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CRYPTOKURTOSIS: FREQUENT TRADING FUELS HIGHER LOSSES

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ABSTRACT

We assess the impact of cryptocurrencies ultra-high frequency trading on financial stability. Focusing on three well-established cryptocurrencies, namely Bitcoin, Ethereum and Sui, we show that as the trading frequency increases, so do the excess potential losses of the investors, over and above the anticipated losses based on the Value-at-Risk. This is led by the exponential growth of the kurtosis that is exhibited at high-frequency trading. Given that currently the minimum capital requirements do not differentiate between the trading frequency but only between the type of crypto assets groups, we show that such overlook poses a threat to the financial stability.

JEL: C40, C54, F30, G10, G15, G17.

Keywords: Block chain, Cryptocurrencies, Finite moments, Risk management, Ultra-high frequency trading.

Disclaimer: The views expressed in this paper are those of the authors and not necessarily those of either the Bank of Greece or the Eurosystem.

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1. Introduction

Financial risk-taking behavior and speculative trading has shifted completely over the last decades, due to the highly sophisticated technology that allows investors (primarily the institutional investors) to make trades in extremely short time-intervals, a trading style that is known as ultra-high frequency trading (UHFT). The UHFT, though, has been considered liable for causing flash crashes or disruptions in the financial markets. In addition, the use of cryptocurrencies or other forms of decentralized digital currencies as financial assets has increased significantly¹, with a considerable part of this trading to be speculative, which could hinder financial stability². Thus, the cryptocurrency market needs to be evaluated in relation to the potential pressure that may impose to the overall financial stability.

Existing research efforts investigate the price behavior of cryptocurrencies (focusing on market depth, stylized facts, market efficiency and risk profile³), showing that such assets seem to exhibit higher tail-risk, skewness and kurtosis, relatively to classical assets. Despite these findings, the impact of UHFT on cryptocurrencies market risk, and by association to the financial stability, has not been studied yet⁴. Thus, this study is both timely and important for both investors and regulators who need to delve more into the assessment of the investment risk in this new market. This importance also stems from the fact that these markets are inherently leveraged through the largely unregulated DeFi ecosystem.

We focus on three widely used cryptocurrencies, namely, the Bitcoin (BTC) and Ethereum (ETH), which are the most widely accepted cryptocurrencies, as well as SUI, which is one of the most promising cryptocurrencies. SUI was introduced in 2023 and it is already among the top 20 cryptos with the highest market capitalization. Using ultra-high

¹ In 2024, the cryptocurrency market had on average a daily trading volume of about \$400billion, which, is considerably higher compared to the \$120billion daily trading in 2020 (<https://coincodex.com/trading-volume/>).

² See, Heimer and Simsek (2019).

³ See, for instance, Brauneis *et al.* (2021), Pele *at al.* (2021), Petukhina *et al.* (2021), Borri and Santucci de Magistris (2021), Härdle *et al.* (2020), Makarov and Schoar (2020), Borri (2019), Urquhart (2016, 2017).

⁴ Financial Stability Board and the European Central Bank discuss the financial risks of the cryptocurrency market, without though quantifying these negative effects (<https://www.fsb.org/uploads/P101018.pdf>, <https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemesen.pdf>).

frequency data we assess whether the higher the trading frequency may lead to higher potential losses by investors and whether the daily risk metrics that are currently used by institutional investors to calculate their minimum capital requirements can adequately provide protection against financial risk.

The remaining paper is structured as follows. Section 2 describes the data used in the study, Section 3 details the methodology and Section 4 analyses the findings of the study before Section 5 concludes the study.

2. Data collection and construction

We use 1-minute data of the BTC, ETH and SUI spot prices, which are obtained from Binance. Our period spans from 1st of January 2018 to 23rd of August 2024 for the BTC and ETH, whereas for SUI from 3rd of May 2023 until 19th of July, 2024.

Figure 1 shows the 1-min closing prices. The first half of 2024 was a bullish period for all cryptocurrencies. Although the US macroeconomic conditions fueled part of this positive momentum⁵, the reasons for the price surge of these cryptocurrencies were not necessarily identical. In the early 2024 there was the approval of the BTC and ETH EFTs by the US Securities and Exchange Commission⁶, as well as, the BTC halving event (April 2024)⁷ and the stacking of about 30% of ETH's supply⁸, which intensified the interest of investors. On the other hand, SUI's network growth in the first few months of 2024, as well as the anticipated unlock even in May 2024, led to SUI's price surge. However, the actual unlock event and the market corrections in the third quarter of 2024 led to significant price corrections for SUI.

[Insert Figure 1 about here]

⁵ <https://www.binance.com/en/square/post/13545370590161>, <https://www.reuters.com/technology/bitcoin-eyes-60000-biggest-monthly-rally-since-late-2020-2024-02-28/>

⁶ <https://www.sec.gov/newsroom/speeches-statements/gensler-statement-spot-bitcoin-011023>

⁷ <https://www.cmegroup.com/articles/2024/bitcoin-halving-2024-this-time-its-different.html>

⁸ <https://za.investing.com/analysis/ethereum-staking-at-30-of-supply-tightens-available-market-float-200618199>

Furthermore, Tables 1 and 2 show the descriptive statistics of BTC, ETH and SUI price changes, at different trading frequencies. SUI (BTC and ETH) exhibits negative (positive) returns across all frequencies during the study periods. Apart from this opposite behavior, there are important similarities in the price returns of the three cryptocurrencies. In particular, the standard deviation increases as the trading frequency decreases, which is rather anticipated as price changes are higher at lower frequencies. Skewness, on the other hand, is mostly negative suggesting that there is material downside risk for the three cryptocurrencies.

