted RV ($\hat{RV}$) from Eq. (12) to examine the effect of various predictors on the Sharpe ratio of liquidity provision.

$$\frac{L_t^R}{\sqrt{\hat{RV}_t}} = a + bX_t + e_t, \tag{13}$$

where X_t includes SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$. This specification accounts for the volatility persistence and enables a more accurate estimation of Sharpe ratios.

Table 8 reports the results of Eq. (13). The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}_{TETHER}^{INNOV}$, show significant predictive power for the Sharpe ratio of the reversal strategy in cryptocurrency market liquidity provision. Specifically, in Model 5, which includes all predictors, a one standard deviation increase in these predictors is associated with changes of -5.403%, 2.166%, 0.962%, 1.590%, 0.830%, 0.932%, and 3.531% in the Sharpe ratio of liquidity provision, respectively. This result highlights that these variables are significant determinants of the Sharpe ratio for liquidity providers in cryptocurrency markets, suggesting that funding constraints act as significant barriers to liquidity provision (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009).

[20]Prior studies (Chen and Ghysels, 2011; Bekaert and Hoerova, 2014) show that RV-based models, which capture the importance of persistence, outperform GARCH-related models in volatility forecasting.

Overall, our results show that the liquidity provision premium, as well as the associated risk premium earned by liquidity providers, co-moves with SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}_{TETHER}^{INNOV}$. The observed comovement of the liquidity provision premium and the Sharpe ratio with uncertainty measures is consistent with Nagel (2012).

[Table 8 about here]

3.9 TVP-VAR analysis

Based on a preliminary analysis using Structural Vector Autoregression (SVAR) methodology, we find that the coefficients and significance of the Impulse Response Functions vary over time. Consequently, we adopt the Time-Varying Parameter Vector Autoregression (TVP-VAR) methodology (Primiceri, 2005). This approach was further extended by Koop and Korobilis (2013) to incorporate a more computationally efficient estimation method using forgetting factors, compared to the traditional reliance on MCMC simulation.

Beyond standard macroeconomic applications (Cogley and Sargent, 2005; Prieto et al., 2016), the TVP-VAR framework has been used to investigate the relationship between stock market liquidity and macro-financial factors (Ellington et al., 2017; Ellington, 2018; Ellington and Milas, 2021). In the cryptocurrency market context, TVP-VAR is commonly employed to assess intra-market connectedness or its linkages with other financial markets (Naeem et al., 2022; Huang et al., 2023; Zieba, 2024), and liquidity spillovers (Nekhili et al., 2023), using the methodology proposed by Antonakakis et al. (2020).

The primary distinction between the TVP-VAR and SVAR methodologies lies in the former's assumption of time-varying model coefficients and a dynamic variance-covariance matrix of residuals. Accordingly, the reduced-form TVP-VAR model can be defined as:

$$Y_t = \beta_{0,t} + \beta_{1,t}Y_{t-1} + ... + \beta_{p,t}Y_{t-p} + \epsilon_t \equiv X_t^{'}\theta_t + \epsilon_t \tag{14}$$

where Y_t is a vector of M endogenous variables, p is the number of lags, and $X_t = (I_M \bigotimes (1, Y_{t-1}^{'}, ..., Y_{t-p}^{'}))$ is a Kronecker product containing lagged values of Y_t and a constant. The residuals ϵ_t follow $\epsilon_t \sim N(0, \omega_t)$, where ω_t is a time-varying variance-covariance matrix. The θ_t matrix, which collects the time-varying parameters, is an $(M \times Mp)$ matrix defined as $\theta_t = (\beta_{0,t}^{'}, ..., \beta_{p,t}^{'})^{'}$. The parameter θ_t is assumed to evolve as a random walk, $\theta_t = \theta_{t-1} + \nu_t$, where $\nu_t \sim N(0, Q_t)$. Following the literature (Ellington, 2018), we use a specification with $M = 4$ and $p = 2$, so that $Y = [L^R, SPOTVOL, LTV, Z]$, where $Z \in \{RV, RA, NCSKEW, Tail, DV_{TETHER}^{INNOV}, CR^M\}$ represents one of the other predictors. We set the forgetting factors to $\alpha = 0.99$, $\delta = 0.99$, a decay factor $\kappa = 0.96$, and the degree of shrinkage $\gamma = 0.1$ (Koop and Korobilis, 2013, 2014; Antonakakis et al., 2020). As TVP-VAR is a Bayesian method requiring prior assumptions, we employ a Minnesota prior (Litterman, 1986; Koop and Korobilis, 2013). Consistent with the main analysis, we standardize SPOTVOL, LTV, RV, RA, NCSKEW, Tail, $\mathrm{DV}_{TETHER}^{INNOV}$, and CR_M so that they all have a mean of 0 and a standard deviation of 1.[21]

[21] The results remain similar when these variables are lagged by five days.

In other words, each model is structured as a four-variable system comprising two VIX components (SPOTVOL and LTV), one additional predictor (Z), and the liquidity provision premium (L^R). Our analysis focuses specifically on the coefficients in the L^R equation (15), as these are central to predicting the liquidity provision premium:

$$
\begin{aligned}
{L_t}^R \;=\;& \beta_1^{LR} L_{t-1}^R + \beta_1^S SPOTVOL_{t-1} + \beta_1^{LTV} LTV_{t-1} + \beta_1^Z Z_{t-1} \\
&+ \beta_2^{LR} L_{t-2}^R + \beta_2^S SPOTVOL_{t-2} + \beta_2^{LTV} LTV_{t-2} + \beta_2^Z Z_{t-2} + \epsilon_t \qquad (15)
\end{aligned}
$$

The estimation of the coefficients β_1^{LR}, β_2^{LR}, β_1^S, β_2^S, β_1^{LTV}, and β_2^{LTV} across models with different Z yields consistent results, as expected. Therefore, we report these coefficients only for the model where $Z = NCSKEW$ and provide the coefficients β_1^Z and β_2^Z for each model with a different Z.

Next, we assess the forecast accuracy of the models using two metrics: MSFE (Mean Squared Forecast Error) and MDA (Mean Directional Accuracy). The analysis of time-varying coefficients, which incorporates the first two lags of each variable, reveals a symmetric evolution in the coefficients for the first and second lags (Figure 2). Specifically, these coefficients experience sharp increases at the beginning of the sample period, coinciding with the cryptocurrency market bubble of 2017–2018. After this bubble, the coefficients stabilize, only to exhibit pronounced increases again towards the end of the period, aligning with the bubble observed at the end of 2021 and the start of 2022. This dynamic is particularly evident for the coefficients of SPOTVOL, LTV, NCSKEW, Tail, RA, and CR_M.

Based on these findings, we divide the forecasting accuracy analysis into three two-year sub-periods: (1) 2017–2018, (2) 2019–2020, and (3) 2021–2022. The models' forecasting accuracy is then compared across these sub-periods and with the estimates for the entire time frame.

[Figure 2 about here]

Table 9 presents the MSFE and MDA results in Panels A and B, respectively. Panel A shows that, over the entire sample period, the TVP-VAR model delivers comparable MSFE across all four-variable models with varying Z. When examining individual sub-periods, however, forecasting accuracy, as measured by MSFE, declines significantly in the second sub-period for models where Z represents NCSKEW, Tail, RV, or CR_M. Additionally, models with RA and $\mathrm{DV}_{TETHER}^{INNOV}$ as Z display lower overall MSFE for the entire period compared to their sub-period MSFEs, except in the first sub-period when Z is NCSKEW.

The MDA results, however, yield slightly different insights. While overall MDA values remain consistent across models and periods, there are two exceptions: models with RA and $\mathrm{DV}_{TETHER}^{INNOV}$ as Z show significantly lower MDA values in the first sub-period. In all other cases, the MDA consistently exceeds 0.84, indicating a high level of directional accuracy across models and sample periods.

[Table 9 about here]

4 Conclusion

When uncertainties haunt the economy, liquidity is squeezed. In this study, we examine whether uncertainty measures can predict the returns of liquidity provision in cryptocurrency markets. We show that spot volatility, left tail volatility, realized volatility, risk aversion, crash risk, tail risk, and Tether liquidity shocks can predict liquidity provision premiums using both in-sample and out-of-sample tests. Specifically, market makers require high returns to provide liquidity to cryptocurrency markets during periods of high left tail volatility, realized volatility, risk aversion, crash risk, tail risk, or Tether liquidity shocks.

