Tail risk in Bitcoin under the Basel framework

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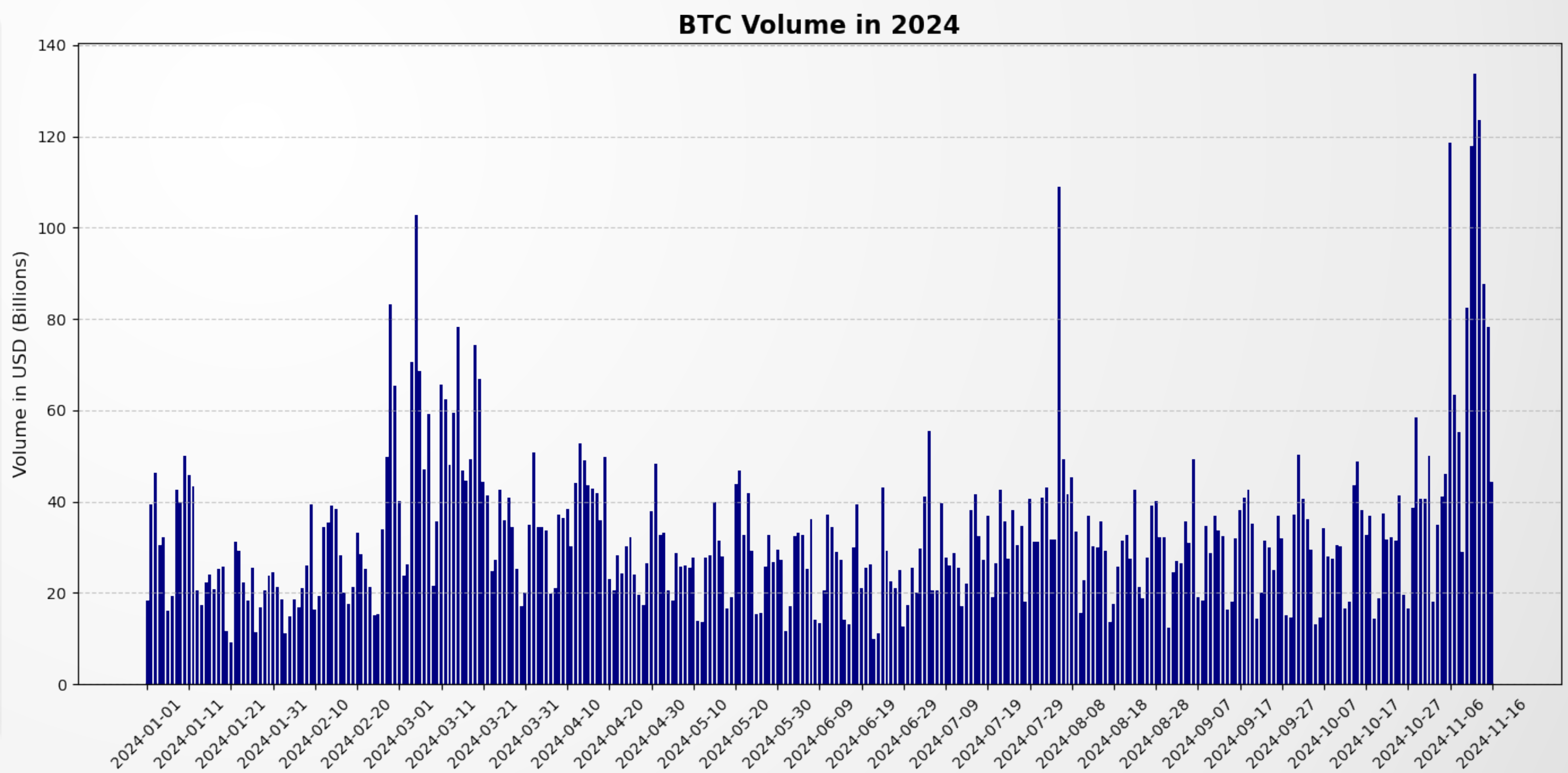
SEC & US Presidential Election

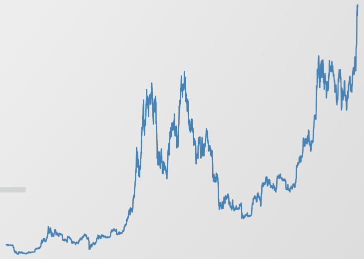
- SEC: Bitcoin ETFs on January 10, 2024
- President TRUMP embrances the cryptocurrencies (CC)

Basel III and Capital Adequacy

- Basel III Compliance requires banks to hold adequate capital for market risk
- Challenge for Crypto-Assets: High volatility & jump risks make traditional models (e.g., BS) unreliable

Source: https://www.cnbc.com

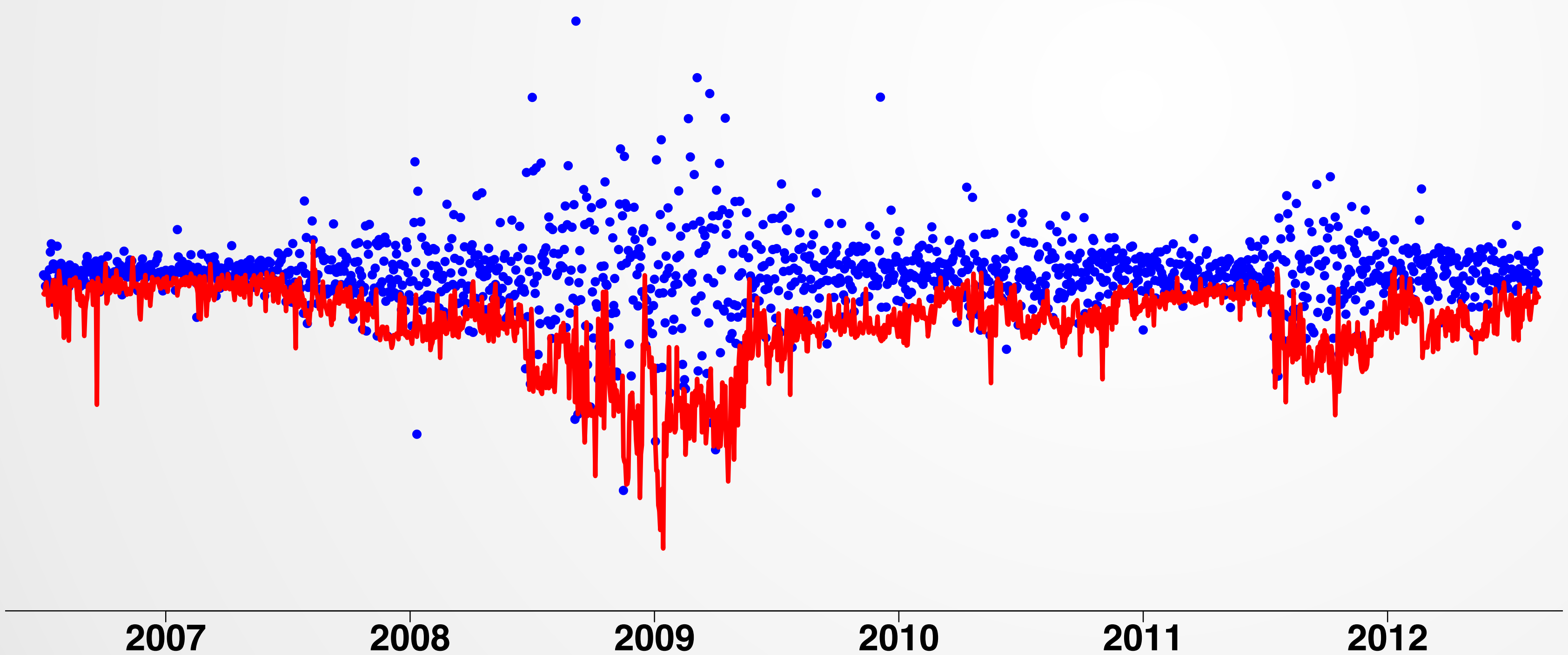




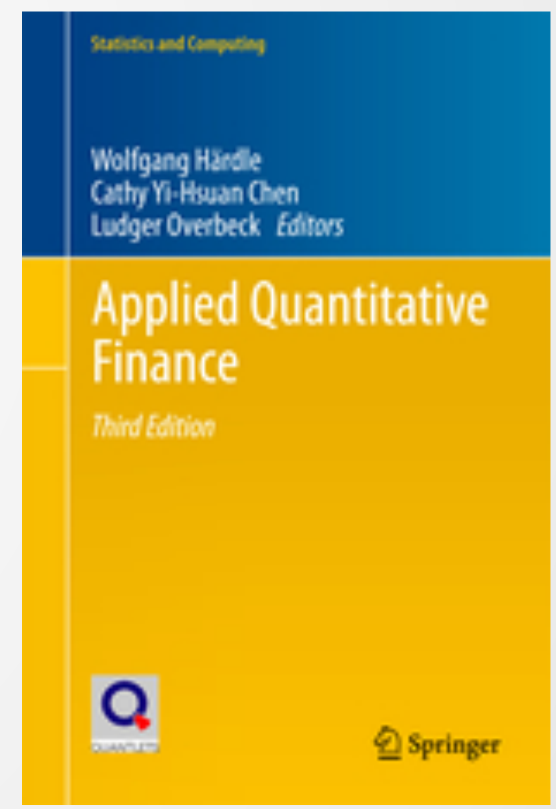
Value at Risk (VaR): Maximum potential loss

- Confidence level α (5% or 1%)
- X_t, return at time t,

$$\mathrm{P}(X_t \leq \mathrm{VaR}_{t,\alpha}) \stackrel{\mathrm{def}}{=} \alpha, \quad \alpha \in (0,1),$$