More importantly, kurtosis exhibits extreme values at the higher trading frequencies, which are decreasing as the frequencies becomes lower. Such extreme kurtosis in the higher frequencies of cryptocurrencies' returns suggests that there more frequent extreme returns (positive or negative), which exposes higher-frequency traders to significant tail risk. This is a similar behavior to these observed by Degiannakis *et al.* (2024) for the major foreign exchange currencies, and it was coined as superkurtosis. Hence, one can easily understand that there is significant downside risk when trading cryptocurrencies, which is rather different across the different trading frequencies.

[Insert Table 1 about here]
[Insert Table 2 about here]
[Insert Table 3 about here]

We use this preliminary analysis to extend Borri and Santucci de Magistris (2022) and Borri *et al.* (2025) work on the joint dependence of skewness and kurtosis and its impact on cryptocurrencies' tail-risk, by explicitly quantifying the behavior of these moments across trading frequencies. In particular, we compute these higher-order moments at multiple sampling frequencies and demonstrate how their co-movement intensifies with higher-frequency trading, thereby amplifying tail-risk in a systematic and economically meaningful way.

Hence, in the remaining of this paper, we assess the impact of these statistical properties, across the different trading frequencies, in a risk management framework.

3. Methodology

As it is standard practice, high-frequency investors use the empirical estimations of the asset returns' moments to compute their VaR and ES measures. However, having inflated fourth moments, which are virtually infinite (see Trapani, 2016), may invalidate the calculation of the actual potential losses. Hence, to asses this we use the following steps:

1) Investigate the descriptive statistics (i.e. mean, variance, skewness and kurtosis) across sampling frequencies that range from one minute up to one week.

2) Create a statistical framework that relates the statistical properties with the properties of risk management measures; such as the VaR and ES .

3) Find the exact impact of trading frequency on potential losses and capital adequacy, by investigating analytically the relationship between sampling frequency and construction of risk measures.

To do so, let us define the intraday log-returns of the three cryptocurrencies, as:

$$y_{t_j} = \log P_{t_j} - \log P_{t_{j-1}}. \quad (1)$$

Subsequently, the excess potential loss of a trader, $L^{(m)}$, over and above the VaR , at the various trading frequencies, is shown as follows:

$$L^{(m)} = \sum_{t=1}^T \sum_{j=1}^{\tau} \left(\left| y_{t_j} - VaR_{(1-p)}^{(m)} \right| * I_{\{y_{t_j} < VaR_{(1-p)}^{(m)}\}} \right), \quad (2)$$

for $I_{\{\cdot\}}$ presenting a binary variable which equals to 1 if $y_{t_j} < VaR_{(1-p)}^{(m)}$ and zero otherwise.

Finally, we adjust the potential profits at the daily frequency, so to allow direct comparison across the different trading frequencies at the most commonly used trading frequency in risk management exercises. The daily adjusted potential excess loss, $\tilde{L}^{(m)}$, is defined as:

$$\tilde{L}^{(m)} = \frac{1440}{m} \left(\sum_{t=1}^T \sum_{j=1}^{\tau} \left(I_{\{y_{t_j} < VaR_{(1-p)}^{(m)}\}} \right) \right)^{-1} \sum_{t=1}^T \sum_{j=1}^{\tau} \left(\left| y_{t_j} - VaR_{(1-p)}^{(m)} \right| * I_{\{y_{t_j} < VaR_{(1-p)}^{(m)}\}} \right). \quad (3)$$

The constant $\frac{1440}{m}$ adjusts the 24-hour trading (i.e. 1440 minutes) with the trading frequency. The $\left(\sum_{t=1}^T \sum_{j=1}^{\tau} \left(I_{\{y_{t,j} < VaR_{(1-p)}^{(m)}\}}\right)\right)$ is the number of times that the $VaR_{(1-p)}^{(m)}$ measure has been violated.

To sum up, from (2) and (3) we assess whether UHFT, which exhibits significantly higher kurtosis (and as such higher tail risk), could pose greater threat for a trader in terms of her potential excess losses and capital depletion.

4. Results

The results on Figure 2 exhibit that the potential losses for BTC, ETH and SUI exponentially increase as the trading frequency increases. For instance, the 1-minute trader on SUI is anticipated to suffer almost 45 times higher losses, than anticipated by the VaR , and in daily adjusted figures, this translates into almost 2 times more capital losses. Similarly, for the BTC (ETH), the 1-minute trader could incur more than 190 (220) times capital losses, as opposed to the anticipated losses by the VaR (this is 1.6 and 1.9 times more in daily adjusted figures, equivalently for BTC and ETH). These figures clearly demonstrate the detrimental effects of the greater tail risk that a trader faces as her trading frequency increases. These findings highlight a significant issue that is related to financial stability, given that the current practice for calculating the daily VaR ignores the trading frequency, and as such it significantly underestimates the potential losses that could be realized by traders who choose to trade in higher than daily frequency.

