Professor Stavros Degiannakis

Hellenic Open University Award

In Memory of Christos Tsoumas

Risk and forecasting in financial markets

1 Superkurtosis

2 Forecasting oil prices

3 Oil price volatility forecasts: objective-based evaluation functions

4 Cryptokurtosis

RESEARCH THEME 01

Superkurtosis

(Journal of Money Credit and Banking, 2023)

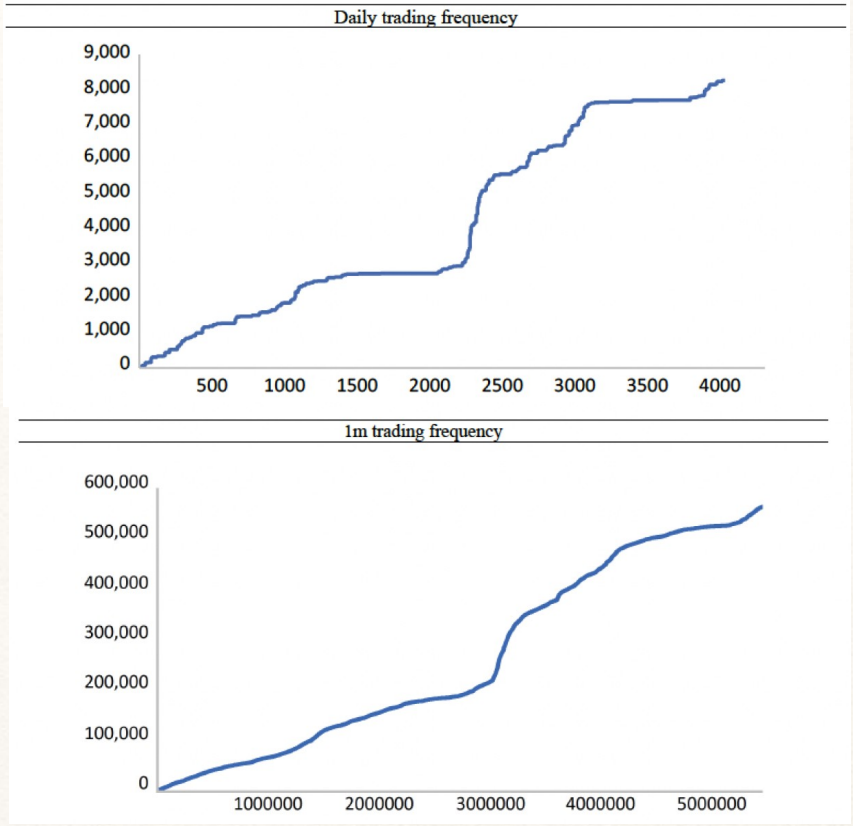
How does trading frequency change the risk of potential losses?

Tests of return distributions, followed by an assessment of losses beyond conventional risk thresholds.