VaR of $\alpha = 5\,\%$



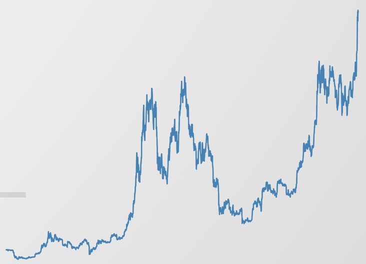
Expected Shortfall (ES): Average loss beyond the VaR

- ES at level α is defined as the conditional expectation of loss given VaR exceedance:

$$ES_{t,\alpha} = \mathbb{E}[X_t \,|\, X_t \leq VaR_{t,\alpha}]$$

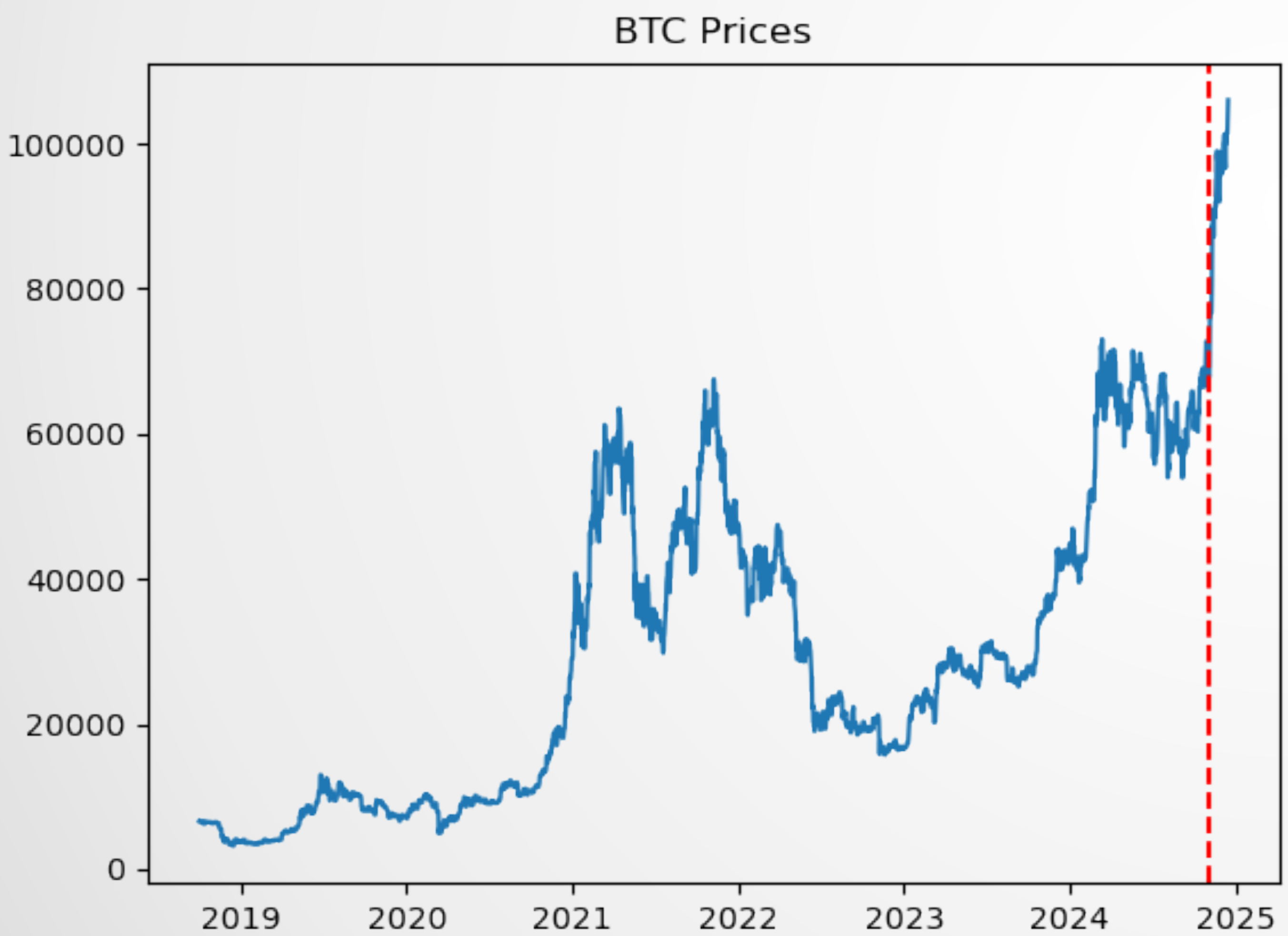
- ES incorporates information on the magnitude of extreme losses

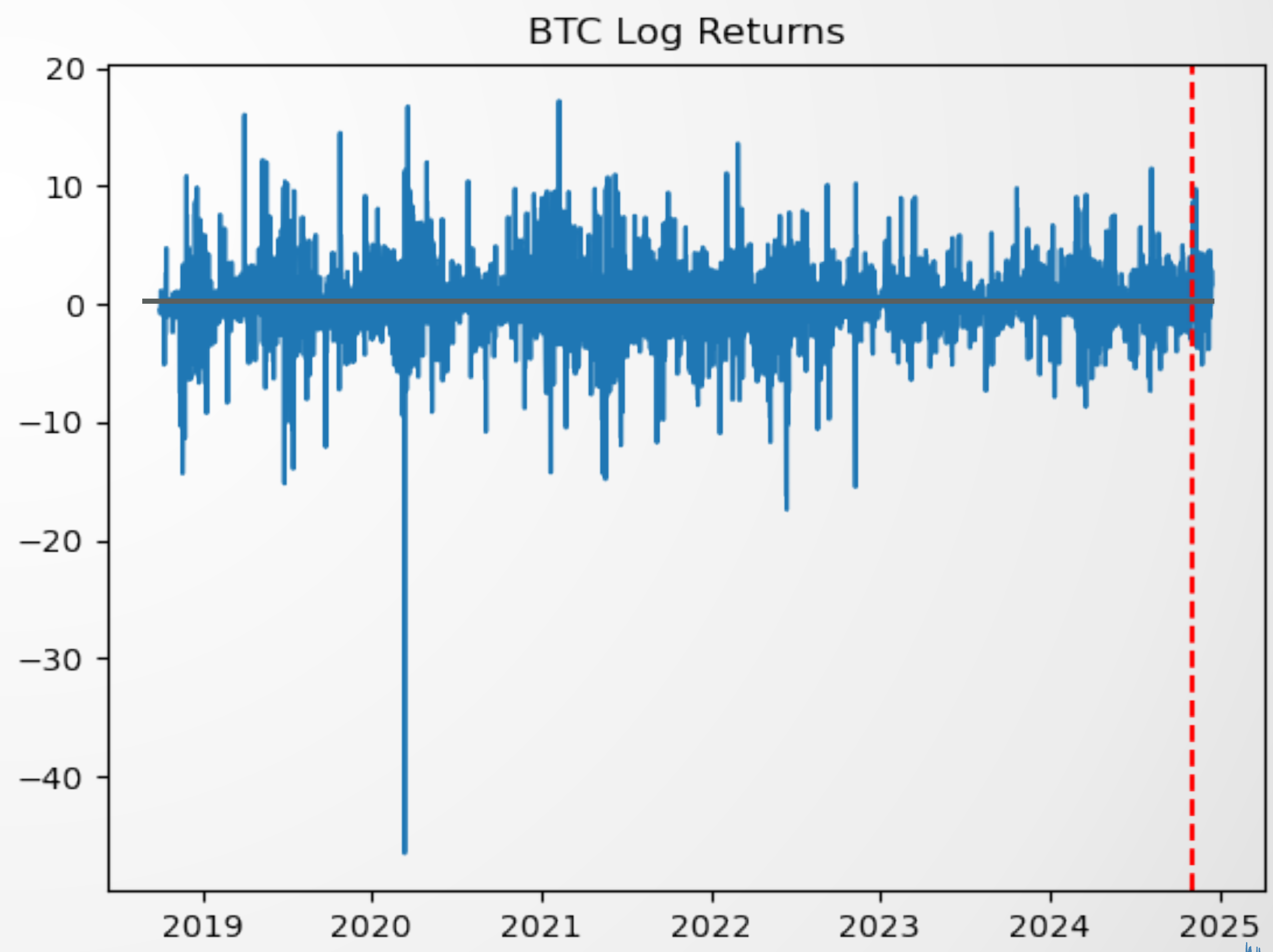
Risk Measure	Focus	Limitation
VaR	Maximum potential loss at confidence level α.	Does not account for the severity of losses beyond the VaR threshold.
ES	Average loss beyond the VaR threshold.	More sensitive to tail assumptions, but more conservative.