[Insert Figure 2 about here]

To elaborate further, we proceed with a simple trading game. We assume that there are five independent traders who have identical trading strategies and horizons, and their only difference is their trading frequency. In particular, we consider 1-minute, 30-minute, 1-hour, 6-hour and daily trader. The initial capital for each trader is \$10,000. Each one

calculates her 95% *VaR* and subsequently she invests in BTC, ETH and SUI the capital that respects the *VaR* calculation. We note that we consider zero potential loss beyond above the *VaR* when traders make positive profits at a particular trade. By contrast, when a trader suffers a loss at a particular point in time, we calculate the excess loss, over and above the *VaR*, for the specific trading frequency. Figures 3-5 illustrate the cumulative potential excess capital losses in dollar terms.

[Insert Figure 3 about here]
[Insert Figure 4 about here]
[Insert Figure 5 about here]

In all three cases, the findings clearly showcase that the issue at hand is rather significant. The potential excess losses for the most UHFT, i.e. the 1-minute trader, are significantly higher compared to the daily trader. More specifically, the excess potential losses could amount the \$160.000 for the 1-minute trader on SUI cryptocurrency, over the sample period, whereas the daily trader could suffer cumulative potential excess losses of about \$3,500. Similarly, for the BTC the 1-minute (1-day) trader's losses could reach to \$1.000.000 (about \$20.000). The results for ETH are equivalent to those of the BTC. In a nutshell the findings suggest that UFHT can suffer capital depletion at very short trading horizon, which is not the case for the low-frequency traders. The results convincingly show that the daily *VaR* heavily misleads the actual potential losses, and as such the necessary capital requirements that institutional investors need to hold when trading in high frequency. This even holds for the Group 2b crypto assets (such as BTC, ETH and SUI) for which the Basel standards require for financial institutions to hold a minimum capital of 1.250% risk-weight (i.e. for every \$100 they need to hold a capital equal to \$1.250)⁹, as in the case of the 1-minute trader the 1.250% risk-weight capital is not sufficient given the potential excess loss shown in Figures 3 and 4. Such misleading *VaR* calculations can also affect the cryptocurrencies' derivatives markets through misestimated pricing, initial margins and collaterals on margin calls, as well as, poor hedging decisions. Overall, such

⁹ <https://www.bis.org/bcbs/publ/d545.pdf>

underestimation of the VaR can pose very serious threat to the financial stability, given the increased positions that institutional investors hold in the cryptocurrency market¹⁰.

5. Conclusion

In this paper we assess how the trading frequency in the cryptocurrencies impacts the potential losses that traders could suffer, over and above the anticipated losses by the VaR estimations. Focusing on BTC, ETH and SUI, we clearly demonstrate that ultra-high frequency in these assets significantly amplifies the tail exposure of traders, which renders the traditional risk management frameworks (i.e. minimum capital requirements) insufficient in safeguarding the financial stability.

Our findings suggest that there is a non-trivial vulnerability in the financial system, which stems from the fact that current minimum capital requirements do not differentiate between the trading frequency but only on the crypto asset groups. Hence, an obvious policy recommendation is for central banks and institutional investors' supervision authorities to complement their toolbox with more appropriate risk metrics that are adjusted for the trading frequency of financial institutions. Future research should extend the analysis across crypto assets and multi-asset portfolios, and it should also quantify the impact of DeFi leverage and regulation on the observed risk dynamics.