Further, improvements in liquidity, trading volume, and transaction count on Uniswap reduce the liquidity provision premium in centralized cryptocurrency markets, while more withdrawals, higher fees, and greater IL on Uniswap lead to a higher liquidity provision premium in centralized markets. This suggests potential competition between centralized and decentralized exchanges.

Finally, the liquidity provision premium in the stock markets of the US and Canada positively predicts the premium in cryptocurrency markets. Conversely, in China and Japan, the premium in the stock markets negatively predicts that in cryptocurrency markets; this suggests that market makers experience common shocks in cryptocurrency markets and the US and Canada stock markets. However, market makers in the Chinese and Japanese stock markets view cryptocurrency markets as a substitute. Overall, our study highlights the interconnectedness of market makers' liquidity provision across cryptocurrency and traditional stock markets.

Our work has some implications for both liquidity providers for cryptocurrency and policymakers. Considering the rapid expansion of both centralized and decentralized cryptocurrency exchanges (Dimpfl and Peter, 2021; Lehar and Parlour, 2021), the returns from liquidity provision hold significant importance within these exchanges. Moreover, our study shows that spot volatility, left tail volatility, realized volatility, risk aversion, crash risk, tail risk, and Tether liquidity shocks help predict liquidity provision premiums. Our results for Tether innovations provide further support for the results of Griffin and Shams (2020) as we show the influence of Tether-related movements on the liquidity provision mechanism in a wider scope of cryptocurrency markets beyond Bitcoin. Furthermore, as policymakers have expressed concerns about the volatility of cryptocurrency markets, they may find our work helpful in effectively monitoring the liquidity provisions in cryptocurrency markets. By understanding the impact of spot volatility, left tail volatility, realized volatility, risk aversion, crash risk, tail risk, and Tether liquidity shocks on liquidity provision premiums, policymakers can make more informed decisions and ultimately promote greater stability in cryptocurrency markets.

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Table 1 **Descriptive statistics**

This table reports descriptive statistics and correlations for the following variables:

L: Liquidity provision premium of cryptocurrencies;

SPOTVOL: spot volatility;

LTV: left tail volatility;

RV: realized variance;

RA: risk aversion;

Tail: tail risk;

NCSKEW: crash risk;

DV^{INNOV}_{TETHER}: Tether liquidity;

CR_M: cumulative equally-weighted cryptocurrency market returns.

Panel A reports the summary statistics. Panel B reports the correlations. The liquidity provision premium is at a 5-minute frequency, while the other variables are at a daily frequency.

Panel A: Descriptive statistics									
	L	SPOTVOL	LTV	RV (10^4)	RA	NCSKEW	Tail	DV^{INNOV}_{Tether}	CR_M
Mean	0.720	12.263	10.189	0.231	3.025	0.014	0.399	0.136	0.544
Stdev	4.526	8.207	3.528	0.839	1.132	1.050	0.068	0.000	0.865
P25	0.003	6.738	7.406	0.040	2.610	-0.584	0.352	0.136	0.039
Median	0.198	9.694	9.250	0.081	2.755	-0.159	0.400	0.136	0.320
P75	0.623	15.687	12.397	0.172	3.162	0.468	0.445	0.137	0.716
Skewness	18.471	2.431	1.261	14.857	11.437	0.319	0.174	5.160	2.629
Kurtosis	1791.357	13.219	5.238	299.604	184.342	2.579	3.424	71.537	12.780

Panel B: Correlation									
	L	SPOTVOL	LTV	RV (10^4)	RA	NCSKEW	Tail	DV^{INNOV}_{Tether}	CR_M
SPOTVOL	-0.012	1.000							
LTV	0.020	0.590	1.000						
RV	0.019	0.021	0.040	1.000					
RA	-0.001	0.749	0.495	0.027	1.000				
NCSKEW	0.008	0.537	0.502	-0.000	0.397	1.000			
Tail	0.005	0.303	0.132	0.047	0.363	0.461	1.000		
DV^{INNOV}_{TETHER}	0.044	0.196	0.358	0.140	0.123	0.166	0.138	1.000	
CR_M	-0.008	-0.318	-0.190	-0.009	-0.150	-0.311	0.039	-0.054	1.000

Table 2 Out of sample R^2 statistics

The table reports the proportional reduction in mean squared forecast error (MSFE) at different h-horizons. We conduct a predictive regression forecast of the log returns of a reversal strategy in the cryptocurrency markets using the predictor variable in the first column compared to the prevailing mean benchmark forecast. Statistical significance is based on the Clark and West (2007) statistic (CW-stat) to test the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE, against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE. The predictor variable includes spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), or Tether liquidity ($\mathrm{DV}_{TETHER}^{INNOV}$).

	$h=2$		$h=3$		$h=6$		$h=12$	
	R^2OS	CW-stat	R^2OS	CW-stat	R^2OS	CW-stat	R^2OS	CW-stat
SPOTVOL	1.335	53.023	2.615	59.916	4.446	54.955	3.226	32.632
LTV	1.392	49.890	2.680	56.821	4.485	52.317	3.141	31.565
RV	1.382	47.203	2.670	55.325	4.497	52.409	3.205	32.451
RA	1.275	53.089	2.531	60.261	4.314	55.666	3.073	33.704
CRASH	1.236	52.834	2.475	61.303	4.224	57.871	2.964	35.581
TAIL	1.236	52.834	2.475	61.303	4.224	57.871	2.964	35.581
$\mathrm{DV}_{TETHER}^{INNOV}$	1.614	48.841	2.904	54.638	4.616	49.822	3.259	29.449

Table 3 Predicting the liquidity provision premium of cryptocurrencies

The table reports the results of regressing the cryptocurrency liquidity provision premium against spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), or Tether liquidity (DV^{INNOV}_{TETHER}) using OLS regressions. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and DV^{INNOV}_{TETHER}, are lagged by five days. The control variable, cumulative equally-weighted cryptocurrency market returns (CR_M), is lagged by five days. The numbers in parentheses are t-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
SPOTVOL	-0.184***	-0.235***	-0.249***	-0.249***	-0.260***
	(-20.79)	(-21.42)	(-23.10)	(-23.18)	(-23.87)
LTV	0.183***	0.177***	0.166***	0.177***	0.100***
	(19.04)	(18.58)	(15.84)	(17.16)	(10.55)
RV	0.081***	0.080***	0.081***	0.079***	0.056***
	(9.80)	(9.74)	(9.83)	(9.52)	(7.15)
RA		0.070***	0.070***	0.056***	0.085***
		(11.13)	(11.31)	(8.93)	(13.02)
NCSKEW			0.040***	0.015**	0.031***
			(5.77)	(2.05)	(4.53)
Tail				0.048***	0.019***
				(7.13)	(2.69)
DV^{INNOV}_{TETHER}					0.187***
					(16.44)
R_M	-0.060***	-0.067***	-0.061***	-0.071***	-0.068***
	(-12.66)	(-13.70)	(-11.87)	(-13.89)	(-13.50)
Constant	0.721***	0.721***	0.720***	0.720***	0.721***
	(100.81)	(100.83)	(100.78)	(100.77)	(101.03)
Observations	629542	629542	629542	629542	629255
Adj-R^2 (%)	0.173	0.183	0.188	0.195	0.337