Features of BTC returns

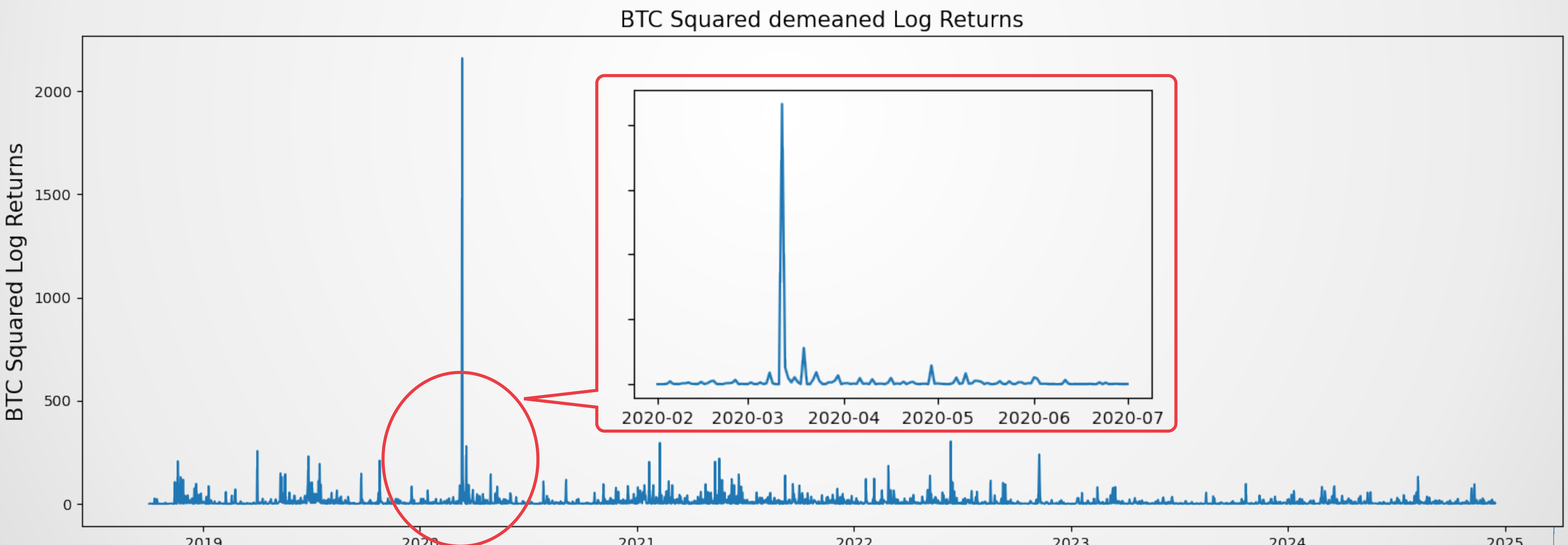
- BTC from Yahoo Finance: October 2018 to December 2024
- Volatility clustering
- Jumps in returns





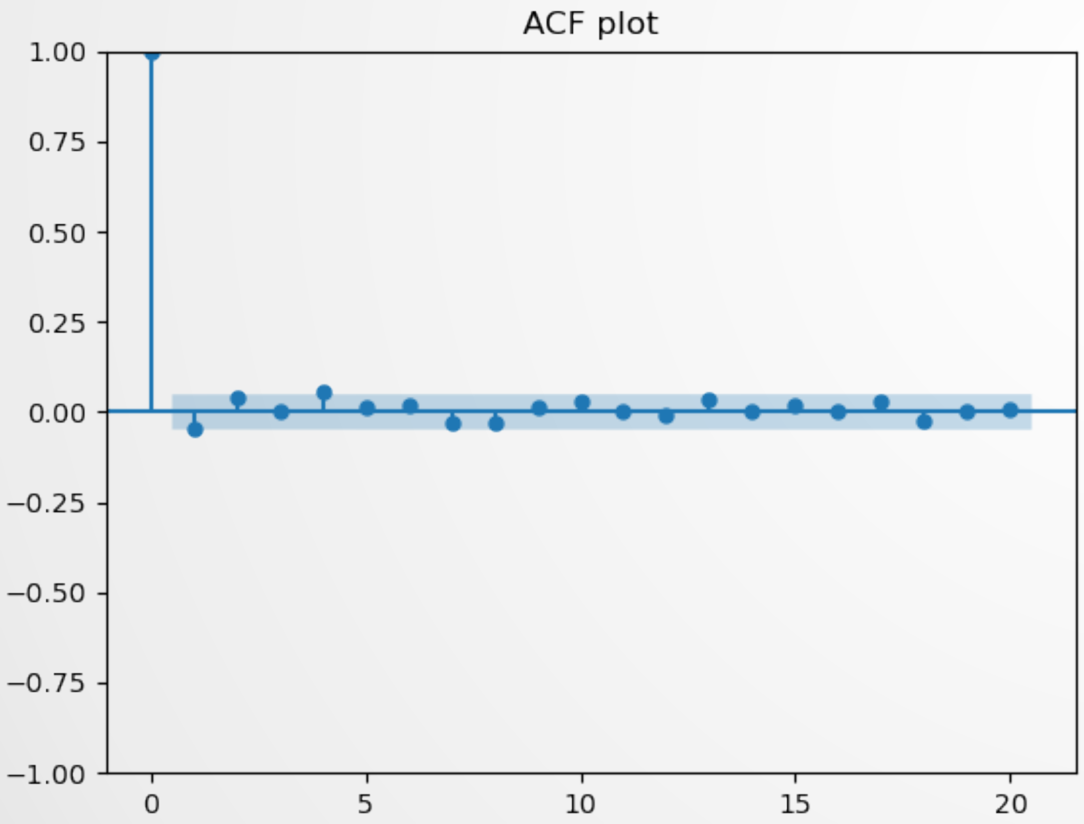
Jumps in variance

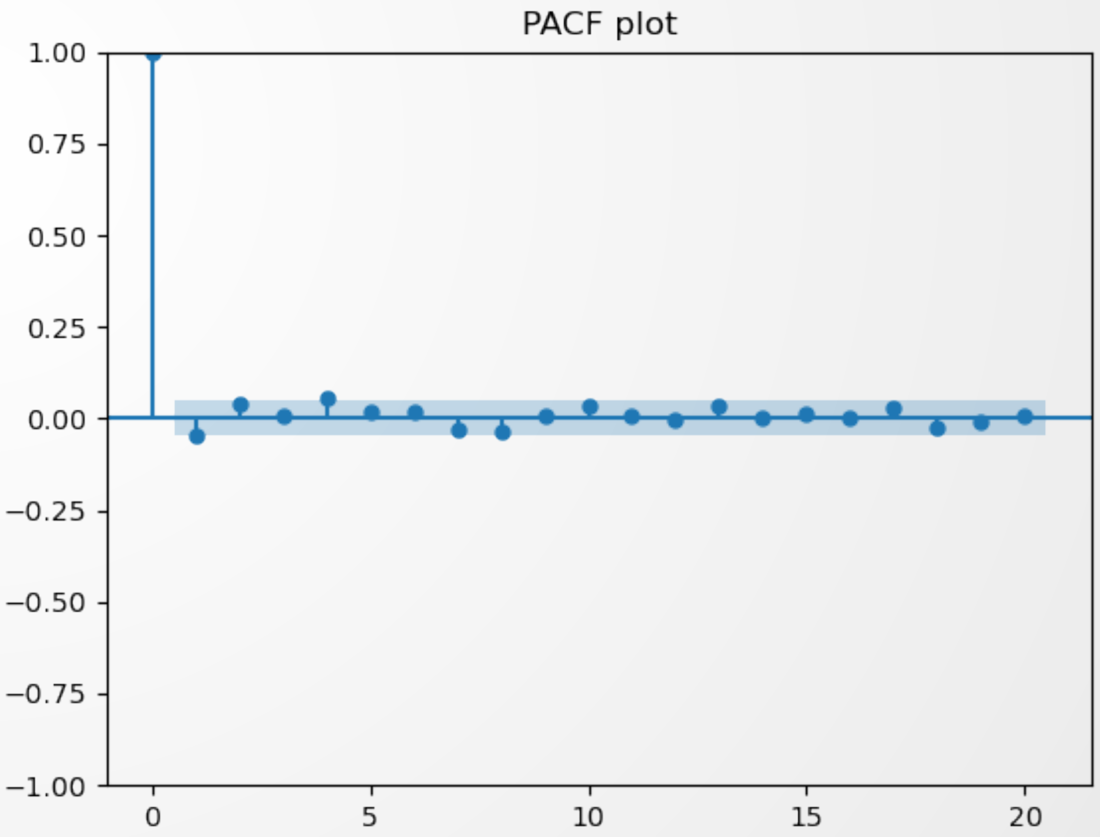
- Squared demeand returns: Mean-reverting in variance

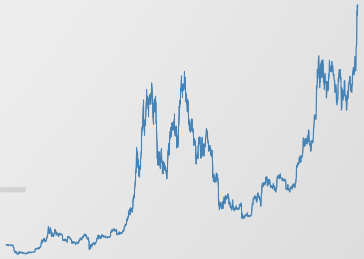


ACF and PACF for BTC returns

- Both are zero lags, suggesting that the series does not exhibit any autoregressive (AR) or moving average (MA) effects.

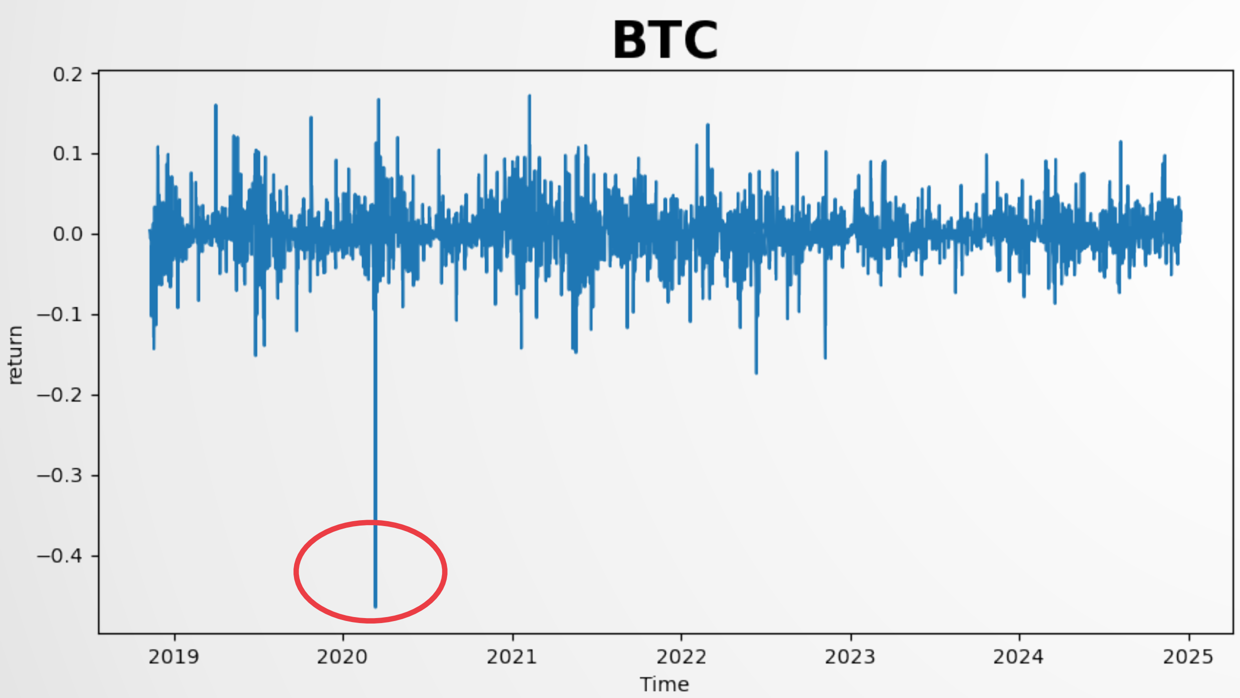






Tail Risk in Crypto Markets

- High kurtosis (16.09), left skewed (–1.17) → extreme jumps and losses
- JB test: Not normal distribution
- ADF test statistic of –18.57: stationary time series!