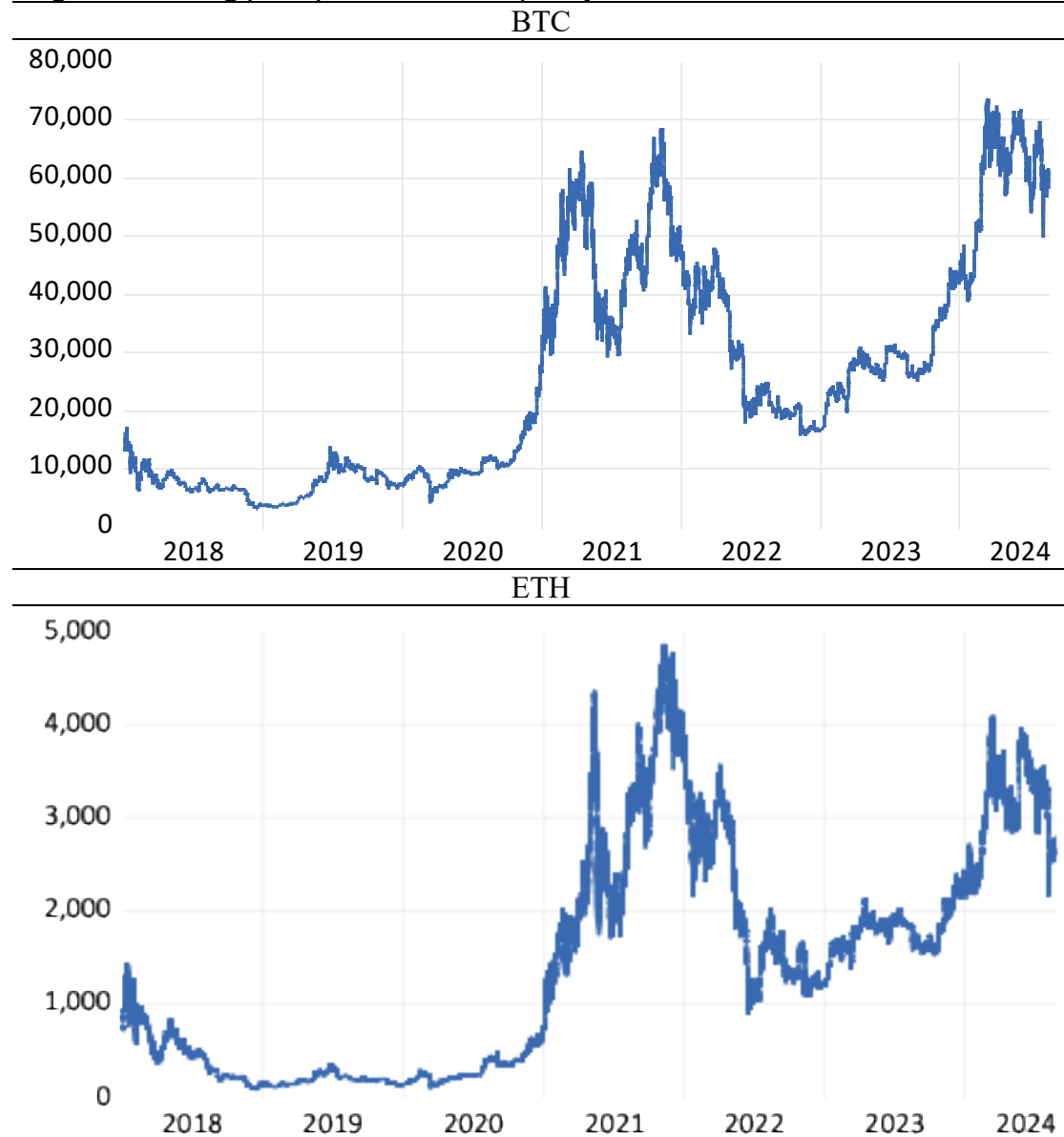
¹⁰https://www.ey.com/en_us/insights/financial-services/growing-enthusiasm-and-adoption-of-digital-assets,
<https://www.banque-france.fr/en/publications-and-statistics/publications/institutional-investments-crypto-exchange-traded-funds-rise>.