Extreme returns depend on the sampling interval

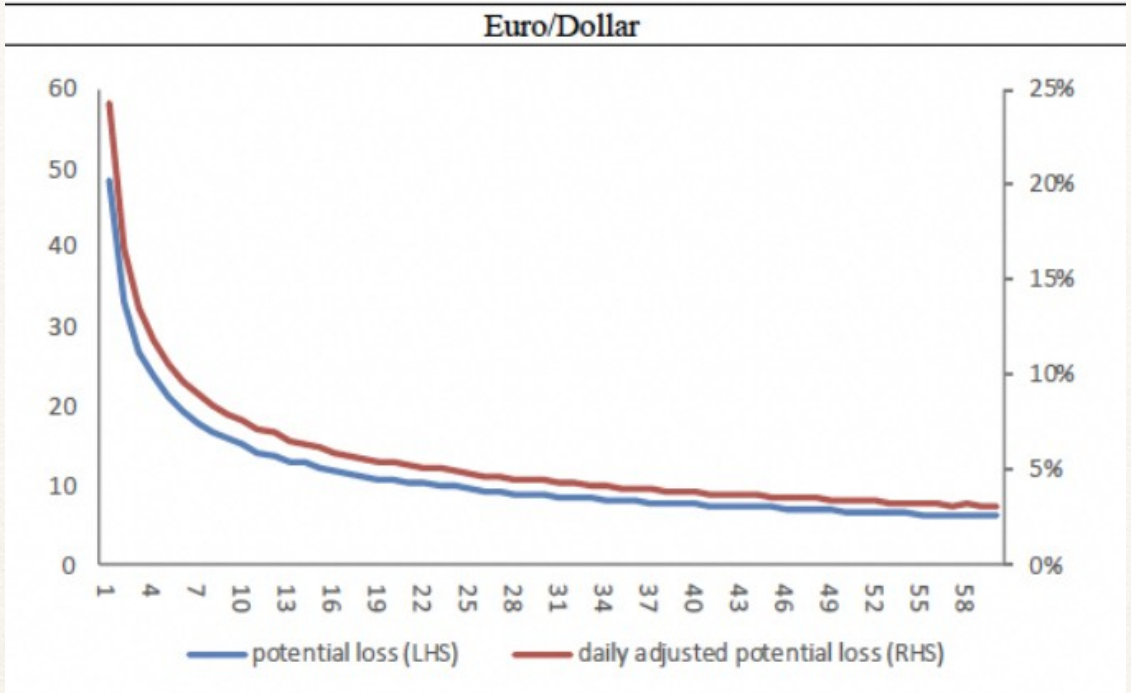
Evidence

Employing traditional risk measures for market participants who engage in intraday trading imposes serious threats to the stability of financial markets.



Contribution: Capital adequacy ratios may be severely underestimated.

Potential losses rise at shorter intervals



Reading the graph

The left side represents faster trading.

Both loss measures rise sharply as the sampling interval becomes shorter.

A daily risk estimate can conceal the exposure of an intraday trader.

Why the result needs more than a chart

Statistical contribution

Tests the finiteness of higher moments of returns.
This goes beyond simply observing unusually large price changes.

Economic contribution

Uses real data and simulations to assess potential losses.

The framework links distributional assumptions to the risk faced by traders.

Trading frequency matters for risk management

Descriptive statistics of the three currency pairs at different sampling (trading) frequencies