Summary Statistics BTC returns

Mean	0.00093
Standard deviation	0.0381
Skewness	-1.17
Kurtosis	16.09
Minimum	-0.46
Medium	0.0009676
Maximum	0.1718
JB	17526.26
ADF	-18.57

Outline

1. Motivation ✓
2. Data ✓
3. Model
4. Empirical Results
5. Conclusion

Stochastic Volatility with Correlated Jumps (SVCJ)

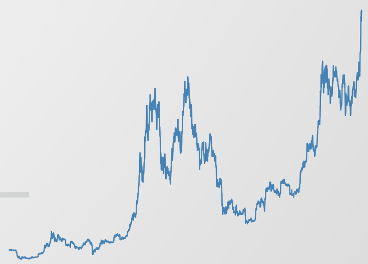
(1) $d \log S_t = \mu dt + \sqrt{V_t} dW_t^s + Z_t^y dN_t$: return process

(2) $dV_t = \kappa(\theta - V_t)dt + \sigma_V \sqrt{V_t} dW_t^v + Z_t^v dN_t$: variance process

(3) $Cov(dW_t^s, dW_t^v) = \rho dt$

(4) $P(dN_t = 1) = \lambda dt$: jump

(5) $Z_t^y \,|\, Z_t^v \sim N(\mu_y + \rho_j Z_t^v, \sigma_y^2);\ \ Z_t^v \sim exp(\mu_v)$



Stochastic Volatility with Correlated Jumps (SVCJ)

expected return

(1) $d\log S_t = \mu dt + \sqrt{V_t} dW_t^s + Z_t^y dN_t$: return process

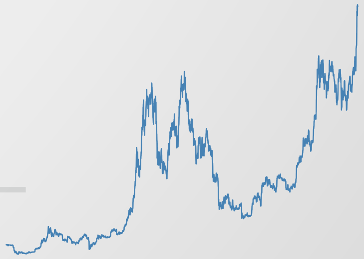
CIR model

(2) $dV_t = \kappa(\theta - V_t)dt + \sigma_V \sqrt{V_t} dW_t^v + Z_t^v dN_t$: variance process

(3) $Cov(dW_t^s, dW_t^v) = \rho dt$

(4) $P(dN_t = 1) = \lambda dt$: jump

(5) $Z_t^y \,|\, Z_t^v \sim N(\mu_y + \rho_j Z_t^v, \sigma_y^2);\ \ Z_t^v \sim exp(\mu_v)$



Stochastic Volatility with Correlated Jumps (SVCJ)

expected log return

(1) $d\log S_t = \mu dt + \sqrt{V_t} dW_t^s + Z_t^y dN_t$: log return process

Mean revertion rate and level standard Brownian motions

(2) $dV_t = \kappa(\theta - V_t)dt + \sigma_V \sqrt{V_t} dW_t^v + Z_t^v dN_t$: variance process

(3) $Cov(dW_t^s, dW_t^v) = \rho dt$

(4) $P(dN_t = 1) = \lambda dt$: jump

(5) $Z_t^y \,|\, Z_t^v \sim N(\mu_y + \rho_j Z_t^v, \sigma_y^2);\; Z_t^v \sim exp(\mu_v)$

Stochastic Volatility with Correlated Jumps (SVCJ)

(1) $d\log S_t = \mu dt + \sqrt{V_t} dW_t^s + Z_t^y dN_t$: return process

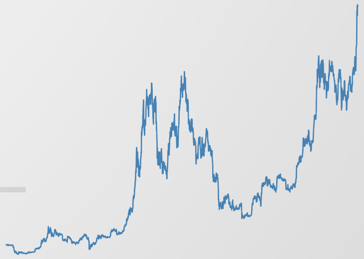
random jump sizes, jump process with jump frequency λ

(2) $dV_t = \kappa(\theta - V_t)dt + \sigma_V \sqrt{V_t} dW_t^v + Z_t^v dN_t$: variance process

(3) $Cov(dW_t^s, dW_t^v) = \rho dt$

(4) $P(dN_t = 1) = \lambda dt$: jump

(5) $Z_t^y \,|\, Z_t^v \sim N(\mu_y + \rho_j Z_t^v, \sigma_y^2);\;\; Z_t^v \sim exp(\mu_v)$



Stochastic Volatility with Correlated Jumps (SVCJ), Duffie (2000)

$$d\log S_t = \mu dt + \sqrt{V_t}dW_t^s + Z_t^y dN_t$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma_V\sqrt{V_t}dW_t^v + Z_t^v dN_t$$

Stochastic Volatility with Jumps (SVJ), Bates (1996) Set $Z_t^v = 0.$

$$d\log S_t = \mu dt + \sqrt{V_t}dW_t^s + Z_t^y dN_t$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma_V\sqrt{V_t}dW_t^v$$

Stochastic Volatility (SV), Heston (1993) Set $\lambda = 0.$

$$d\log S_t = \mu dt + \sqrt{V_t}dW_t^s$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma_V\sqrt{V_t}dW_t^v$$

Black and Scholes (BS) Set $\kappa = \theta = \sigma_V = 0$ and define $Z_t^v = Z_t^y = 0.$

$$d\log S_t = \mu dt + \sqrt{V_t}dW_t^s$$

$$dV_t = 0$$

MCMC algorithm

1. **For parameters : Draw ten parameters from prior distribution.**

Draw $\Theta_1^{(j)}$ from $p\left(\Theta_1^{(j)} \mid Y, \Theta_2^{(j-1)}, \Theta_3^{(j-1)}, \cdots, \Theta_K^{(j-1)}, V^{(j-1)}, J^{(j-1)}, Z^{V(j-1)}, Z^{Y(j-1)}\right)$

$\vdots$

Draw $\Theta_K^{(j)}$ from $p\left(\Theta_K^{(j)} \mid Y, \Theta_1^{(j)}, \Theta_2^{(j)}, \cdots, \Theta_{K-1}^{(j)}, V^{(j-1)}, J^{(j-1)}, Z^{V(j-1)}, Z^{Y(j-1)}\right)$

2. **For jump times $t = 1,2,\cdots,T$.**

Draw $J_t^{(j)}$ from $p\left(J_t^{(j)} = 1 \mid Y, \Theta^{(j)}, V^{(j-1)}, Z^{V(j-1)}, Z^{Y(j-1)}\right)$

3. **For jump sizes $t = 1,2,\cdots,T$.**

Draw $Z_t^{V(j)}$ from $p\left(Z_t^{V(j)} \mid Y, \Theta^{(j)}, V^{(j-1)}, J_t^{(j)}, Z_t^{Y(j-1)}\right)$

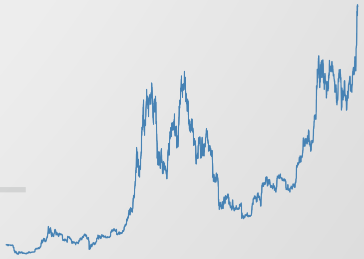
Draw $Z_t^{Y(j)}$ from $p\left(Z_t^{Y(j)} \mid Y, \Theta^{(j)}, V^{(j-1)}, J_t^{(j)}, Z_t^{V(j)}\right)$

4. **For spot volatilities**

Draw $V_1^{(j)}$ from $p\left(V_1^{(j)} \mid Y, \Theta^{(j)}, V_0^{(j)}, V_2^{(j-1)}, J^{(j)}, Z^{V(j)}, Z^{Y(j)}\right)$

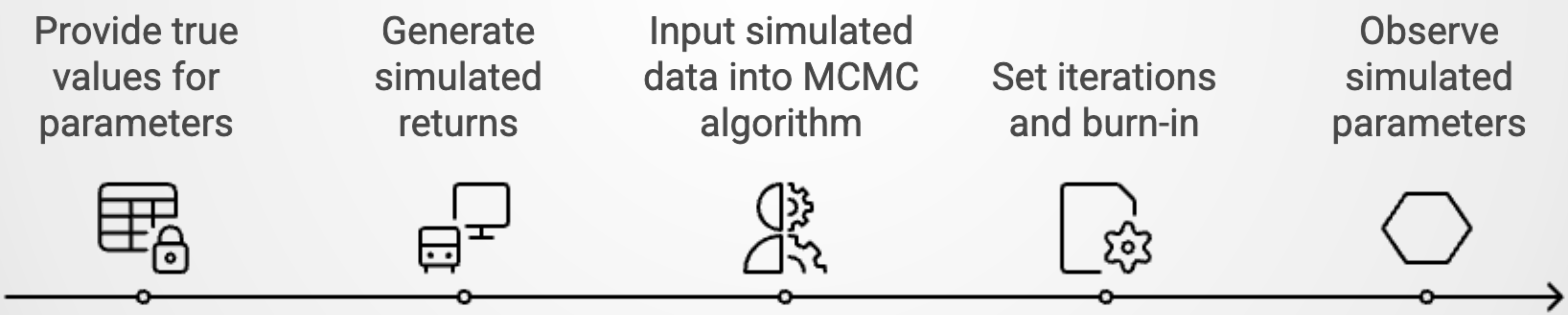
$\vdots$

Draw $V_T^{(j)}$ from $p\left(V_T^{(j)} \mid Y, \Theta^{(j)}, V_{((t-1))}^{(j)}, V_{(T+1)}^{(j-1)}, J^{(j)}, Z^{V(j)}, Z^{Y(j)}\right)$