Table 4 Robustness tests

The table reports the results of regressing the cryptocurrency liquidity provision premium against spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), or Tether liquidity (DV_{TETHER}^{INNOV}) using OLS regressions. In Panel A, we use the risk-adjusted premium of cryptocurrency liquidity provision. In Panel B, we control for liquidity supply proxied by idiosyncratic risk. We calculate idiosyncratic risk (IVOL) as the cross-sectional standard deviation of cryptocurrency returns. In Panel C, we control for the network effect proxied by the growth rate of the unique addresses ($Address_G$). In Panel D, we control for the cryptocurrency factors, including the cryptocurrency market (CMKT), size (CSIZE), and momentum (CMOM) factors. In Panel E, we control for the volume of futures contracts proxied by the innovations of Bitcoin futures volumes ($Volume_{Futures}^{INNOV}$). In Panel F, we use the 5-minute price of Proshares Short VIX Short-Term Futures ETF as a proxy for VIX. We construct the 5-minute RV, crash risk, tail risk, and Tether liquidity measures using the rolling estimates over the previous week, similar to their corresponding daily measures. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and DV_{TETHER}^{INNOV}, are lagged by five days. The control variables, cumulative equally-weighted cryptocurrency market returns (CR_M), IVOL, $Address_G$, CMKT, CSIZE, CMOM, and $Volume_{Futures}^{INNOV}$, are lagged by five days. The numbers in parentheses are *t*-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
	Panel A: risk-adjusted premium					Panel B: liquidity supply				
SPOTVOL	-0.184***	-0.234***	-0.247***	-0.247***	-0.259***	-0.183***	-0.234***	-0.247***	-0.247***	-0.262***
	(-20.79)	(-21.47)	(-23.19)	(-23.27)	(-23.95)	(-20.57)	(-21.11)	(-22.64)	(-22.70)	(-23.56)
LTV	0.182***	0.177***	0.166***	0.177***	0.100***	0.181***	0.176***	0.165***	0.176***	0.101***
	(19.03)	(18.59)	(15.82)	(17.12)	(10.54)	(18.88)	(18.50)	(15.89)	(17.17)	(10.61)
RV	0.081***	0.080***	0.081***	0.079***	0.056***	0.081***	0.080***	0.081***	0.078***	0.057***
	(9.81)	(9.76)	(9.85)	(9.54)	(7.16)	(9.90)	(9.87)	(9.96)	(9.64)	(7.32)
RA		0.068***	0.069***	0.054***	0.083***		0.069***	0.069***	0.055***	0.086***
		(11.07)	(11.26)	(8.86)	(12.99)		(10.72)	(10.90)	(8.60)	(12.81)
NCSKEW			0.040***	0.015**	0.032***			0.040***	0.014*	0.032***
			(5.75)	(2.07)	(4.56)			(5.66)	(1.96)	(4.58)
Tail				0.048***	0.018***				0.048***	0.018***
				(7.16)	(2.65)				(7.15)	(2.63)
DV_{TETHER}^{INNOV}					0.187***					0.188***
					(16.50)					(16.60)
IVOL						0.013**	0.010	0.008	0.009	-0.009
						(2.07)	(1.50)	(1.26)	(1.43)	(-1.39)
CR_M	-0.062***	-0.069***	-0.063***	-0.072***	-0.070***	-0.065***	-0.071***	-0.064***	-0.074***	-0.065***
	(-12.81)	(-13.80)	(-12.09)	(-14.08)	(-13.69)	(-12.11)	(-13.01)	(-11.01)	(-13.08)	(-11.70)
Constant	0.718***	0.718***	0.718***	0.718***	0.718***	0.721***	0.721***	0.720***	0.720***	0.721***
	(100.42)	(100.44)	(100.38)	(100.37)	(100.62)	(100.23)	(100.25)	(100.20)	(100.20)	(100.46)
Observations	629542	629542	629542	629542	629255	629542	629542	629542	629542	629255
Adj-R^2 (%)	0.173	0.183	0.188	0.195	0.337	0.173	0.183	0.188	0.195	0.337

Table 4 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
	Panel C: network effect					Panel D: cryptocurrency factors				
SPOTVOL	-0.184***	-0.235***	-0.248***	-0.248***	-0.260***	-0.190***	-0.243***	-0.257***	-0.260***	-0.271***
	(-20.79)	(-21.52)	(-23.27)	(-23.34)	(-24.00)	(-20.87)	(-21.78)	(-23.53)	(-23.82)	(-24.45)
LTV	0.182***	0.176***	0.165***	0.177***	0.099***	0.189***	0.183***	0.171***	0.189***	0.111***
	(19.05)	(18.60)	(15.88)	(17.26)	(10.58)	(19.29)	(18.84)	(16.27)	(17.74)	(11.41)
RV	0.081***	0.080***	0.081***	0.078***	0.056***	0.081***	0.080***	0.081***	0.077***	0.055***
	(9.82)	(9.77)	(9.86)	(9.54)	(7.16)	(9.88)	(9.83)	(9.91)	(9.45)	(7.06)
RA		0.070***	0.070***	0.055***	0.084***		0.072***	0.073***	0.052***	0.080***
		(11.13)	(11.31)	(8.82)	(12.84)		(11.32)	(11.49)	(8.35)	(12.42)
NCSKEW			0.040***	0.014**	0.031***			0.042***	0.008	0.026***
			(5.80)	(1.98)	(4.45)			(6.29)	(1.07)	(3.69)
Tail				0.049***	0.020***				0.068***	0.039***
				(7.22)	(2.82)				(10.19)	(5.72)
DV_{TETHER}^{INNOV}					0.187***					0.186***
					(16.68)					(16.82)
CR_M	-0.059***	-0.066***	-0.060***	-0.070***	-0.068***	-0.091***	-0.100***	-0.091***	-0.108***	-0.097***
	(-12.31)	(-13.32)	(-11.56)	(-13.63)	(-13.24)	(-12.44)	(-13.27)	(-11.82)	(-13.69)	(-12.41)
$Address_G$	-0.023***	-0.023***	-0.023***	-0.024***	-0.024***					
	(-2.85)	(-2.85)	(-2.86)	(-3.04)	(-3.05)					
CMKT						-0.005	-0.003	-0.007	-0.018***	-0.027***
						(-0.71)	(-0.39)	(-1.08)	(-2.64)	(-3.90)
CSIZE						0.056***	0.059***	0.059***	0.073***	0.066***
						(7.36)	(7.62)	(7.69)	(9.30)	(8.46)
CMOM						0.007*	0.008*	0.006	0.006	-0.000
						(1.73)	(1.89)	(1.40)	(1.40)	(-0.11)
Constant	0.720***	0.721***	0.720***	0.720***	0.721***	0.720***	0.720***	0.720***	0.720***	0.721***
	(100.48)	(100.50)	(100.45)	(100.45)	(100.70)	(101.34)	(101.37)	(101.30)	(101.31)	(101.58)
Observations	629542	629542	629542	629542	629255	629542	629542	629542	629542	629255
Adj-R^2 (%)	0.175	0.185	0.190	0.198	0.339	0.184	0.194	0.200	0.213	0.353
	Panel E: volume of futures contracts					Panel F: high-frequency control variables				
SPOTVOL	-0.184***	-0.235***	-0.248***	-0.248***	-0.259***					
	(-20.72)	(-21.50)	(-23.24)	(-23.31)	(-23.95)					
LTV	0.183***	0.177***	0.166***	0.178***	0.099***					
	(19.15)	(18.69)	(15.91)	(17.26)	(10.47)					
VIX						0.053***	0.065***	0.051***	0.033***	
						(19.25)	(21.62)	(16.44)	(11.02)	
RV	0.081***	0.080***	0.081***	0.079***	0.058***	0.063***	0.061***	0.052***	0.041***	
	(9.90)	(9.82)	(9.95)	(9.65)	(7.46)	(5.23)	(5.01)	(4.38)	(3.42)	
RA		0.070***	0.070***	0.055***	0.082***					
		(11.52)	(11.69)	(9.11)	(13.15)					
NCSKEW			0.041***	0.015**	0.036***		0.135***	0.133***	0.130***	
			(5.59)	(2.07)	(4.98)		(10.97)	(10.87)	(10.75)	
Tail				0.048***	0.019***			0.105***	0.092***	
				(7.04)	(2.77)			(15.07)	(13.26)	
DV_{TETHER}^{INNOV}					0.191***				0.118***	
					(16.73)				(12.23)	
CR_M	-0.060***	-0.067***	-0.061***	-0.071***	-0.069***	0.147***	0.133***	0.131***	0.126***	
	(-12.05)	(-13.04)	(-11.53)	(-13.53)	(-13.27)	(7.52)	(6.58)	(6.46)	(6.27)	
$Volume_{Futures}^{INNOV}$	-0.002	0.001	-0.003	-0.005	-0.030***					
	(-0.25)	(0.14)	(-0.45)	(-0.68)	(-4.19)					
Constant	0.721***	0.721***	0.720***	0.720***	0.721***	0.721***	0.721***	0.720***	0.720***	
	(100.47)	(100.49)	(100.43)	(100.43)	(100.69)	(90.76)	(90.96)	(91.14)	(91.25)	
Observations	629542	629542	629542	629542	629255	628385	628385	625243	625241	
Adj-R^2 (%)	0.173	0.183	0.187	0.195	0.341	0.163	0.249	0.299	0.363	