Frequency	Mean	Std.Dev.	Skewness	Kurtosis	Mean	Std.Dev.	Skewness	Kurtosis
	EUR/USD futures				*EUR/USD spot*			
1m	1.34×10^{-8}	1.88×10^{-4}	1.806	729.97	8.29×10^{-8}	1.80×10^{-4}	0.337	79.58
2m	2.68×10^{-8}	2.63×10^{-4}	1.396	395.10	1.66×10^{-7}	2.55×10^{-4}	0.117	71.02
5m	6.70×10^{-8}	4.07×10^{-4}	0.799	161.38	4.14×10^{-7}	3.97×10^{-4}	0.155	45.01
10m	1.34×10^{-7}	5.69×10^{-4}	0.545	85.43	8.29×10^{-7}	5.55×10^{-4}	0.071	26.34
15m	2.01×10^{-7}	6.92×10^{-4}	0.439	62.34	1.24×10^{-6}	6.78×10^{-4}	0.353	30.59
20m	2.68×10^{-7}	7.94×10^{-4}	0.469	52.64	1.66×10^{-6}	7.78×10^{-4}	-0.001	20.03
30m	4.01×10^{-7}	9.70×10^{-4}	0.304	36.85	2.49×10^{-6}	9.51×10^{-4}	0.173	20.65
60m	8.02×10^{-7}	13.28×10^{-4}	0.271	24.67	4.97×10^{-6}	13.35×10^{-4}	0.047	13.93
Daily	8.99×10^{-5}	64.48×10^{-4}	0.033	4.33	5.93×10^{-6}	63.12×10^{-4}	0.198	6.55
	GBP/USD futures				*GBP/USD spot*			
1m	-6.52×10^{-9}	1.78×10^{-4}	-0.487	269.39	-7.92×10^{-9}	1.74×10^{-4}	-0.025	46.44
2m	-1.30×10^{-8}	2.12×10^{-4}	-0.500	119.22	-1.59×10^{-8}	2.47×10^{-4}	-0.088	48.42
5m	-3.25×10^{-8}	3.16×10^{-4}	-0.422	85.45	-3.99×10^{-8}	3.86×10^{-4}	-0.096	32.66
10m	-6.49×10^{-8}	4.42×10^{-4}	-0.364	61.41	-8.17×10^{-8}	5.41×10^{-4}	-0.107	25.23
15m	-9.76×10^{-8}	5.29×10^{-4}	-0.348	36.53	-1.23×10^{-7}	6.55×10^{-4}	-0.075	21.23
20m	-1.30×10^{-7}	6.16×10^{-4}	-0.345	41.92	-1.67×10^{-7}	7.57×10^{-4}	-0.129	24.21
30m	-1.95×10^{-7}	7.44×10^{-4}	-0.317	27.83	-2.45×10^{-7}	9.18×10^{-4}	-0.056	17.84
60m	-3.93×10^{-7}	10.14×10^{-4}	-0.288	19.71	-4.94×10^{-7}	12.91×10^{-4}	-0.113	16.15
Daily	6.22×10^{-5}	56.79×10^{-4}	-0.321	5.33	-5.96×10^{-6}	60.99×10^{-4}	0.357	8.12
	CAD/USD futures				*CAD/USD spot*			
1m	1.63×10^{-8}	1.87×10^{-4}	0.116	103.30	1.74×10^{-8}	1.97×10^{-4}	0.049	40.32
2m	3.25×10^{-8}	2.57×10^{-4}	0.067	64.32	3.48×10^{-8}	2.77×10^{-4}	-0.045	40.25
5m	8.14×10^{-8}	3.96×10^{-4}	0.029	39.46	8.59×10^{-8}	4.32×10^{-4}	-0.033	24.17
10m	1.63×10^{-7}	5.51×10^{-4}	0.049	29.89	1.73×10^{-7}	6.00×10^{-4}	-0.079	19.89
15m	2.44×10^{-7}	6.64×10^{-4}	-0.035	24.33	2.59×10^{-7}	7.34×10^{-4}	-0.002	18.88
20m	3.25×10^{-7}	7.63×10^{-4}	0.067	22.01	3.45×10^{-7}	8.41×10^{-4}	-0.038	16.45
30m	4.87×10^{-7}	9.24×10^{-4}	0.021	19.25	5.18×10^{-7}	10.26×10^{-4}	0.067	15.13
60m	9.71×10^{-7}	12.31×10^{-4}	0.192	17.48	1.03×10^{-6}	14.35×10^{-4}	0.044	14.50
Daily	5.09×10^{-5}	58.10×10^{-4}	-0.142	6.01	1.50×10^{-5}	65.76×10^{-4}	0.002	6.40

RESEARCH THEME 02

Forecasting oil prices
(Energy Economics, 2018)

Can fast financial signals improve monthly oil-price forecasts?

Combines daily market information with slower-moving oil fundamentals in a mixed-frequency model.

Monthly forecasts with daily information

Oil fundamentals

Global activity, production, inventories and capacity use.

These describe slower changes in supply and demand.

Financial information

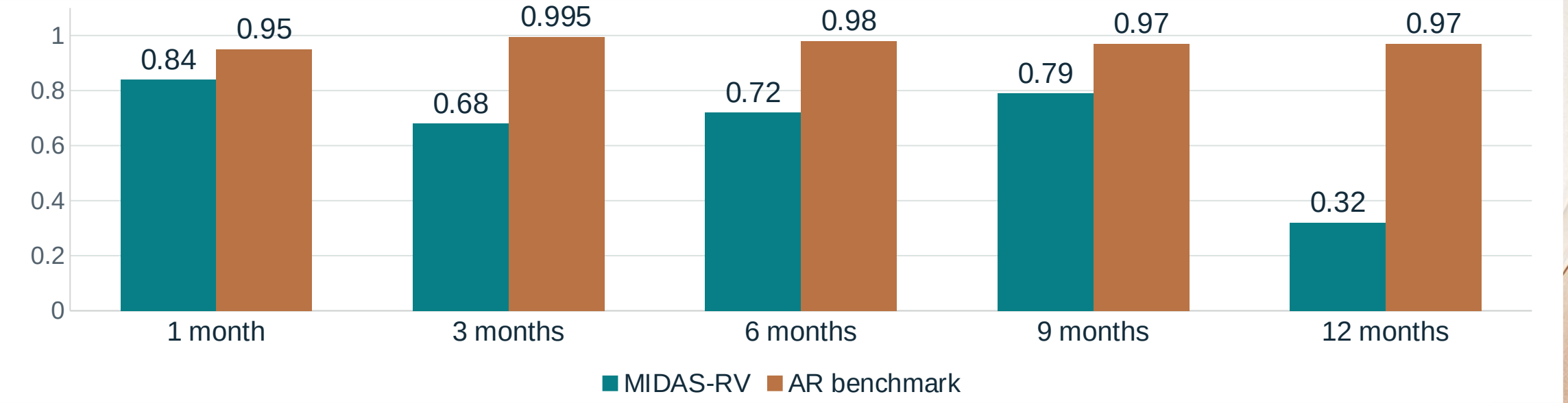
Ultra-high frequency from commodities, currencies, stocks and macro indicators.