Methodology

- Bayesian inference: posterior distribution of parameters
- Difficulty: posterior distribution typically does not have a closed form
- Employ Markov Chain Monte Carlo (MCMC)



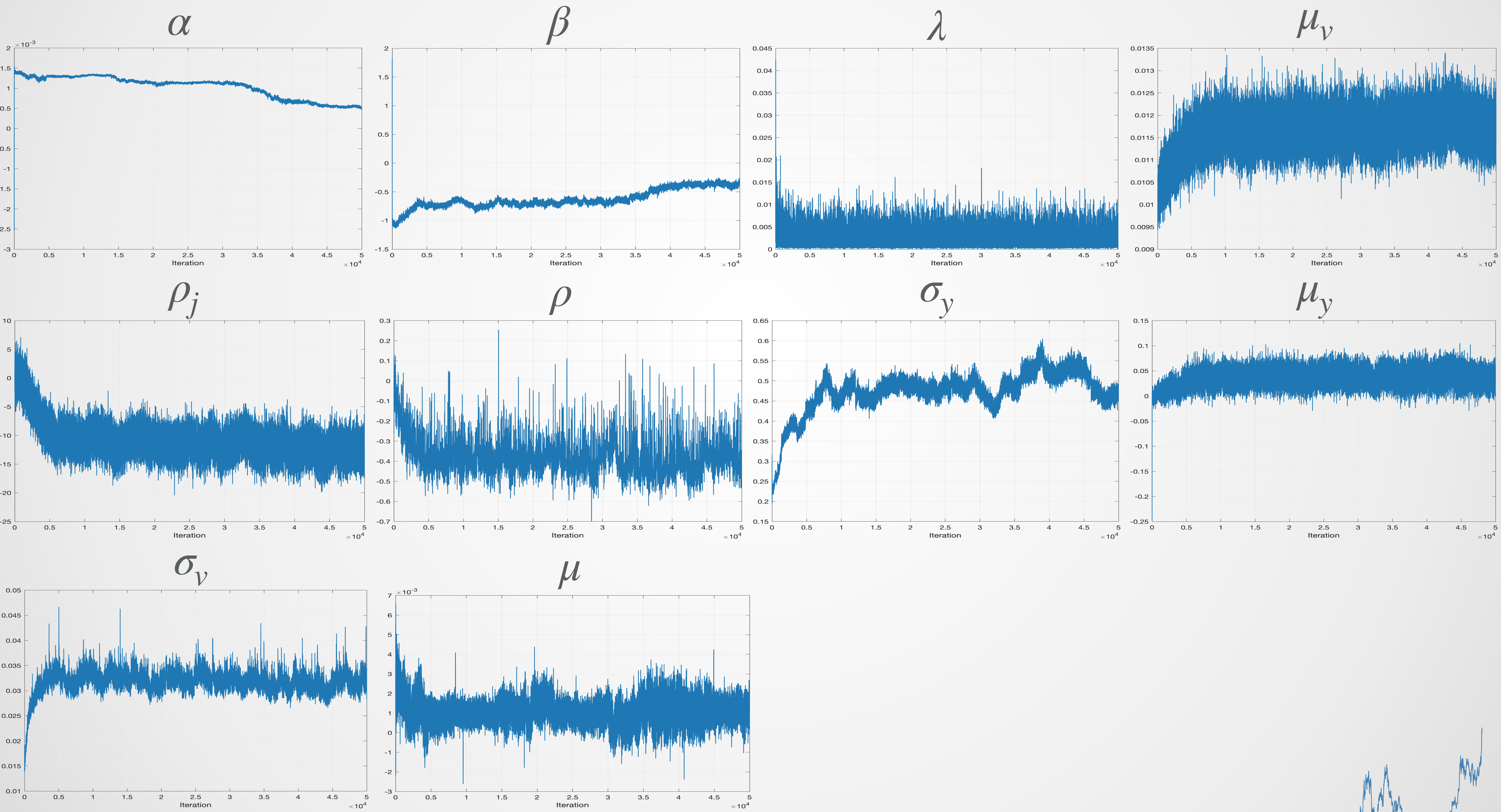
Steps of Simulation Study for MCMC algorithms

Simulation studies for SVCJ

					APE (%)	APE (%)	APE (%)
Parameters	True value	T = 10	T = 100	T = 1,000	T = 10	T = 100	T = 1,000
V_0	0.0014	0.0069	0.0045	0.0017	392.9%	221.4%	21.4%
μ	0.0009	0.0090	0.0062	0.0019	900.0%	588.9%	111.1%
μ_y	0.3166	-0.0283	0.00068	0.0023	108.9%	99.8%	99.3%
σ_y	0.0161	3.0906	0.3883	0.0399	19096.3%	2311.8%	147.8%
λ	0.0033	0.0479	0.0150	0.0019	1351.5%	354.5%	42.4%
α	0.000594	-8.0169E-05	5.2066E-07	2.7488E-05	113.5%	99.9%	95.4%
β	-0.7425	0.0162	0.0108	-0.0187	-102.2%	-101.5%	-97.5%
ρ	-0.6245	-0.0390	0.00042	0.0039	-93.8%	-100.1%	-100.6%
σ_v	0.0024	0.0184	0.0020	1.9950E-04	666.7%	16.7%	91.7%
ρ_j	-1.0821	-0.0015	0.0152	-0.0149	-99.9%	-101.4%	-98.6%
μ_v	0.0206	0.7141	0.0961	0.0100	3366.5%	366.5%	51.5%

Trace plots after burn-in

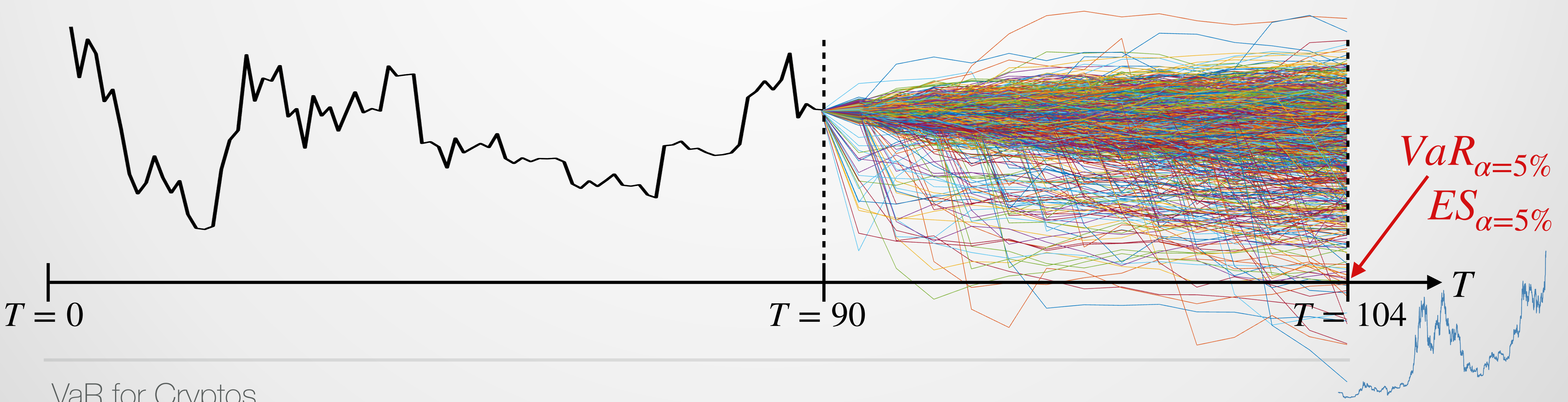
- Set number of iterations $50{,}000$ and $T = 1{,}000$.



Research plan

- Model: BS, SV, SVJ, SVCJ
- Confidence level α : $5\,\%$, $1\,\%$,
- Estimation windows H: 30, 90
- Holding period (forecast horizon) h: 1, 14, 28
- Rolling-window approach