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Figures and Tables

Figure 1. Closing price per 1 minute frequency.



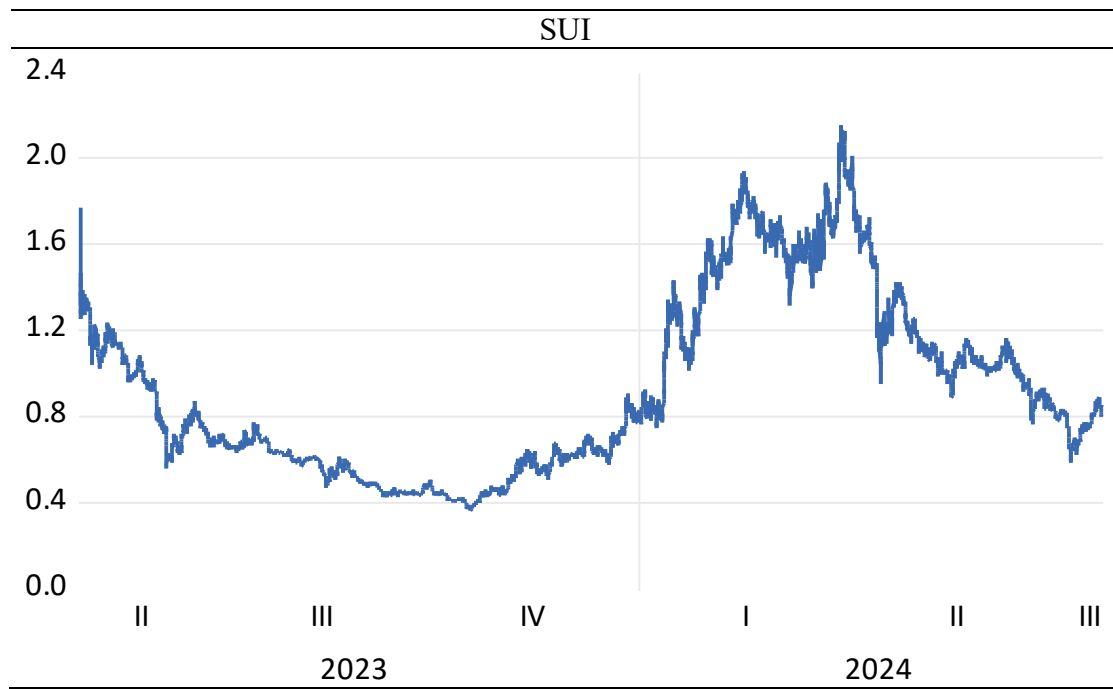
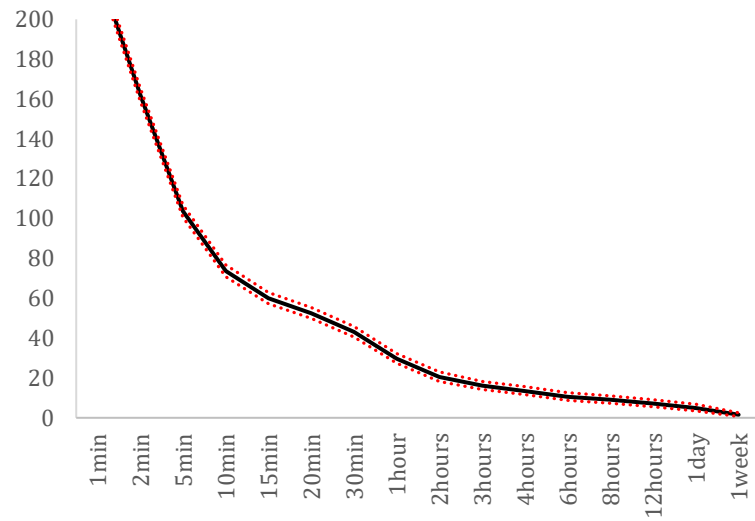
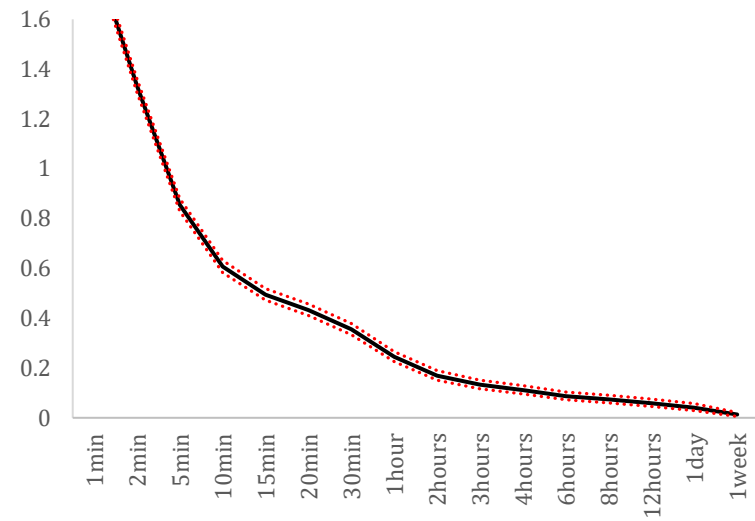