MIDAS combines these with the monthly fundamentals.

Contribution: connects information arriving at different speeds.

Forecast gains vary with the horizon

Mean squared prediction error • no-change forecast = 1



Ratios below 1 indicate smaller errors than the no-change forecast.

RESEARCH THEME 03

Oil price volatility forecasts

(Journal of International Money and Finance, 2022)

Objective-based evaluation functions

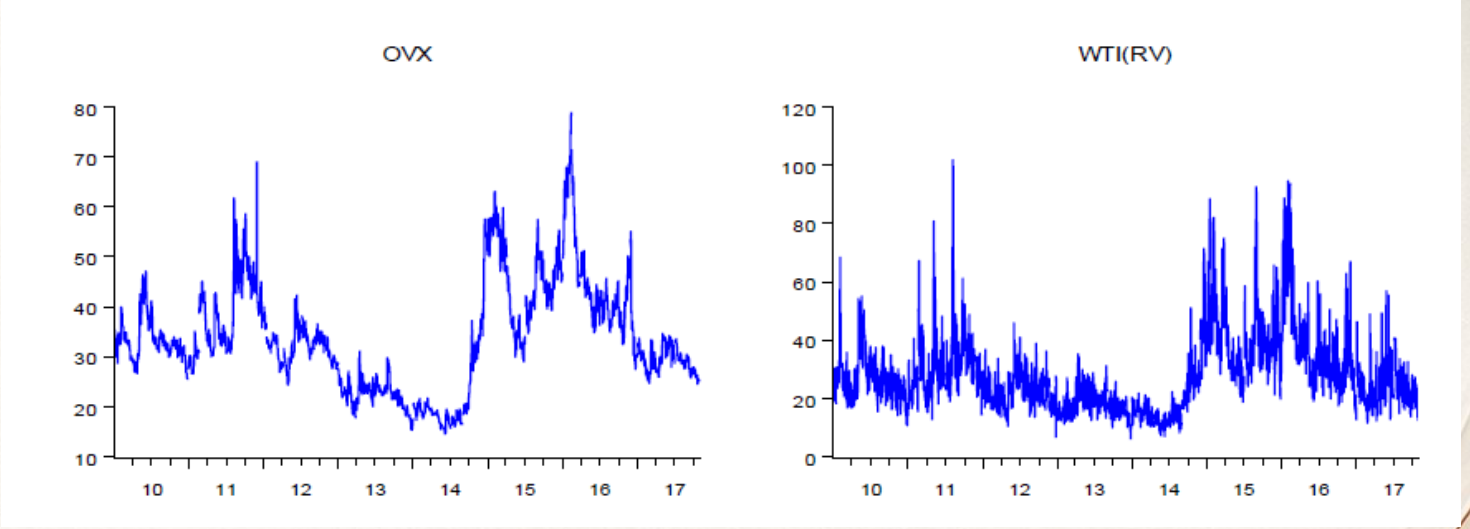
Which volatility forecast is useful depends on the investment decision it supports.

Expected fluctuations and realised movements

Two views of volatility

Implied volatility reflects expectations embedded in option prices.

Realised volatility summarises observed intraday price movements.