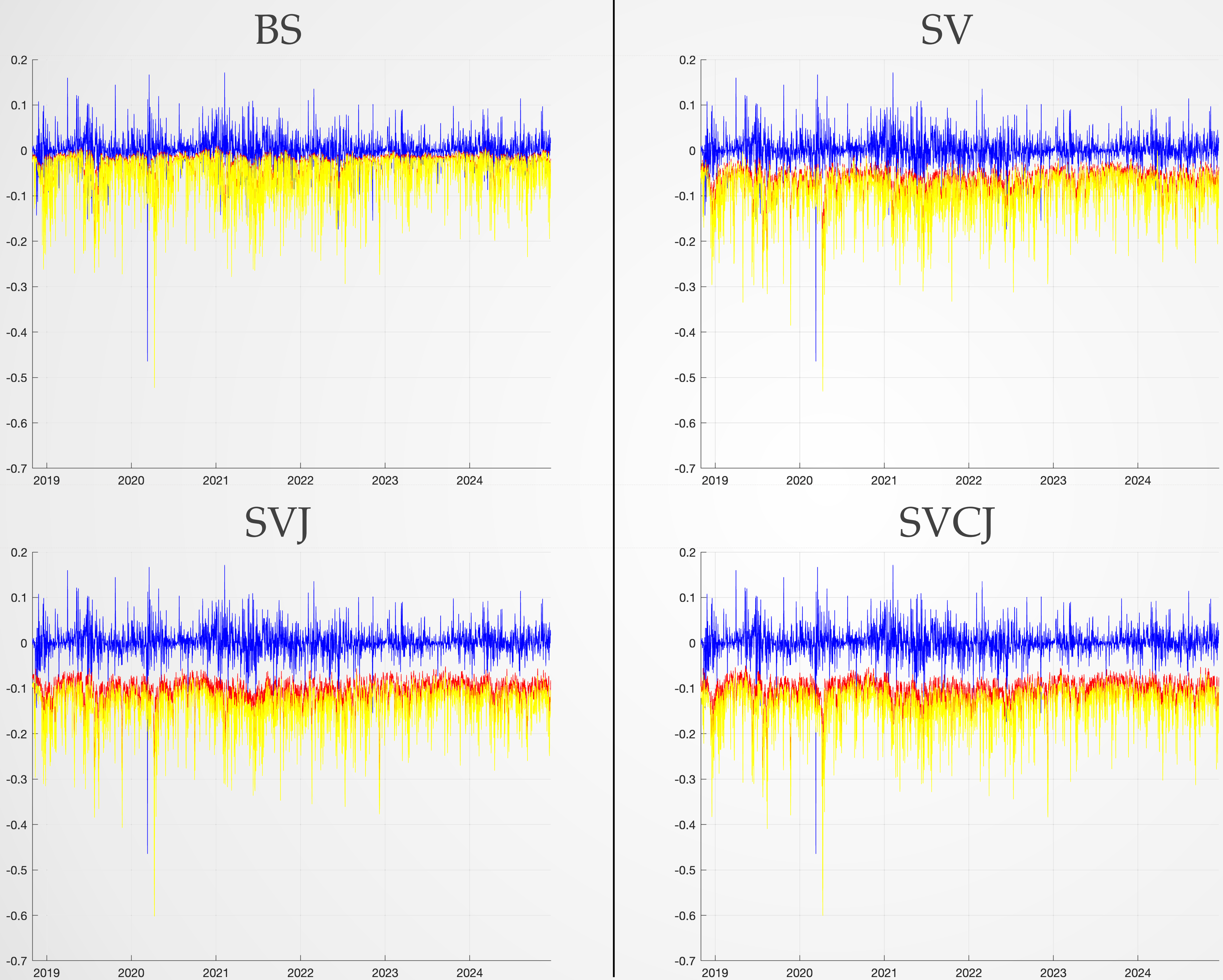
Example rolling window visualization for $H = 90$, $h = 14$



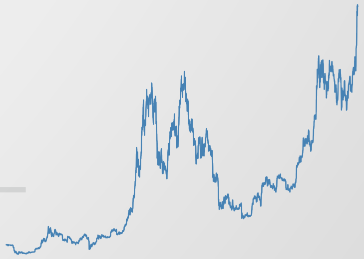
Backtesting

- An essential tool in assessing the accuracy and robustness of VaR models in risk management.
- Value-at-Risk (VaR)
  - Traffic Light Approach (Basel Committee on Banking Supervision, 1996)
  - Kupiec's POF test (Kupiec et al., 1995)
  - Christoffersen's Independence Test (Christoffersen, 2008): Check if exceedances occur independently across two consecutive days
- Expected Shortfall (ES) (Acerbi and Szekey, 2014)
  - Z_1 Test: test the average size of tail losses
  - Z_2 Test: test the variability of tail losses
  - Z_3 Test: test the model's ordering and distribution of tail losses
  - Embrechts evaluation: Measures average deviation between observed tail losses and predicted ES

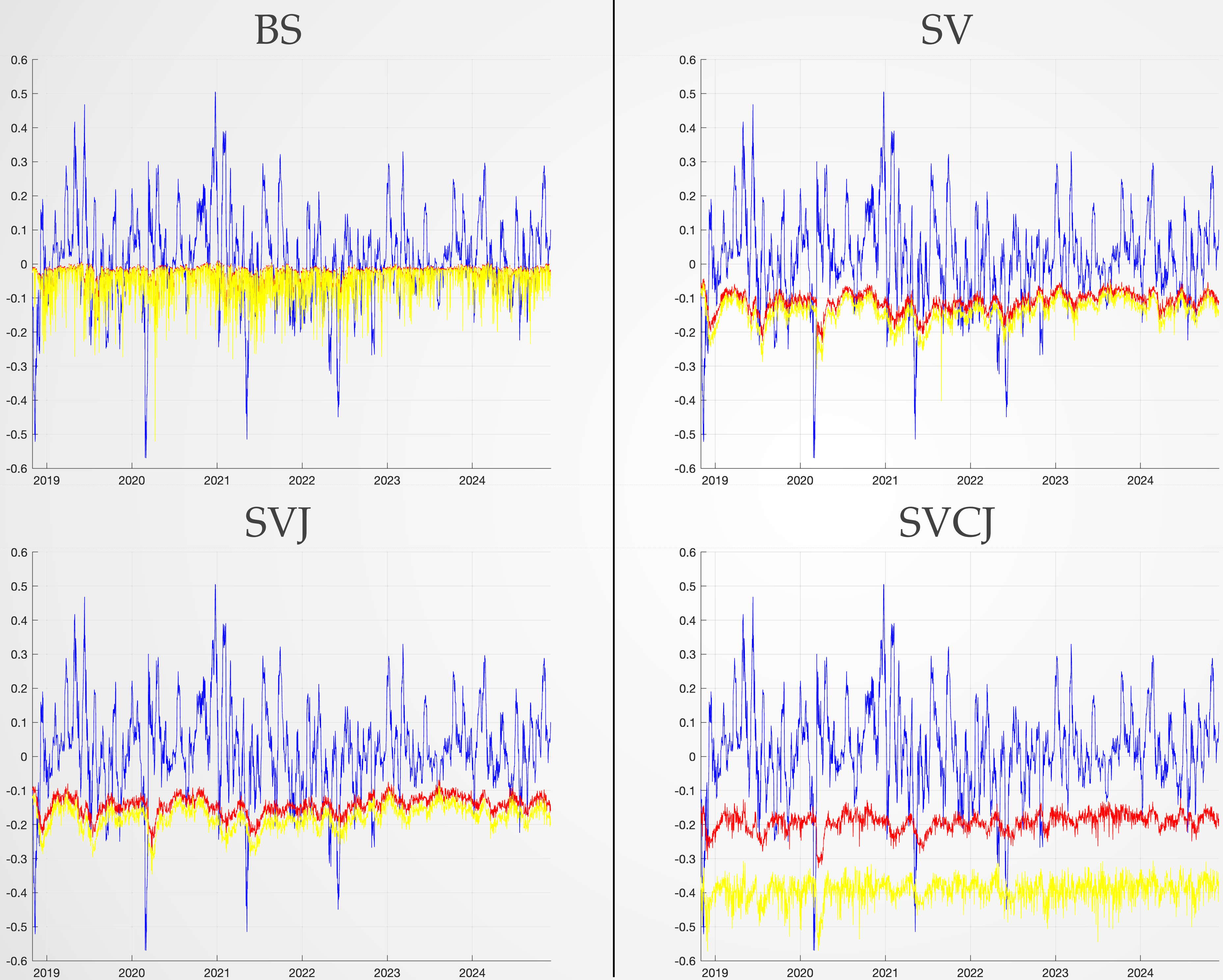
$H = 30, h = 1, \alpha = 5\,\%$



h=1	Exceedance rate (%)
BS	15.9517%
SV	3.8427%
SVJ	0.9383%
SVCJ	0.9383%



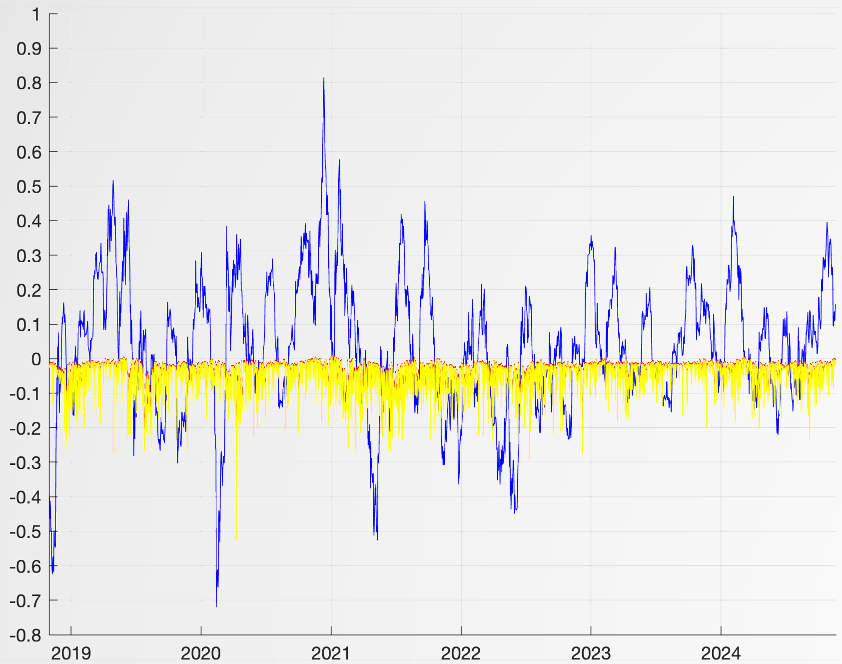
$H = 30, h = 14, \alpha = 5\,\%$



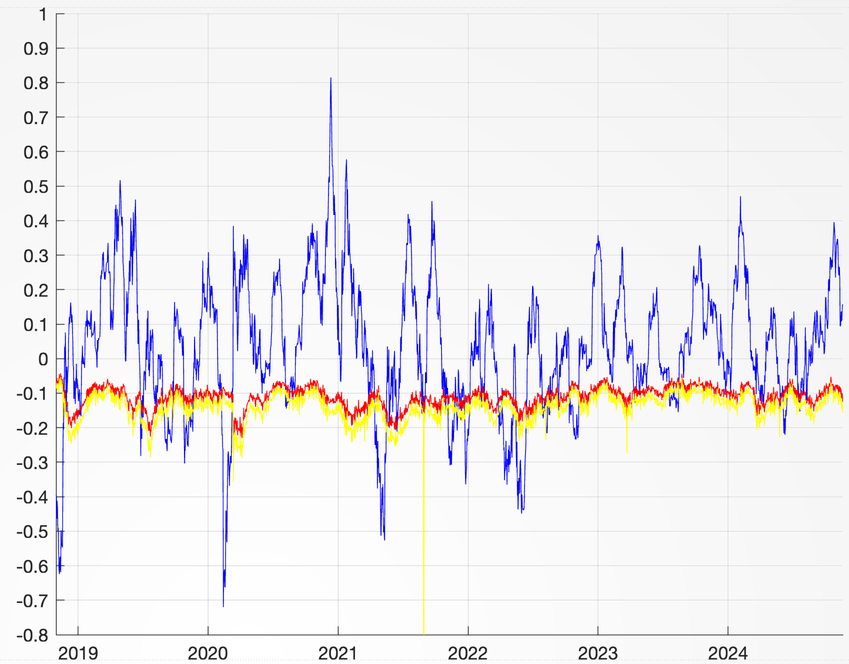
h=14	Exceedance rate (%)
BS	29.4382%
SV	13.0787%
SVJ	9.5730%
SVCJ	5.1236%