Table 5 Predicting the liquidity provision premium of cryptocurrencies using the liquidity change in Uniswap

The table reports the results of regressing the cryptocurrency liquidity provision premium against the impact of impermanent loss (IL), fees, changes in liquidity, trading volume, transaction count, and withdrawals on Uniswap V2 using OLS regressions. The predictor, namely the liquidity change in Uniswap, is lagged by five days. The control variables, namely spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), innovations of Tether liquidity ($\text{DV}_{TETHER}^{INNOV}$), and the cumulative equally-weighted cryptocurrency market returns (CR_M), are lagged by five days. The numbers in parentheses are t-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Liquidity	-0.034***					
	(-5.37)					
Volume		-0.080***				
		(-2.88)				
Transaction count			-0.132***			
			(-7.05)			
withdrawals				0.024***		
				(3.75)		
Impermanent Loss					0.027***	
					(4.86)	
Fees						0.043*
						(1.80)
Constant	8.872*	10.072**	3.350	9.714**	8.691*	11.912**
	(1.81)	(2.05)	(0.66)	(1.98)	(1.76)	(2.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	277920	276768	276768	276480	276768	278208
Adjusted R^2 (%)	0.539	0.539	0.581	0.549	0.550	0.538

Table 6 Predicting the liquidity provision premium of cryptocurrencies using the liquidity provision premium of stock markets

The table reports the results of regressing the cryptocurrency liquidity provision premium against the liquidity provision premium of stock markets using OLS regressions. The control variables, namely spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), innovations of Tether liquidity ($\mathrm{DV}_{TETHER}^{INNOV}$), and cumulative equally-weighted cryptocurrency market returns (CR_M), are lagged by five days. The liquidity provision premiums of the stock markets are based on the US, Canada, the UK, China, and Japan (L_{Stock}^{US}, L_{Stock}^{Canada}, L_{Stock}^{UK}, L_{Stock}^{China}, and L_{Stock}^{Japan}). L_{Stock}^{US} is estimated from a sample from CRSP US stocks. L_{Stock}^{Canada} is estimated from a sample from the Standard and Poor's Toronto Stock Exchange Composite Index. L_{Stock}^{UK} is estimated from a sample from the FTSE 100 Index. L_{Stock}^{China} is estimated from a sample from the CSMAR Chinese stocks. L_{Stock}^{Japan} is estimated from a sample from the Tokyo Stock Exchange. The liquidity provision premium of stock markets is lagged by five days. The numbers in parentheses are t-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

L_{Stock}^{US}	-0.012***
	(-2.58)
$\mathrm{L}_{Stock}^{Canada}$	-0.064***
	(-10.32)
$\mathrm{L}_{Stock}^{China}$	0.114***
	(16.25)
$\mathrm{L}_{Stock}^{Japan}$	0.011*
	(1.66)
CR_M	-0.062***
	(-12.38)
Constant	0.721***
	(101.33)
Controls	Yes
Observations	629255
Adj-R^2 (%)	0.411

Table 7 Predicting cryptocurrency liquidity provision premium: size subsamples

The table reports the results of the forecast of cryptocurrency liquidity provision premium on spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), and Tether liquidity (DV^{INNOV}_{TETHER}) using OLS regressions. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and DV^{INNOV}_{TETHER}, are lagged by five days. The control variable, cumulative equally-weighted cryptocurrency market returns (CR_M), is lagged by five days. We divide the sample into two groups based on their market capitalization (MV). We define cryptocurrencies below the 30% of market capitalization as "small-MV", and those above the 70% of market capitalization as "large-MV". The numbers in parentheses are t-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
	Panel A: Small-MV subsample					Panel B: Large-MV subsample				
SPOTVOL	-0.144***	-0.190***	-0.203***	-0.202***	-0.207***	-0.006*	-0.004	0.000	0.000	-0.001
	(-18.42)	(-19.63)	(-21.98)	(-22.04)	(-21.94)	(-1.79)	(-0.97)	(0.07)	(0.06)	(-0.17)
LTV	0.102***	0.097***	0.086***	0.097***	0.067***	0.006**	0.006**	0.009***	0.005*	-0.001
	(12.94)	(12.43)	(10.09)	(11.42)	(8.99)	(2.17)	(2.25)	(3.05)	(1.85)	(-0.35)
RV	0.229***	0.228***	0.231***	0.232***	0.226***	0.000	0.000	0.000	0.001	0.000
	(9.89)	(9.85)	(9.93)	(9.98)	(9.71)	(0.35)	(0.35)	(0.31)	(0.80)	(0.14)
RA		0.063***	0.063***	0.049***	0.061***		-0.003	-0.003*	0.003*	0.005***
		(10.23)	(10.39)	(7.69)	(8.92)		(-1.64)	(-1.76)	(1.67)	(2.76)
NCSKEW			0.037***	0.013***	0.020***			-0.012***	-0.002	-0.001
			(7.77)	(2.60)	(4.15)			(-6.15)	(-1.06)	(-0.53)
Tail				0.046***	0.034***				-0.018***	-0.020***
				(8.84)	(6.06)				(-5.00)	(-5.52)
DV^{INNOV}_{TETHER}					0.073***					0.014***
					(9.98)					(3.62)
CR_M	-0.043***	-0.050***	-0.044***	-0.053***	-0.052***	0.015***	0.015***	0.013***	0.017***	0.017***
	(-10.34)	(-11.45)	(-9.75)	(-12.34)	(-12.14)	(7.07)	(6.96)	(5.75)	(6.81)	(6.95)
Constant	0.454***	0.454***	0.454***	0.454***	0.454***	0.056***	0.056***	0.056***	0.056***	0.056***
	(78.11)	(78.13)	(78.05)	(78.10)	(78.12)	(21.17)	(21.17)	(21.17)	(21.14)	(21.12)
Observations	629568	629568	629568	629568	629280	629568	629568	629568	629568	629280
Adj-R^2 (%)	0.660	0.676	0.684	0.697	0.740	0.006	0.006	0.008	0.013	0.016

Table 8 Predicting the liquidity provision Sharpe ratio of cryptocurrencies

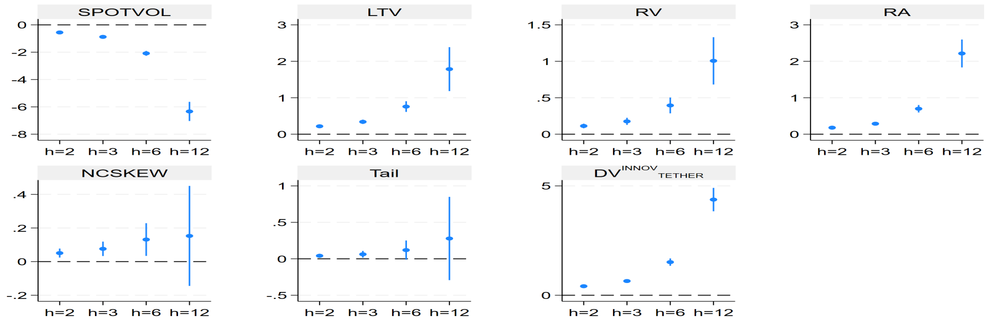
The table reports the results of regressing the cryptocurrency liquidity provision Sharpe ratio against spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), and Tether liquidity (DV_{TETHER}^{INNOV}) using OLS regressions. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and DV_{TETHER}^{INNOV}, are lagged by five days. The control variable, cumulative equally-weighted cryptocurrency market returns (CR_M), is lagged by five days. The numbers in parentheses are t-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
SPOTVOL	-3.670***	-4.749***	-5.183***	-5.180***	-5.403***
	(-18.18)	(-18.93)	(-20.90)	(-20.97)	(-21.52)
LTV	3.751***	3.632***	3.264***	3.629***	2.166***
	(16.57)	(16.12)	(13.18)	(14.83)	(9.81)
RV	1.447***	1.433***	1.458***	1.383***	0.962***
	(8.67)	(8.61)	(8.75)	(8.30)	(5.94)
RA		1.473***	1.492***	1.039***	1.590***
		(10.59)	(10.83)	(7.71)	(11.37)
NCSKEW			1.308***	0.518***	0.830***
			(7.73)	(2.88)	(4.81)
Tail				1.484***	0.932***
				(9.18)	(5.67)
DV_{TETHER}^{INNOV}					3.531***
					(14.15)
CR_M	-1.104***	-1.248***	-1.048***	-1.348***	-1.307***
	(-8.90)	(-9.80)	(-8.07)	(-10.22)	(-9.91)
Constant	15.914***	15.915***	15.910***	15.914***	15.918***
	(95.35)	(95.36)	(95.32)	(95.29)	(95.41)
Observations	629542	629542	629542	629542	629255
Adj-R^2(%)	0.141	0.150	0.161	0.176	0.282