Contribution: compares volatility measures and information from other markets.

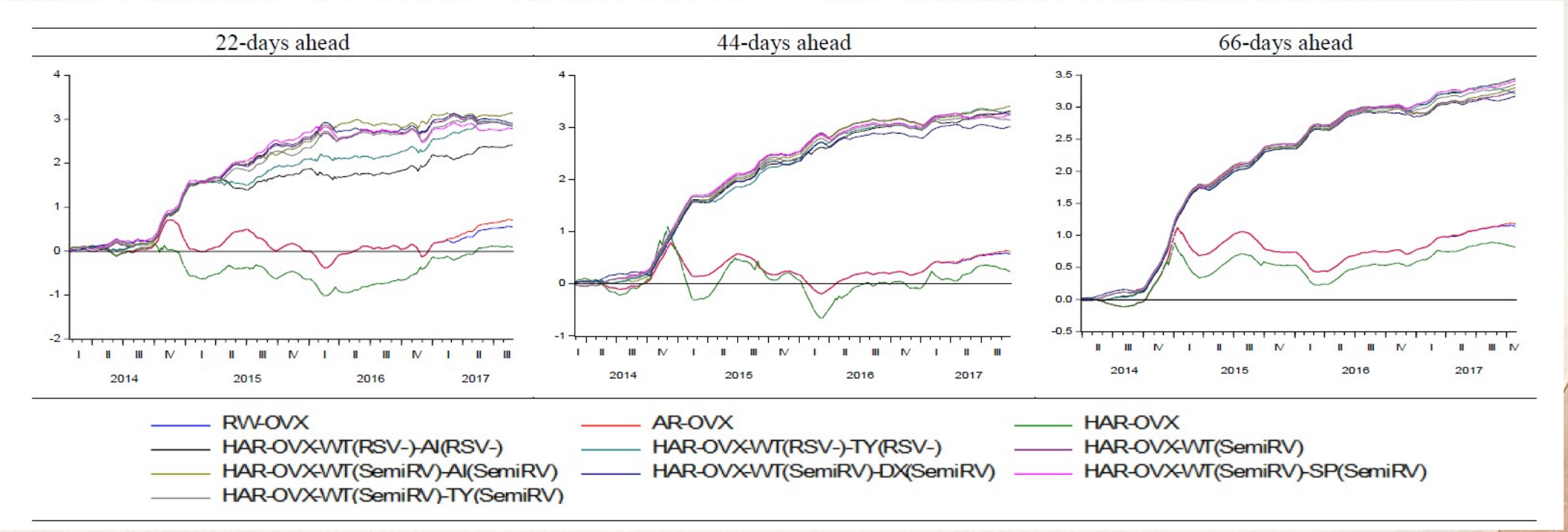
Four uses of a volatility forecast

01	**Trading OVX**	Using forecasts of implied volatility
02	**Trading OVX**	Using forecasts of realised volatility
03	**Trading option straddles**	Using forecasts of implied volatility
04	**Trading the oil ETF**	Using either type of volatility forecast

Models are judged by the trading outcomes associated with each use.

Trading performance

Profits from trading OVX (oil volatility) based on the forecasts



Compare financial outcomes, rather than statistical errors alone.