$H = 30, h = 28, \alpha = 5\,\%$

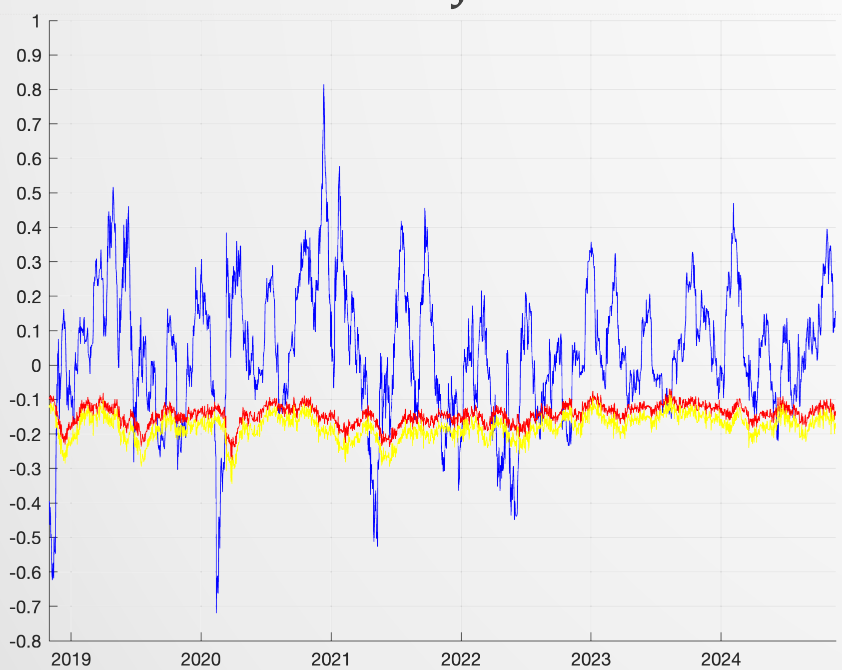
BS



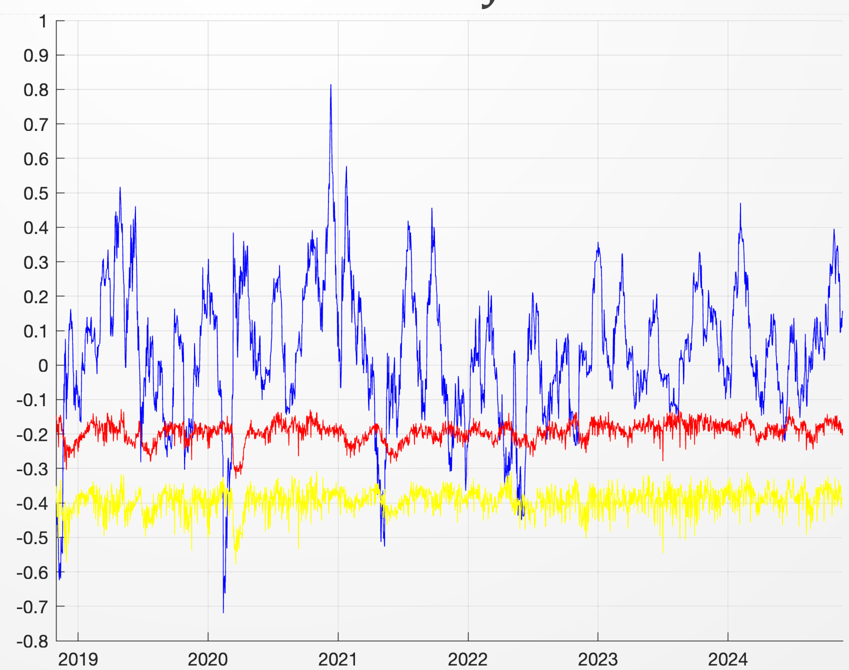
SV



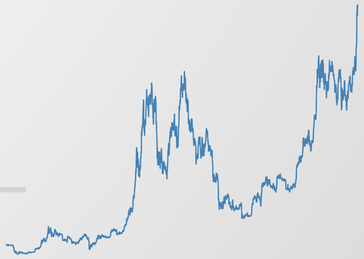
SVJ



SVCJ



h=28	Exceedance rate (%)
BS	32.5192%
SV	18.5436%
SVJ	15.3777%
SVCJ	10.0407%

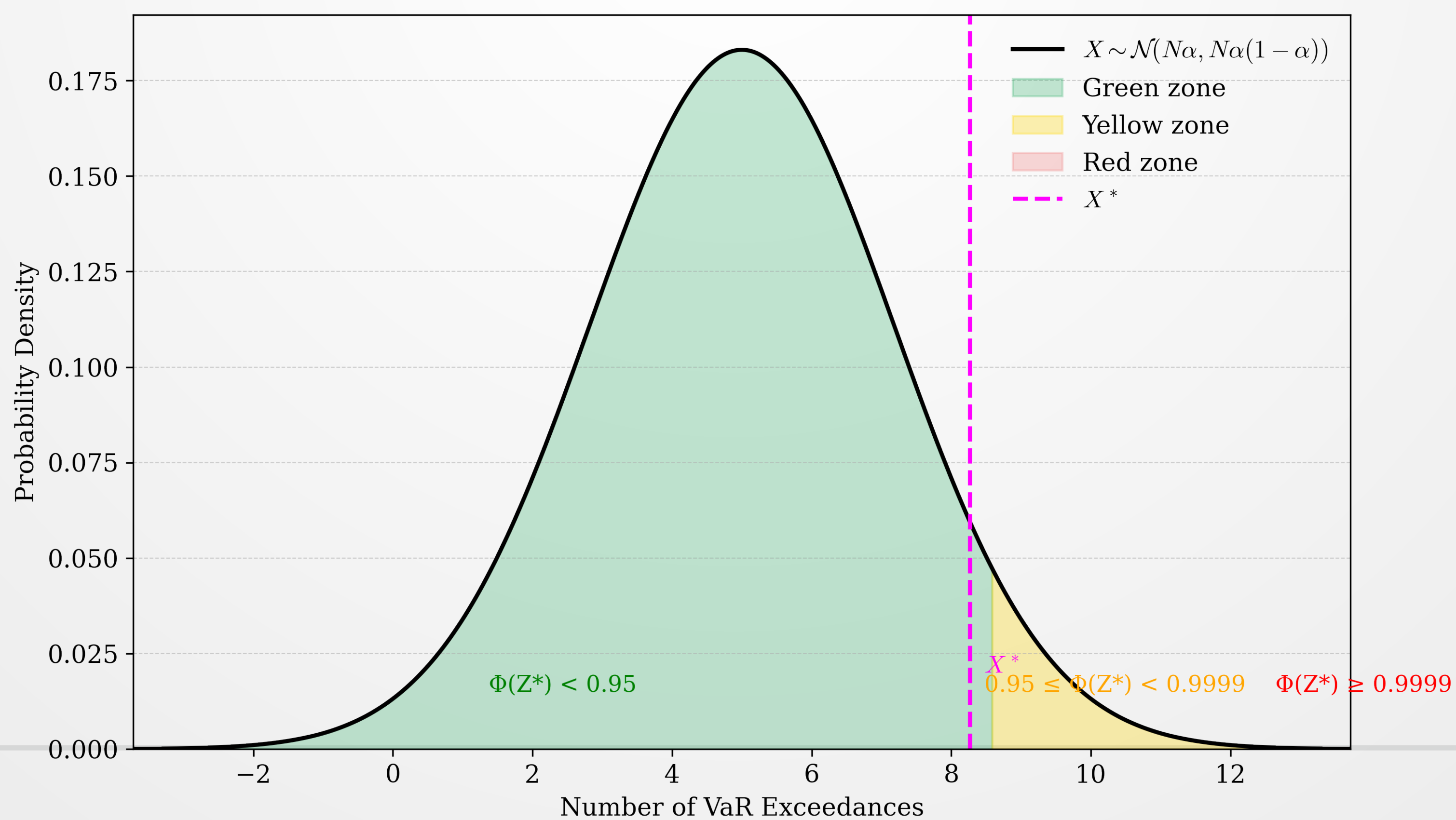


Traffic Light Approach

- Assume H_0 is correct, let $\mu = N\alpha$, $\sigma = \sqrt{N\alpha(1-\alpha)}$.
- Suppose the realized value of X is X^*, CLT gives

$$P(X \leq X^*) = P\left(\frac{X-\mu}{\sigma} \leq \frac{X^*-\mu}{\sigma}\right) \approx P(Z \leq Z^*) = \Phi(Z^*)$$

- Classify VaR performance into three distinct zones:
  - Green if $\Phi(z) < 0.95$, acceptable performance.
  - Yellow if $0.95 < \Phi(z) < 0.9999$, potential issues.
  - Red if $\Phi(z) \geq 0.9999$, unacceptable.