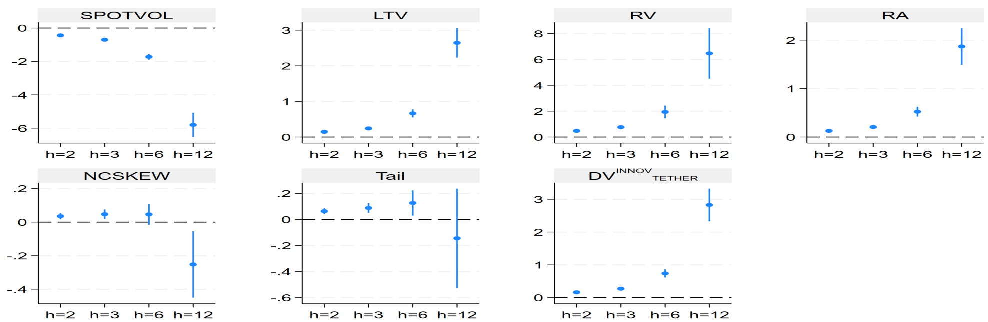
Table 9 Accuracy of the forecast using the TVP-VAR model

The table reports the forecast accuracy metrics from a recursive forecast using a 4-variable TVP-VAR model as specified in Eq. (15), where Z_t represents one of the following: realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), Tether liquidity (DV_{TETHER}^{INNOV}), or cumulative equally-weighted cryptocurrency market returns (CR_M). The forecast is performed over the full sample period (2017/01/01 - 2022/12/31), sub-period 1 (2017/01/01 - 2018/12/31), sub-period 2 (2019/01/01 - 2020/12/31), and sub-period 3 (2021/01/01 - 2022/12/31). Panel A reports the Mean Squared Forecast Error (MSFE), and Panel B reports the Mean Directional Accuracy (MDA).

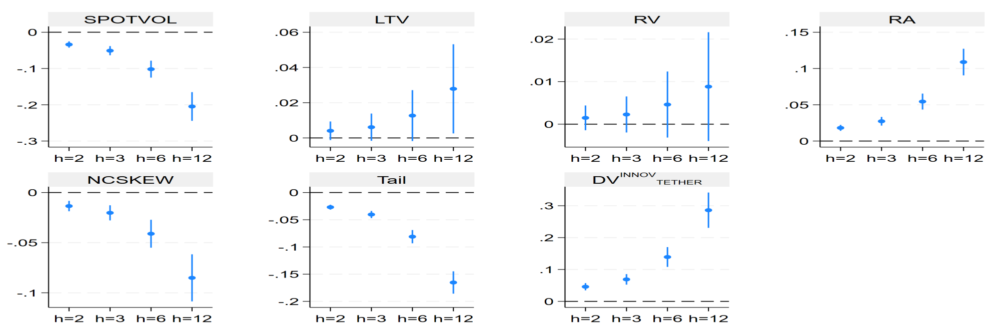
Panel A: Mean Squared Forecast Error				
Z	Entire Period	Sub-period 1	Sub-period 2	Sub-period 3
NCSKEW	0.00058	0.00057	0.00155	0.00093
Tail	0.00054	0.00072	0.00094	0.00083
RA	0.00058	0.00429	0.00127	0.00078
RV	0.00057	0.00064	0.00095	0.00070
DV_{TETHER}^{INNOV}	0.00061	0.04334	0.00114	0.00149
CR_M	0.00048	0.00084	0.00100	0.00075
Panel B: Mean Directional Accuracy				
Z	Entire Period	Sub-period 1	Sub-period 2	Sub-period 3
NCSKEW	0.88797	0.88981	0.85440	0.85970
Tail	0.88249	0.84573	0.88599	0.87070
RA	0.87060	0.71212	0.88187	0.85695
RV	0.87883	0.84848	0.87912	0.88171
DV_{TETHER}^{INNOV}	0.87334	0.60193	0.86538	0.84732
CR_M	0.88797	0.87741	0.88187	0.85282



(a) Panel A: full sample



(b) Panel B: small-MV subsample



(c) Panel C: large-MV subsample

Fig. 1. Predicting cryptocurrency liquidity provision premium at the h-horizon These figures plot the coefficients and 95% confidence intervals of the forecast of cryptocurrency liquidity provision premium ($L^R_{t,t+h}$) on spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), and Tether liquidity ($\text{DV}^{INNOV}_{TETHER}$) using OLS regressions at the h-horizon. $L^R_{t,t+h}$ is the cumulative liquidity provision premium of cryptocurrencies from t to $t+h$. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}^{INNOV}_{TETHER}$, are lagged by five days. The control variable, cumulative equally-weighted cryptocurrency market returns (CR_M), is lagged by five days. We divide the sample into two groups based on their market capitalization (MV). We define cryptocurrencies below the 30% of market capitalization as "small-MV", and those above the 70% of market capitalization as "large-MV". Confidence intervals are based on Newey and West (1987) standard errors with six lags.