RESEARCH THEME 04

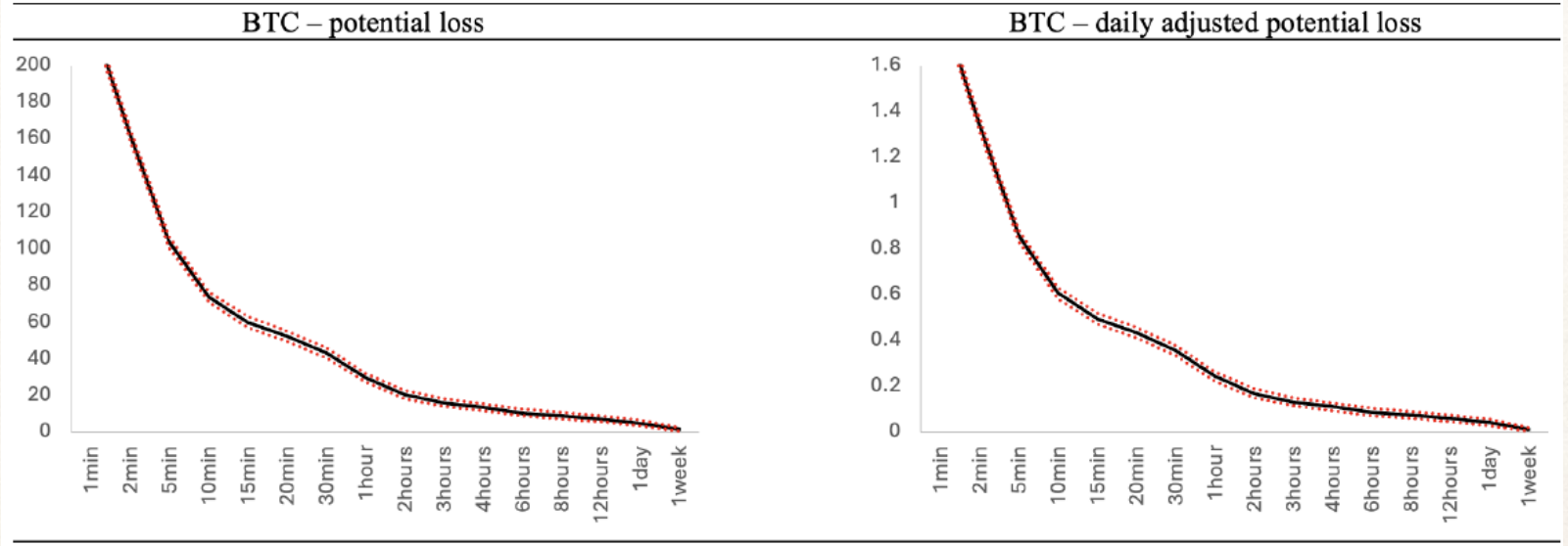
Cryptokurtosis
(Economics Letters, 2026)

Does frequent crypto trading amplify losses beyond conventional risk estimates?

Applies the trading-frequency framework to Bitcoin, Ethereum and Sui.