Figure 2. The potential loss, $L^{(m)}$ and the daily adjusted potential loss, $\tilde{L}^{(m)}$, across various sampling frequencies, m , for $(1 - p)=95\%$.

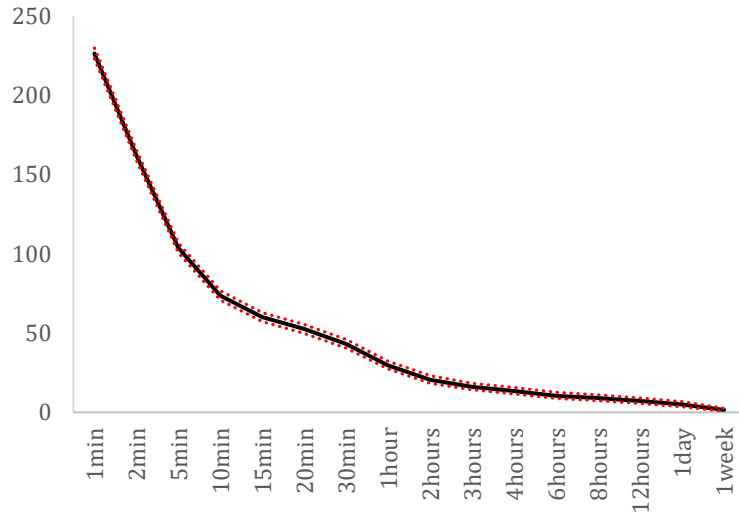
BTC – potential loss



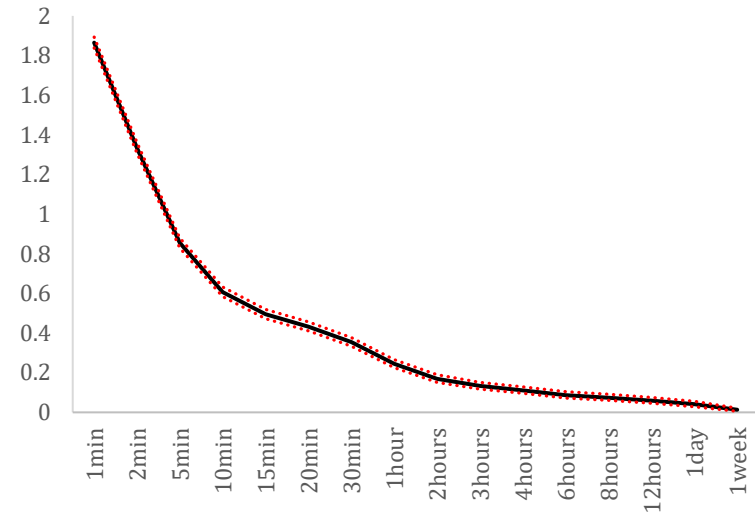
BTC – daily adjusted potential loss



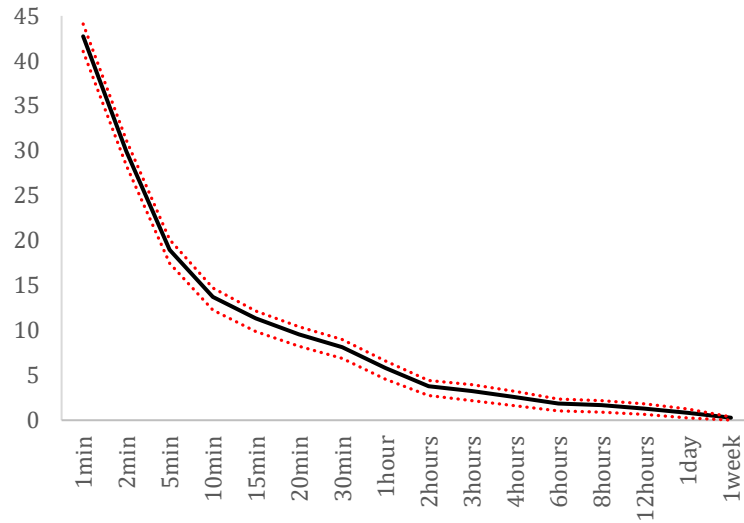
ETH – potential loss



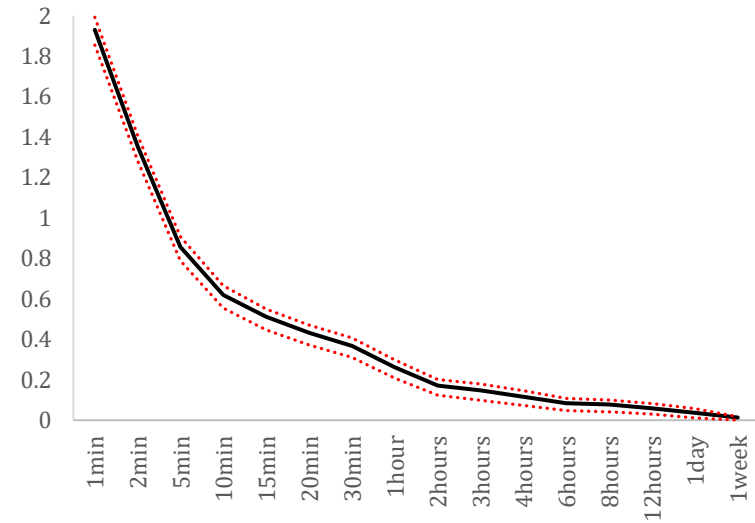
ETH – daily adjusted potential loss



SUI – potential loss



SUI – daily adjusted potential loss



Note: Black line denotes the potential loss (left column) and daily adjusted potential loss (right column). Dotted red lines denote the 95% bootstrap confident intervals based on 2000 bootstrap replications and block length of size 12.

Figure 3. The BTC case: The potential excess loss at various trading frequencies.

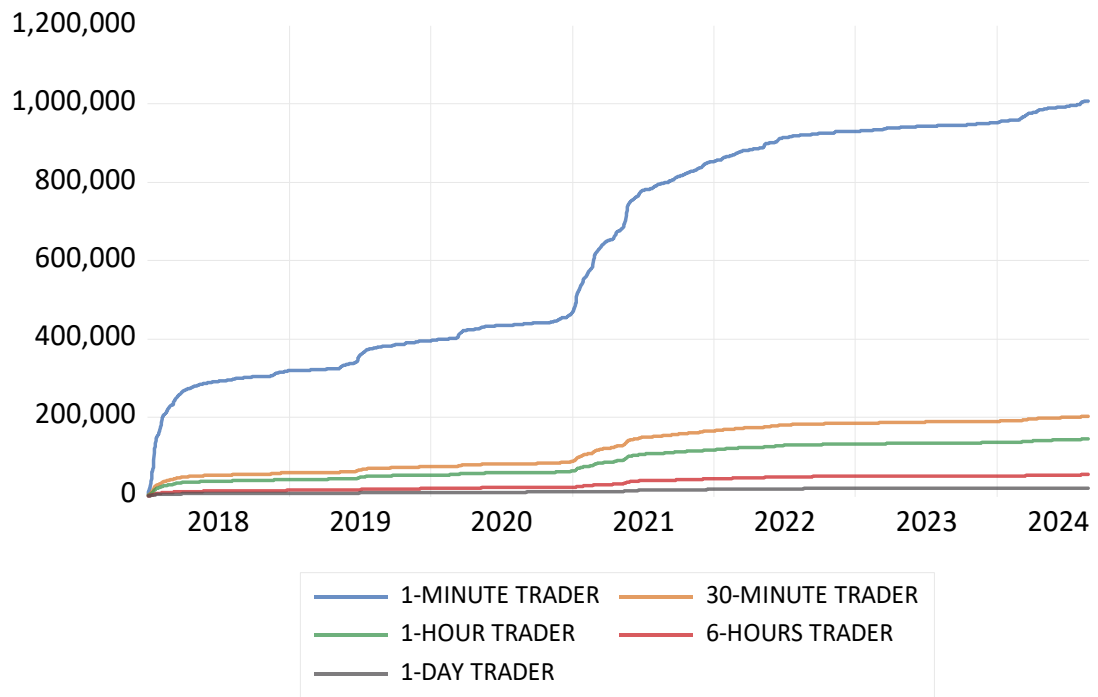


Figure 4. The ETH case: The potential excess loss at various trading frequencies.