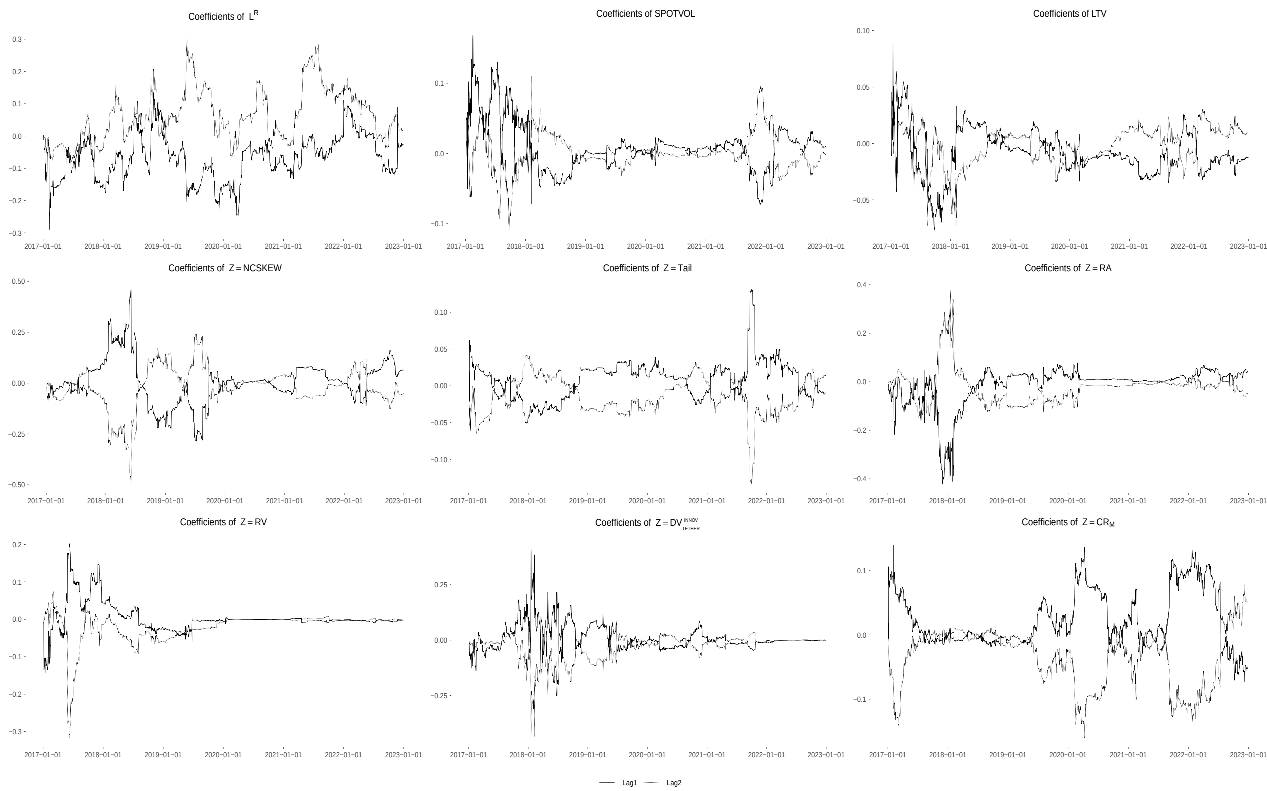


Fig. 2. TVP-VAR coefficients for the L_t^R equation in the TVP-VAR model These figures plot the coefficients of the equation for L_t^R in the TVP-VAR model, estimated with different Z_t. The first row presents the coefficients of liquidity premium (L_t^R), spot volatility (SPOTVOL), and left tail volatility (LTV) estimated in the model where $Z_t = NCSKEW$. This model is shown as an example because these coefficients are nearly identical across all models with different Z_t. The second and third rows show the coefficients for various Z_t variables, including crash risk (NCSKEW), tail risk (Tail), risk aversion (RA), realized variance (RV), Tether liquidity ($\text{DV}_{TETHER}^{INNOV}$), and cumulative equally-weighted cryptocurrency market returns (CR_M).

Table A.1 Predicting cryptocurrency liquidity provision premium at the h-horizon

The table reports the results of the forecast of cryptocurrency liquidity provision premium ($L^{R}_{t,t+h}$) on spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), and Tether liquidity ($\mathrm{DV}^{INNOV}_{TETHER}$) using OLS regressions at the h-horizon. $L^{R}_{t,t+h}$ is the cumulative liquidity provision premium of cryptocurrencies from t to $t+h$. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\mathrm{DV}^{INNOV}_{TETHER}$, are lagged by five days. The control variable, cumulative equally-weighted cryptocurrency market returns (CR_M), is lagged by five days. Panels A, B, C, and D present the results for the full sample. Panels E, F, G, and H present the results for the Small-MV subsample. Panels E, F, G, and H present the results for the Large-MV subsample. We divide the sample into two groups based on their market capitalization (MV). We define cryptocurrencies below the 30% of market capitalization as "small-MV", and those above the 70% of market capitalization as "large-MV". The numbers in parentheses are t-statistics based on Newey and West (1987) standard errors with six lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
	Panel A: $h=2$					Panel B: $h=3$				
SPOTVOL	-0.399***	-0.505***	-0.529***	-0.529***	-0.555***	-0.630***	-0.799***	-0.833***	-0.833***	-0.874***
	(-22.04)	(-22.70)	(-24.48)	(-24.57)	(-25.30)	(-22.01)	(-22.74)	(-24.59)	(-24.68)	(-25.37)
LTV	0.393***	0.381***	0.362***	0.388***	0.217***	0.612***	0.593***	0.565***	0.605***	0.338***
	(20.51)	(20.06)	(17.19)	(18.76)	(11.51)	(20.10)	(19.66)	(16.86)	(18.46)	(11.34)
RV	0.168***	0.167***	0.168***	0.163***	0.114***	0.261***	0.259***	0.261***	0.252***	0.176***
	(9.92)	(9.87)	(9.95)	(9.61)	(7.07)	(10.07)	(10.01)	(10.09)	(9.75)	(7.15)
RA		0.145***	0.146***	0.114***	0.178***		0.231***	0.232***	0.182***	0.283***
		(11.85)	(12.03)	(9.30)	(13.71)		(12.26)	(12.43)	(9.68)	(14.07)
NCSKEW			0.070***	0.014	0.050***			0.102***	0.015	0.072***
			(5.12)	(1.01)	(3.75)			(4.80)	(0.72)	(3.52)
Tail				0.106***	0.042***				0.163***	0.063***
				(7.81)	(2.93)				(7.64)	(2.79)
$\mathrm{DV}^{INNOV}_{Tether}$					0.411***					0.644***
					(17.98)					(18.22)
CR_M	-0.131***	-0.145***	-0.134***	-0.155***	-0.151***	-0.209***	-0.231***	-0.216***	-0.249***	-0.241***
	(-13.51)	(-14.51)	(-12.86)	(-15.16)	(-14.72)	(-14.03)	(-15.01)	(-13.37)	(-15.72)	(-15.29)
Constant	1.483***	1.483***	1.483***	1.483***	1.483***	2.265***	2.266***	2.265***	2.266***	2.266***
	(102.42)	(102.44)	(102.38)	(102.39)	(102.71)	(99.01)	(99.03)	(98.98)	(98.99)	(99.29)
Observations	629472	629472	629472	629472	629185	629437	629437	629437	629437	629150
Adj-R^2 (%)	0.351	0.370	0.377	0.393	0.695	0.456	0.481	0.489	0.509	0.903
	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
	Panel C: $h=6$					Panel D: $h=12$				
SPOTVOL	-1.501***	-1.904***	-1.962***	-1.961***	-2.056***	-4.544***	-5.811***	-5.882***	-5.880***	-6.151***
	(-21.37)	(-22.20)	(-24.15)	(-24.23)	(-24.78)	(-18.02)	(-18.83)	(-20.49)	(-20.53)	(-20.82)
LTV	1.381***	1.336***	1.288***	1.377***	0.758***	3.660***	3.520***	3.460***	3.707***	1.940***
	(18.24)	(17.82)	(15.30)	(16.93)	(10.43)	(12.91)	(12.52)	(10.77)	(12.23)	(7.29)
RV	0.580***	0.575***	0.578***	0.560***	0.382***	1.476***	1.460***	1.464***	1.412***	0.904***
	(10.32)	(10.26)	(10.33)	(9.97)	(7.22)	(10.15)	(10.08)	(10.16)	(9.68)	(6.64)
RA		0.551***	0.554***	0.443***	0.676***		1.729***	1.733***	1.426***	2.092***
		(13.35)	(13.50)	(10.65)	(14.80)		(13.95)	(14.02)	(11.28)	(14.23)
NCSKEW			0.174***	-0.020	0.112**			0.213	-0.323**	0.050
			(3.58)	(-0.43)	(2.52)			(1.29)	(-2.36)	(0.39)
Tail				0.363***	0.130**				1.006***	0.340*
				(7.00)	(2.38)				(5.41)	(1.73)
$\mathrm{DV}^{INNOV}_{Tether}$					1.495***					4.270***
					(18.58)					(17.67)
CR_M	-0.510***	-0.564***	-0.537***	-0.611***	-0.594***	-1.666***	-1.836***	-1.803***	-2.007***	-1.958***
	(-14.98)	(-15.83)	(-14.41)	(-16.83)	(-16.44)	(-15.24)	(-15.72)	(-14.85)	(-17.13)	(-16.88)
Constant	4.823***	4.823***	4.822***	4.823***	4.825***	11.489***	11.489***	11.489***	11.491***	11.499***
	(86.14)	(86.16)	(86.13)	(86.13)	(86.35)	(55.33)	(55.34)	(55.35)	(55.34)	(55.42)
Observations	629332	629332	629332	629332	629045	629122	629122	629122	629122	628835
Adj-R^2(%)	0.585	0.620	0.625	0.650	1.162	0.392	0.421	0.422	0.437	0.786

Table A.1 (continued)