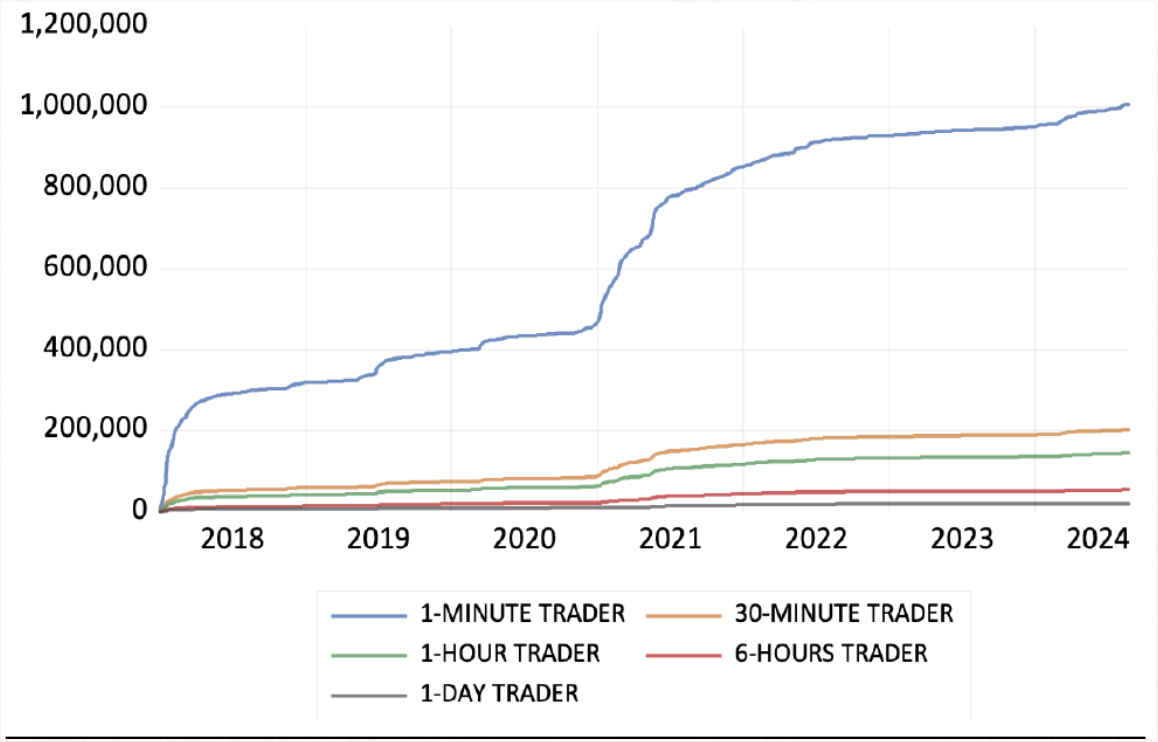
Bitcoin losses and trading frequency

Daily adjustment makes different trading intervals more comparable.



Potential losses increase sharply at the shortest intervals.

Potential excess losses accumulate differently



The comparison

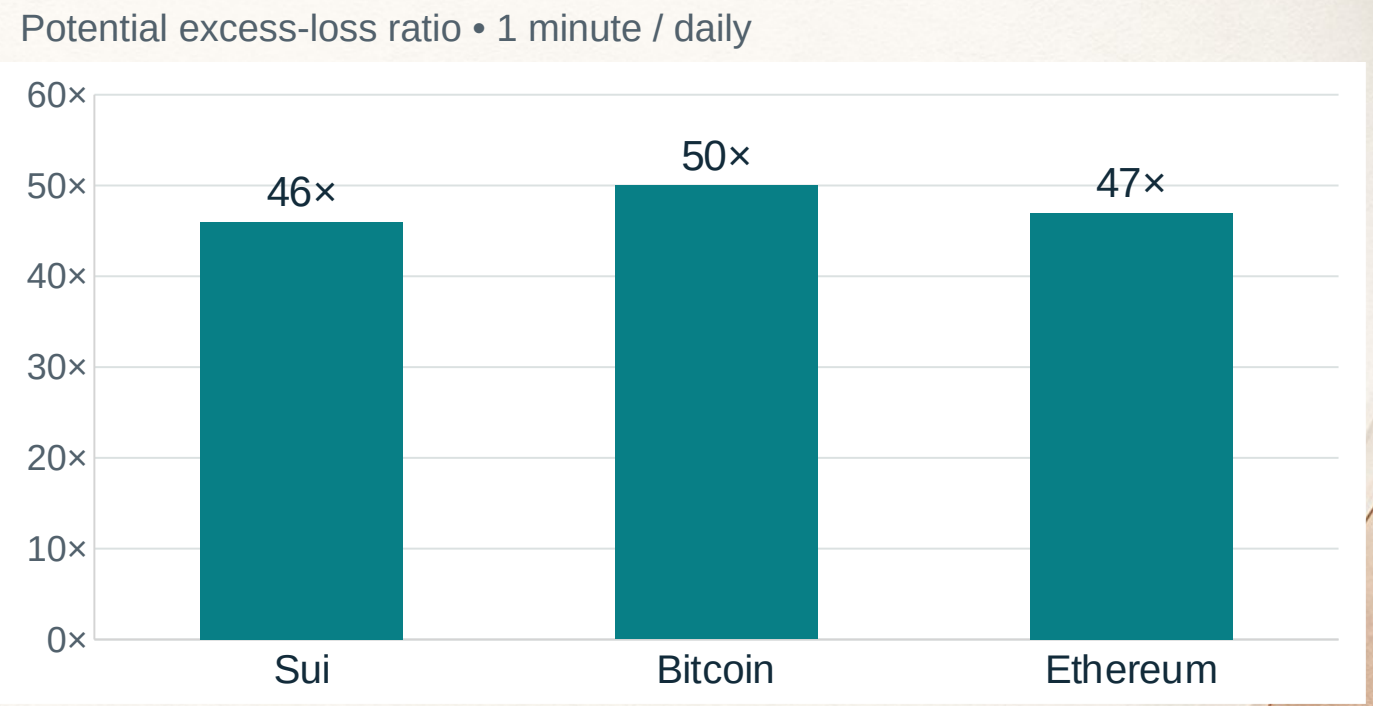
The same asset and study period produce very different cumulative loss exposure across trading frequencies.