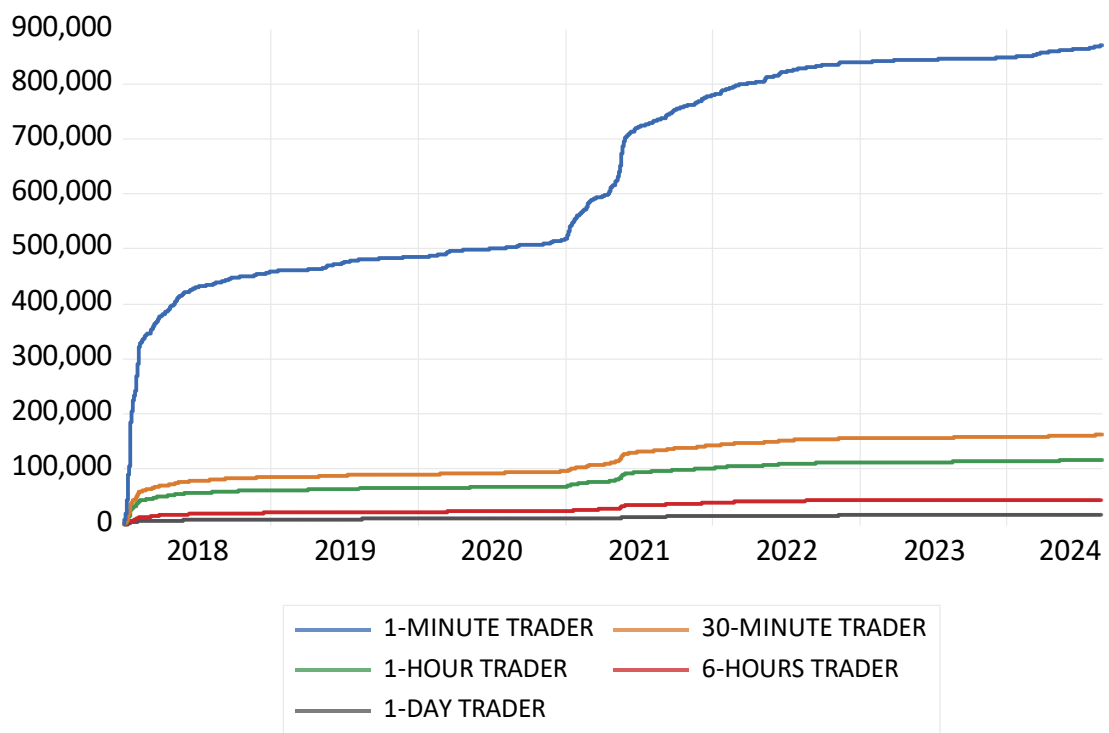


Figure 5. The SUI case: The potential excess loss at various trading frequencies.

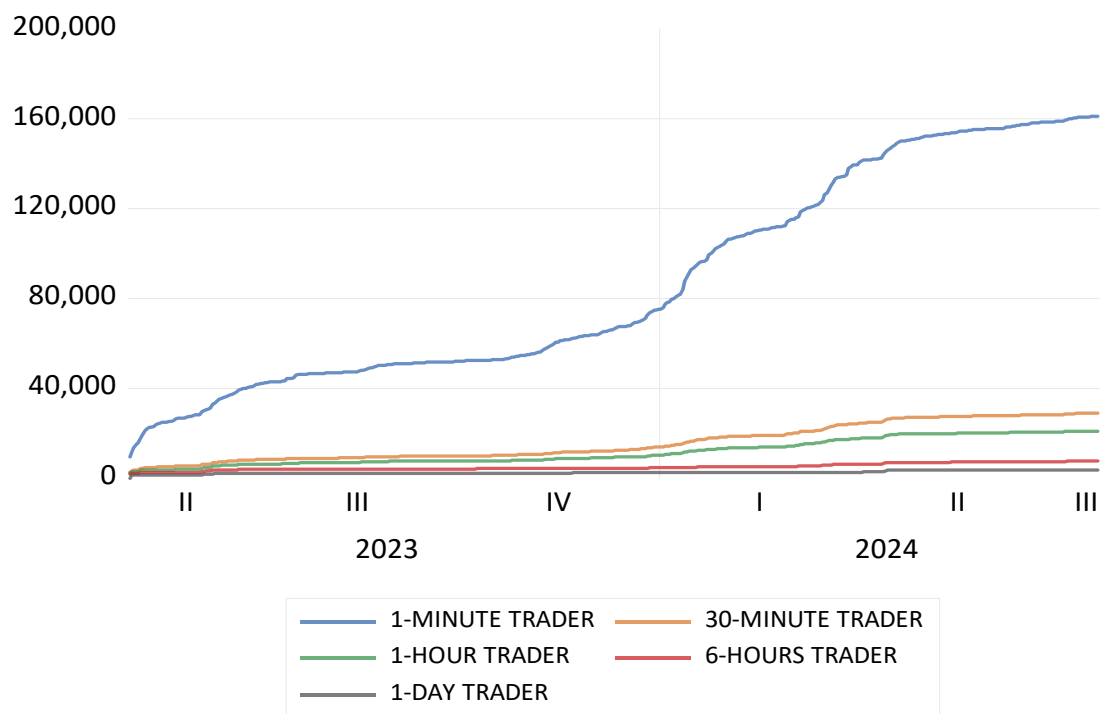


Table 1. Descriptive statistics of BTC across various sampling frequencies.