	Model 21	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30
	Panel E: Small-MV subsample $h = 2$					Panel F: Small-MV subsample $h = 3$				
SPOTVOL	-0.314***	-0.411***	-0.433***	-0.433***	-0.444***	-0.514***	-0.668***	-0.698***	-0.697***	-0.716***
	(-17.98)	(-19.11)	(-21.35)	(-21.39)	(-21.26)	(-17.44)	(-18.42)	(-20.49)	(-20.52)	(-20.38)
LTV	0.225***	0.215***	0.195***	0.217***	0.149***	0.376***	0.359***	0.333***	0.365***	0.250***
	(13.18)	(12.72)	(10.57)	(11.75)	(9.37)	(13.35)	(12.94)	(10.97)	(12.04)	(9.79)
RV	0.501***	0.499***	0.503***	0.505***	0.493***	0.814***	0.811***	0.816***	0.820***	0.799***
	(9.61)	(9.56)	(9.63)	(9.67)	(9.41)	(9.39)	(9.35)	(9.40)	(9.44)	(9.17)
RA		0.132***	0.133***	0.106***	0.132***		0.211***	0.212***	0.171***	0.216***
		(10.53)	(10.68)	(7.98)	(9.23)		(10.83)	(10.98)	(8.24)	(9.46)
NCSKEW			0.068***	0.020**	0.035***			0.090***	0.021	0.046***
			(6.96)	(2.01)	(3.70)			(5.98)	(1.32)	(3.12)
Tail				0.090***	0.062***				0.132***	0.085***
				(7.94)	(5.09)				(7.04)	(4.19)
DV_{Tether}^{INNOV}					0.165***					0.277***
					(10.39)					(10.61)
CR_M	-0.097***	-0.110***	-0.100***	-0.118***	-0.115***	-0.162***	-0.183***	-0.169***	-0.196***	-0.191***
	(-10.75)	(-11.78)	(-10.21)	(-12.77)	(-12.58)	(-10.92)	(-11.86)	(-10.42)	(-13.00)	(-12.83)
Constant	0.931***	0.931***	0.931***	0.931***	0.931***	1.433***	1.433***	1.433***	1.433***	1.434***
	(73.23)	(73.25)	(73.16)	(73.21)	(73.24)	(67.67)	(67.68)	(67.60)	(67.65)	(67.67)
Observations	629564	629564	629564	629564	629276	629562	629562	629562	629562	629274
Adj-R^2 (%)	1.043	1.067	1.075	1.092	1.164	1.214	1.240	1.247	1.262	1.351
	Model 31	Model 32	Model 33	Model 34	Model 35	Model 36	Model 37	Model 38	Model 39	Model 40
	Panel G: Small-MV subsample $h = 6$					Panel H: Small-MV subsample $h = 12$				
SPOTVOL	-1.352***	-1.725***	-1.755***	-1.753***	-1.807***	-5.270***	-6.553***	-6.375***	-6.373***	-6.597***
	(-15.60)	(-16.14)	(-17.64)	(-17.65)	(-17.52)	(-10.57)	(-10.52)	(-11.01)	(-11.01)	(-10.96)
LTV	1.043***	1.002***	0.977***	1.036***	0.714***	4.394***	4.254***	4.409***	4.491***	3.136***
	(13.07)	(12.82)	(11.42)	(12.09)	(10.31)	(9.90)	(9.85)	(9.38)	(9.44)	(8.63)
RV	2.058***	2.050***	2.055***	2.062***	2.003***	6.959***	6.930***	6.900***	6.909***	6.662***
	(8.72)	(8.69)	(8.71)	(8.73)	(8.47)	(6.51)	(6.48)	(6.46)	(6.46)	(6.22)
RA		0.509***	0.510***	0.435***	0.559***		1.747***	1.740***	1.636***	2.159***
		(11.17)	(11.28)	(8.63)	(9.71)		(8.62)	(8.62)	(7.28)	(7.85)
NCSKEW			0.090**	-0.040	0.033			-0.545***	-0.724***	-0.421***
			(2.56)	(-1.06)	(0.93)			(-3.67)	(-4.30)	(-2.82)
Tail				0.245***	0.114**				0.338	-0.214
				(5.00)	(2.13)				(1.59)	(-0.92)
DV_{Tether}^{INNOV}					0.776***					3.267***
					(10.77)					(8.68)
R_M	-0.440***	-0.489***	-0.476***	-0.525***	-0.513***	-1.751***	-1.922***	-2.004***	-2.073***	-2.021***
	(-11.28)	(-11.99)	(-10.89)	(-13.22)	(-13.10)	(-9.79)	(-10.04)	(-9.56)	(-10.71)	(-10.68)
Constant	3.124***	3.125***	3.124***	3.125***	3.125***	8.099***	8.099***	8.101***	8.102***	8.104***
	(52.48)	(52.49)	(52.42)	(52.46)	(52.47)	(25.40)	(25.40)	(25.37)	(25.38)	(25.38)
Observations	629556	629556	629556	629556	629268	629544	629544	629544	629544	629256
Adj-R^2 (%)	1.313	1.338	1.339	1.348	1.463	0.638	0.649	0.650	0.651	0.730

Table A.1 (continued)

	Model 41	Model 42	Model 43	Model 44	Model 45	Model 46	Model 47	Model 48	Model 49	Model 50
	Panel I: Large-MV subsample $h=2$					Panel J: Large-MV subsample $h=3$				
SPOTVOL	-0.037***	-0.041***	-0.031***	-0.031***	-0.034***	-0.055***	-0.061***	-0.047***	-0.047***	-0.051***
	(-9.74)	(-9.12)	(-7.10)	(-7.11)	(-7.52)	(-9.97)	(-9.34)	(-7.28)	(-7.29)	(-7.70)
LTV	0.021***	0.021***	0.029***	0.024***	0.004	0.032***	0.031***	0.043***	0.036***	0.007*
	(6.49)	(6.38)	(7.80)	(6.29)	(1.60)	(6.62)	(6.51)	(7.96)	(6.44)	(1.69)
RV	0.004**	0.004**	0.004**	0.004***	0.001	0.006**	0.006**	0.005**	0.006***	0.002
	(2.45)	(2.44)	(2.37)	(2.84)	(0.92)	(2.50)	(2.49)	(2.41)	(2.90)	(0.92)
RA		0.005**	0.005**	0.011***	0.018***		0.008**	0.007**	0.016***	0.027***
		(2.48)	(2.28)	(4.98)	(7.81)		(2.51)	(2.30)	(5.08)	(7.97)
NCSKEW			-0.028***	-0.018***	-0.014***			-0.043***	-0.027***	-0.021***
			(-11.20)	(-6.05)	(-5.14)			(-11.51)	(-6.26)	(-5.33)
Tail				-0.019***	-0.027***				-0.029***	-0.040***
				(-8.35)	(-11.39)				(-8.56)	(-11.66)
$\text{DV}_{Tether}^{INNOV}$					0.046***					0.070***
					(7.93)					(8.08)
CR_M	0.010***	0.009***	0.005**	0.009***	0.010***	0.015***	0.014***	0.008**	0.014***	0.014***
	(4.44)	(4.16)	(2.12)	(3.66)	(3.95)	(4.52)	(4.24)	(2.14)	(3.71)	(4.02)
Constant	0.143***	0.143***	0.143***	0.143***	0.143***	0.214***	0.214***	0.214***	0.214***	0.214***
	(57.44)	(57.44)	(57.37)	(57.33)	(57.36)	(58.70)	(58.71)	(58.63)	(58.60)	(58.62)
Observations	629466	629466	629466	629466	629178	629416	629416	629416	629416	629128
Adj-R^2 (%)	0.059	0.060	0.086	0.099	0.194	0.087	0.087	0.126	0.145	0.283
	Model 51	Model 52	Model 53	Model 54	Model 55	Model 56	Model 57	Model 58	Model 59	Model 60
	Panel K: Large-MV subsample $h=6$					Panel L: Large-MV subsample $h=12$				
SPOTVOL	-0.111***	-0.123***	-0.094***	-0.094***	-0.103***	-0.226***	-0.249***	-0.190***	-0.190***	-0.208***
	(-10.76)	(-10.11)	(-7.91)	(-7.91)	(-8.35)	(-12.83)	(-12.12)	(-9.52)	(-9.53)	(-10.03)
LTV	0.065***	0.064***	0.088***	0.074***	0.015*	0.134***	0.132***	0.182***	0.154***	0.032**
	(7.13)	(7.02)	(8.57)	(6.97)	(1.93)	(8.42)	(8.29)	(10.12)	(8.30)	(2.39)
RV	0.011***	0.011***	0.011***	0.013***	0.004	0.021***	0.021***	0.020***	0.025***	0.007
	(2.72)	(2.71)	(2.62)	(3.15)	(0.97)	(3.18)	(3.16)	(3.07)	(3.70)	(1.00)
RA		0.016***	0.014**	0.032***	0.054***		0.031***	0.028***	0.063***	0.109***
		(2.71)	(2.49)	(5.52)	(8.67)		(3.28)	(3.00)	(6.69)	(10.53)
NCSKEW			-0.087***	-0.056***	-0.043***			-0.178***	-0.117***	-0.090***
			(-12.60)	(-6.92)	(-5.95)			(-15.18)	(-8.50)	(-7.40)
Tail				-0.058***	-0.081***				-0.116***	-0.162***
				(-9.19)	(-12.54)				(-10.78)	(-14.77)
$\text{DV}_{Tether}^{INNOV}$					0.141***					0.290***
					(8.64)					(10.07)
CR_M	0.030***	0.028***	0.015**	0.027***	0.028***	0.059***	0.056***	0.029**	0.053***	0.056***
	(4.81)	(4.51)	(2.24)	(3.92)	(4.25)	(5.60)	(5.26)	(2.55)	(4.50)	(4.91)
Constant	0.431***	0.431***	0.431***	0.431***	0.431***	0.869***	0.869***	0.870***	0.870***	0.870***
	(63.22)	(63.22)	(63.14)	(63.11)	(63.15)	(74.38)	(74.38)	(74.31)	(74.27)	(74.36)
Observations	629274	629274	629274	629274	628986	629031	629031	629031	629031	628743
Adj-R^2 (%)	0.162	0.164	0.238	0.273	0.534	0.288	0.290	0.426	0.486	0.963