The one-minute trading path is far above the daily path in the source exercise.

Much larger exposure for one-minute trading

Within each asset

Traders with the same strategy and initial capital, differing in ***trading frequency***.



About 46–50 times the daily trader’s exposure in the reported exercise.

Crypto risk depends on trading frequency, as well!

Contribution

Extends the analysis of extreme returns to cryptoassets and quantifies the loss exposure.

Implication

Risk limits and capital assessments need to consider how frequently the asset is traded.

The asset label alone does not describe the trader’s risk.

The common contribution

Trading frequency changes risk exposure.

High Frequency Financial signals can improve *low frequency* economic forecasts.

Forecasts need evaluation against their intended use.

Time Travel and Frequency-Dependent Risk

Lorentzian geometry versus sampling-scale tail risk

Relativistic time travel

Proper-time functional

$$\tau[\gamma] = \frac{1}{c}\int_{\lambda_0}^{\lambda_1} \sqrt{-\,g_{\mu\nu}(x)\,\dot{x}^{\mu}\dot{x}^{\nu}}\,d\lambda, \qquad g(\dot{\gamma},\dot{\gamma}) < 0$$

Timelike geodesic

$$\frac{Du^{\mu}}{d\tau} = 0 \quad \Longleftrightarrow \quad \ddot{x}^{\mu} + \Gamma^{\mu}{}_{\alpha\beta}\dot{x}^{\alpha}\dot{x}^{\beta} = 0$$

Closed timelike curve

$$\gamma : S^1 \to (M, g), \qquad \gamma(0) = \gamma(1), \qquad g_{\mu\nu}\dot{\gamma}^{\mu}\dot{\gamma}^{\nu} < 0$$

Tail risk by sampling frequency

Returns and tail index under regular variation

$$y_{t,j}^{(m)} = \log P_{t,j} - \log P_{t,j-1}, \qquad \Pr\left(|y^{(m)}| > x\right) \sim L_m(x)x^{-\alpha_m}$$

$$\mathbb{E}|y^{(m)}|^k < \infty \quad \Longleftrightarrow \quad k < \alpha_m$$

Finite-moment test

$$H_0 : \mathbb{E}|y^{(m)}|^k = \infty, \qquad H_A : \mathbb{E}|y^{(m)}|^k < \infty$$

$$\mu_k^{(m)} = c_k \frac{T_m^{-1}\Sigma_i |y_i^{(m)}|^k}{\left(T_m^{-1}\Sigma_i |y_i^{(m)}|^p\right)^{k/p}}, \qquad p = \min\{k-1, 2\}$$

$$\psi_k^{(m)} = e^{\mu_k^{(m)}} - 1, \qquad \psi_k^{(m)} \xrightarrow{a.s.} \infty\ (H_0), \quad \psi_k^{(m)} \xrightarrow{a.s.} 0\ (H_A)$$

VaR exceedance loss

$$VaR_{1-p}^{(m)} = Q_p\left(y^{(m)}\right), \qquad \ell_{t,j}^{(m)} = \left(VaR_{1-p}^{(m)} - y_{t,j}^{(m)}\right)_+$$

$$L^{(m)} = \sum_{t=1}^{T}\sum_{j=1}^{\tau_m} \ell_{t,j}^{(m)}, \qquad \bar{L}^{(m)} = \frac{1361}{mN_m}L^{(m)}$$

Time scale enters the estimand

Relativity makes elapsed time path dependent. Superkurtosis makes tail risk sampling dependent: at intraday frequencies, the third and fourth absolute moments are not finite, so finite-moment capital approximations understate exposure.

Morris et al. (1988), Degiannakis et al. (2023)

Time Travel and Algorithmic Investing

RELATIVISTIC TRAVELER

Curved spacetime

Worldline geometry

ALGORITHMIC INVESTOR

Model-driven allocation

Sampling frequency and model inference



Geometry governs the astronaut’s elapsed time. Algorithms convert sampled market data into investment decisions.


Thank you !!!
Questions and discussion