Sampling Frequency	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
1 min	0.000042	0.000000	7.229	-7.511	0.106	0.019	120.307
2 min	0.000085	0.000000	11.784	-8.595	0.151	0.210	157.981
5 min	0.000212	0.000065	16.914	-10.787	0.234	0.077	124.563
10 min	0.000424	0.001001	21.048	-15.747	0.328	0.521	132.977
15 min	0.000637	0.001670	20.399	-14.124	0.396	0.079	86.197
20 min	0.000849	0.002578	25.291	-14.786	0.456	0.559	98.760
30 min	0.001273	0.003886	15.957	-18.187	0.554	-0.298	53.657
1 hour	0.002546	0.007652	16.028	-20.103	0.770	-0.508	40.564
2 hours	0.005093	0.012675	22.391	-19.268	1.084	-0.222	31.848
3 hours	0.007639	0.015749	11.669	-19.559	1.271	-0.468	17.107
4 hours	0.010186	0.020694	13.758	-22.937	1.473	-0.522	18.038
6 hours	0.015278	0.023564	11.569	-24.207	1.792	-0.581	15.608
8 hours	0.020371	0.025577	18.769	-24.493	2.060	-0.403	13.531
12 hours	0.030557	0.049251	16.241	-26.836	2.522	-0.577	11.744
1 day	0.061114	0.059780	17.845	-50.261	3.683	-1.186	19.908
1 week	0.419020	0.538682	25.282	-40.439	9.558	-0.602	4.919

Note: The reference period is 1st of January 2018 – 23rd of August 2024. A total of 2426 trading days and 3.493.440 1-minute data points are used.

Table 2. Descriptive statistics of ETH across various sampling frequencies.

Sampling Frequency	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
1 min	0.00004	0.000000	8.182	-9.736	0.129	-0.167	119.149
2 min	0.00008	0.000000	8.656	-10.813	0.181	-0.274	89.354
5 min	0.00019	0.000000	11.872	-16.066	0.287	-0.642	98.104
10 min	0.00038	0.00056	20.177	-16.796	0.403	-0.175	87.049
15 min	0.00057	0.00105	16.833	-15.575	0.494	-0.196	57.700
20 min	0.00076	0.00191	18.852	-17.255	0.563	-0.415	47.862
30 min	0.00114	0.00434	21.296	-23.479	0.697	-0.402	52.830
1 hour	0.00228	0.00584	15.349	-27.067	0.974	-0.561	32.644
2 hours	0.00458	0.01621	22.699	-20.172	1.371	-0.193	20.234
3 hours	0.00682	0.01521	13.816	-21.140	1.626	-0.405	13.750
4 hours	0.00908	0.02615	16.010	-22.916	1.889	-0.484	13.322
6 hours	0.01357	0.03613	15.669	-28.071	2.280	-0.530	11.859
8 hours	0.01776	0.04512	24.687	-24.606	2.641	-0.306	11.162
12 hours	0.02653	0.03162	21.142	-35.283	3.236	-0.699	10.934
1 day	0.05258	0.06769	24.014	-57.189	4.705	-1.000	14.979
1 week	0.36729	0.45440	42.696	-52.895	12.680	-0.583	5.423

Note: The reference period is 1st of January 2018 – 23rd of August 2024. A total of 2426 trading days and 3.493.440 1-minute data points are used.

Table 3. Descriptive statistics of SUI across various sampling frequencies.

Sampling Frequency	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
1 min	-0.00012	0.00000	5.960	-9.694	0.159	-2.562	152.993
2 min	-0.00025	0.00000	6.247	-14.451	0.224	-3.397	193.440
5 min	-0.00061	0.00000	5.562	-16.192	0.354	-2.811	109.056
10 min	-0.00123	0.00000	7.151	-18.933	0.501	-2.591	88.680
15 min	-0.00184	0.00000	6.627	-25.617	0.620	-3.121	104.929
20 min	-0.00245	0.00000	5.483	-27.988	0.703	-2.771	98.792
30 min	-0.00368	0.00000	6.680	-35.547	0.883	-3.658	138.429
1 hour	-0.00735	0.00000	9.197	-32.186	1.230	-2.196	56.724
2 hours	-0.01470	-0.01208	10.422	-31.039	1.683	-1.538	31.661
3 hours	-0.02205	-0.02048	11.134	-34.776	2.109	-1.566	29.913
4 hours	-0.02940	-0.03343	11.167	-30.723	2.353	-1.121	18.509
6 hours	-0.04410	-0.04547	12.302	-28.362	2.823	-0.875	15.663
8 hours	-0.05878	-0.06579	14.993	-30.723	3.143	-0.845	13.808
12 hours	-0.08820	-0.13137	19.286	-23.337	3.799	-0.082	7.145
1 day	-0.17621	-0.36581	26.063	-23.337	5.317	0.224	5.910
1 week	-1.13230	-4.50601	46.460	-40.191	14.390	0.539	4.164

Note: The reference period is 3rd of May 2023 – 19th of July 2024. A total of 443 trading days and 637.200 1-minute data points are used.

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