Table A.2 Predicting cryptocurrency liquidity provision premium with Hodrick (1992) standard errors

The table reports the results of the forecast of cryptocurrency liquidity provision premium ($L^R_{t,t+h}$) on spot volatility (SPOTVOL), left tail volatility (LTV), realized variance (RV), risk aversion (RA), crash risk (NCSKEW), tail risk (Tail), and Tether liquidity ($\text{DV}^{INNOV}_{TETHER}$) using OLS regressions at the h-horizon. $L^R_{t,t+h}$ is the cumulative liquidity provision premium of cryptocurrencies from t to $t+h$. The predictors, namely SPOTVOL, LTV, RV, RA, NCSKEW, Tail, and $\text{DV}^{INNOV}_{TETHER}$, are lagged by five days. The control variable, cumulative equally-weighted cryptocurrency market returns (CR_M), is lagged by five days. The numbers in parentheses are t-statistics based on Hodrick (1992) standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
	Panel A: $h = 1$					Panel B: $h = 2$				
SPOTVOL	-0.184***	-0.235***	-0.249***	-0.248***	-0.260***	-0.388***	-0.496***	-0.521***	-0.521***	-0.546***
	(-27.07)	(-27.66)	(-29.03)	(-29.04)	(-30.03)	(-28.54)	(-29.15)	(-30.45)	(-30.46)	(-31.5)
LTV	0.183***	0.177***	0.166***	0.177***	0.100***	0.379***	0.367***	0.346***	0.370***	0.207***
	(25.15)	(24.49)	(21.16)	(22.65)	(13.83)	(26.12)	(25.43)	(22.07)	(23.6)	(14.31)
RV	0.081***	0.08***	0.081***	0.078***	0.056***	0.167***	0.166***	0.167***	0.162***	0.115***
	(12.75)	(12.66)	(12.79)	(12.37)	(8.91)	(13.23)	(13.13)	(13.26)	(12.83)	(9.19)
RA		0.070***	0.070***	0.056***	0.085***		0.146***	0.147***	0.118***	0.179***
		(13.8)	(13.9)	(10.83)	(16.12)		(14.52)	(14.61)	(11.47)	(17.04)
NCSKEW			0.040***	0.015**	0.031***			0.078***	0.025**	0.060***
			(6.79)	(2.36)	(5.2)			(6.54)	(2.04)	(5.01)
Tail				0.048***	0.019***				0.098***	0.037***
				(9.05)	(3.47)				(9.24)	(3.38)
$\text{DV}^{INNOV}_{TETHER}$					0.187***					0.393***
					(22.61)					(23.76)
CR_M	-0.060***	-0.067***	-0.061***	-0.071***	-0.068***	-0.129***	-0.143***	-0.131***	-0.151***	-0.146***
	(-15.12)	(-16.52)	(-14.4)	(-16.86)	(-16.38)	(-16.13)	(-17.6)	(-15.49)	(-18.0)	(-17.51)
Constant	0.721***	0.721***	0.72***	0.72***	0.721***	1.466***	1.466***	1.466***	1.466***	1.466***
	(126.4)	(126.41)	(126.34)	(126.31)	(126.32)	(128.59)	(128.59)	(128.52)	(128.49)	(128.51)
Observations	629541	629541	629541	629541	629254	629540	629540	629540	629540	629253
Adj-R^2 (%)	0.172	0.182	0.187	0.194	0.337	0.309	0.327	0.334	0.347	0.604
	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
	Panel C: $h = 3$					Panel D: $h = 6$				
SPOTVOL	-0.615***	-0.787***	-0.826***	-0.826***	-0.865***	-1.478***	-1.896***	-1.965***	-1.965***	-2.056***
	(-30.15)	(-30.87)	(-32.15)	(-32.17)	(-33.26)	(-36.22)	(-37.17)	(-38.26)	(-38.28)	(-39.56)
LTV	0.595***	0.576***	0.543***	0.580***	0.323***	1.349***	1.303***	1.244***	1.326***	0.723***
	(27.29)	(26.55)	(23.11)	(24.69)	(14.92)	(30.92)	(30.01)	(26.44)	(28.16)	(16.66)
RV	0.262***	0.259***	0.262***	0.254***	0.108***	0.594***	0.588***	0.592***	0.576***	0.402***
	(13.82)	(13.72)	(13.84)	(13.4)	(9.57)	(15.81)	(15.68)	(15.8)	(15.31)	(10.78)
RA		0.235***	0.236***	0.190***	0.287***		0.570***	0.573***	0.472***	0.699***
		(15.53)	(15.62)	(12.37)	(18.21)		(18.81)	(18.89)	(15.32)	(22.15)
NCSKEW			0.116***	0.036*	0.090***			0.210***	0.033	0.162***
			(6.52)	(1.9)	(5.0)			(5.87)	(0.88)	(4.47)
Tail				0.152***	0.055***				0.331***	0.104***
				(9.53)	(3.38)				(10.41)	(3.21)
$\text{DV}^{INNOV}_{TETHER}$					0.620***					1.455***
					(24.97)					(29.3)
CR_M	-0.206***	-0.229***	-0.211***	-0.242***	-0.235***	-0.517***	-0.573***	-0.541***	-0.608***	-0.591***
	(-17.23)	(-18.8)	(-16.64)	(-19.24)	(-18.72)	(-21.65)	(-23.54)	(-21.33)	(-24.2)	(-23.59)
Constant	2.244***	2.244***	2.244***	2.244***	2.245***	4.803***	4.803***	4.803***	4.803***	4.805***
	(131.22)	(131.23)	(131.16)	(131.12)	(131.14)	(140.45)	(140.45)	(140.38)	(140.34)	(140.37)
Observations	629539	629539	629539	629539	629252	629536	629536	629536	629536	629249
Adj-R^2 (%)	0.358	0.380	0.388	0.402	0.701	0.379	0.404	0.409	0.422	0.743

Table A.2 (continued)

	Model 21	Model 22	Model 23	Model 24	Model 25
	Panel D: $h = 12$				
SPOTVOL	-4.562***	-5.899***	-6.009***	-6.007***	-6.274***
	(-55.89)	(-57.85)	(-58.51)	(-58.54)	(-60.36)
LTV	3.488***	3.340***	3.247***	3.470***	1.712***
	(39.93)	(38.42)	(34.47)	(36.81)	(19.7)
RV	1.584***	1.568***	1.574***	1.528***	1.022***
	(21.06)	(20.85)	(20.95)	(20.29)	(13.67)
RA		1.825***	1.830***	1.554***	2.216***
		(30.12)	(30.15)	(25.21)	(35.09)
NCSKEW			0.330***	-0.152**	0.221***
			(4.62)	(-2.02)	(3.06)
Tail				0.904***	0.242***
				(14.22)	(3.74)
DV_{TETHER}^{INNOV}					4.242***
					(42.79)
CR_M	-1.782***	-1.962***	-1.911***	-2.094***	-2.045***
	(-37.31)	(-40.29)	(-37.67)	(-41.67)	(-40.81)
Constant	11.634***	11.634***	11.633***	11.635***	11.640***
	(170.08)	(170.1)	(170.01)	(169.97)	(170.03)
Observations	629530	629530	629530	629530	629243
Adj-R^2 (%)	0.220	0.238	0.238	0.245	0.436