Kupiec's POF-test (proportion of failure)

- The null hypothesis:

$$H_0 : p = \alpha,$$

  where x is number of exceptions, n is total sample size,

  p is the true exception probability. We estimate $\hat{p} = x/n$.

- The binomial likelihood ratio test is conducted as:

$$LR_{POF} = -2ln\left(\frac{(1-\alpha)^{n-x}\alpha^{x}}{(1-x/n)^{n-x}(x/n)^{x}}\right)$$

- If $LR_{POF} > \chi^2_{1,(1-\alpha)}$ → reject $H_0 : p = \alpha$

  → the model is inadequately calibrated.

- Disadvantage: statistically weak for small sample sizes and examining testing only the failure rate and not the succession of occurrence.

Christoffersen’s Independence Test (Markov test)

- Exceedance indicator:

$$Indicator\ (I_t) = \begin{cases} 0\ if\ VaR\ is\ not\ breached, \\ 1\ otherwise \end{cases}$$

- The test statistic of independence test is:

$$LR_M = -2ln\left(\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1^{n_{11}}}\right),$$

  where $\pi_0 = \dfrac{n_{01}}{n_{00}+n_{01}}$, $\pi_1 = \dfrac{n_{11}}{n_{10}+n_{11}}$, $\pi = \dfrac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}}$

  follows a χ^2 distribution with $df = 1$.

- $H_0 : \pi_0 = \pi_1$, exceptions are independent across days.
- Disadvantage: It has limited power against clustering, as it only tests for the independence of exceptions on two consecutive days.

Z_1 Test: testing ES after VaR

- Z_1 examines whether ES is accurate in the long run.
- From $ES_{\alpha,t} = \mathbb{E}[X_t \,|\, X_t > VaR_{\alpha,t}]$, can easily derive

$$\mathbb{E}\left[\frac{X_t}{ES_{\alpha,t}} - 1 \,\middle|\, X_t - VaR_{\alpha,t} > 0\right] = 0$$

- Test statistic:

$$Z_1(\vec{X}) = \frac{\sum_{t=1}^{T} X_t I_t}{N_T ES_{\alpha,t}} - 1$$

- $H_0 : F_t^{[1-\alpha]} = P_t^{[1-\alpha]}, \forall t$

  $H_1 : ES^F_{\alpha,t} \geq ES_{\alpha,t}, \forall t \text{ and } > \text{ for some } t.$

  $\boxed{VaR^F_{\alpha,t} = VaR_{\alpha,t},} \forall t$

Z_2 Test: testing ES directly

- Z_2 focusing on tail losses, identifies clustering effects in extreme losses.
- Test statistic:

$$Z_2(\overrightarrow{X}) = \sum_{t=1}^{T} \frac{X_t I_t}{T(1-\alpha)ES_{\alpha,t}} - 1$$

- $H_0 : F_t^{[1-\alpha]} = P_t^{[1-\alpha]}, \forall t$

  $H_1 : ES^F_{\alpha,t} \geq ES_{\alpha,t}, \forall t \ and > for \ some \ t \, .$

  $\boxed{VaR^F_{\alpha,t} \geq VaR_{\alpha,t},} \forall t$

- If $\mathbb{E}(Z_2) = 0$, ES estimation model is correctly specified.

  If $\mathbb{E}(Z_2) > 0$, the actual loss is greater than the expected ES, underestimates the actual underlying risk.

  If $\mathbb{E}(Z_2) < 0$, overestimate risk.

Z_3 Test: estimating ES from realized ranks

- If P_t is correct, we can backtest by checking if the observed ranks $U_t = P_t(X_t)$ are i.i.d. $U(0,1)$.
  i.e.The model should not be able to "predict" tomorrow's losses.
- The rank U_t is the cumulated probability associated to the observed loss X_t.
- If the distribution of U_t deviates from a uniform distribution, it indicates that the risk model has systematic errors.
  - If U_t is skewed towards 0 (too many extreme losses): The risk model underestimates market risk
  - If U_t is skewed towards 1 (predicted losses are consistently larger than actual losses): The risk model is overly conservative.

$\alpha = 5\,\%\,,\, H = 30$

		VaR			ES			
h=1	$\hat{p}$	Traffic Light	POF test	Independence test	Z1	Z2	Z3	Embrechts evaluation
BS	15.95%	Red	367.5 (0.00)	0.0 (0.88)	1.56	-0.57	0.99	0.0353
SV	3.84%	Green	6.8 (0.01)	3.5 (0.06)	0.35	-0.95	-0.59	0.0174
SVJ	0.94%	Green	115.4 (0.00)	6.0 (0.01)	0.20	-0.99	-0.79	0.0324
SVCJ	0.94%	Green	115.4 (0.00)	6.0 (0.01)	0.13	-0.99	-0.85	0.0297
h=14								
BS	29.44%	Red	1388.6 (0.00)	853.2 (0.00)	6.95	1.46	8.42	0.1718
SV	13.08%	Red	215.9 (0.00)	869.4 (0.00)	0.62	-0.78	-0.16	0.1180
SVJ	9.57%	Red	78.2 (0.00)	703.9 (0.00)	0.38	-0.86	-0.48	0.0929
SVCJ	5.12%	Green	0.1 (0.79)	508.0 (0.00)	-0.24	-0.96	-1.20	0.0904
h=28								
BS	32.52%	Red	1671.9 (0.00)	1176.0 (0.00)	5.89	1.36	7.25	0.2422
SV	18.54%	Red	520.7 (0.00)	1341.2 (0.00)	0.91	-0.63	0.28	0.1871
SVJ	15.38%	Red	331.1 (0.00)	1245.6 (0.00)	0.56	-0.75	-0.18	0.1606
SVCJ	10.04%	Red	92.7 (0.00)	1008.0 (0.00)	-0.17	-0.91	-1.08	0.0438

$\alpha = 1\,\%\,, H = 30$

		VaR			ES			
h=1	$\hat{p}$	Traffic Light	POF test	Independence test	Z1	Z2	Z3	Embrechts evaluation
BS	11.04%	Red	760.5 (0.00)	0.1 (0.78)	1.39	-0.73	0.66	0.0609
SV	2.14%	Red	22.3 (0.00)	0.8 (0.38)	0.34	-0.97	-0.63	0.0391
SVJ	0.45%	Green	8.7 (0.00)	0.1 (0.76)	0.12	-0.99	-0.88	0.0169
SVCJ	0.40%	Green	10.4 (0.00)	0.1 (0.79)	0.08	-1.00	-0.92	0.0176
h=14								
BS	26.16%	Red	2836.0 (0.00)	709.4 (0.00)	3.52	0.20	3.72	0.2527
SV	8.63%	Red	501.5 (0.00)	659.5 (0.00)	0.52	-0.87	-0.35	0.1889
SVJ	4.85%	Red	173.1 (0.00)	486.9 (0.00)	0.39	-0.93	-0.54	0.1653
SVCJ	0.27%	Green	16.9 (0.00)	29.0 (0.00)	-0.32	-1.00	-1.31	0.2955
h=28								
BS	29.04%	Red	3280.4 (0.00)	978.9 (0.00)	4.48	0.61	5.08	0.3370
SV	13.89%	Red	1084.3 (0.00)	1206.6	0.72	-0.76	-0.03	0.2862
SVJ	9.91%	Red	628.8 (0.00)	958.0 (0.00)	0.48	-0.85	-0.37	0.2500
SVCJ	0.81%	Green	0.8 (0.36)	103.3 (0.00)	-0.26	-0.99	-1.26	0.2242

$\alpha = 5\,\%\,, H = 90$

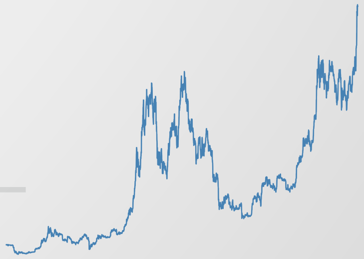
		VaR			ES			
h=1	$\hat{p}$	Traffic Light	POF test	Independence test	Z1	Z2	Z3	Embrechts evaluation
BS	12.49%	Red	185.0 (0.00)	7.1 (0.01)	6.83	0.03	6.86	0.0324
SV	6.34%	Yellow	7.6 (0.01)	3.2 (0.07)	0.50	-0.90	-0.39	0.0212
SVJ	1.56%	Green	73.3 (0.00)	2.5 (0.11)	0.26	-0.98	-0.72	0.0186
SVCJ	1.65%	Green	68.6 (0.00)	0.2 (0.63)	0.28	-0.98	-0.70	0.0165
h=14								
BS	27.81%	Red	1207.7	788.0 (0.00)	4.82	0.70	5.53	0.1485
SV	15.20%	Red	314.5 (0.00)	955.7 (0.00)	0.55	-0.75	-0.21	0.1103
SVJ	13.16%	Red	213.9 (0.00)	871.0 (0.00)	0.46	-0.80	-0.34	0.1012
SVCJ	11.13%	Red	129.0 (0.00)	822.3 (0.00)	-0.03	-0.89	-0.92	0.0357
h=28								
BS	30.40%	Red	1429.5	1154.7	9.39	2.33	11.72	0.2090
SV	21.90%	Red	733.2 (0.00)	1352.7	0.77	-0.59	0.18	0.1694
SVJ	19.76%	Red	585.2 (0.00)	1260.6	0.64	-0.66	-0.02	0.1586
SVCJ	16.92%	Red	408.3 (0.00)	1218.9	0.10	-0.80	-0.70	0.0894

$\alpha = 1\,\%\,,\, H = 90$

		VaR			ES			
h=1	$\hat{p}$	Traffic Light	POF test	Independence test	Z1	Z2	Z3	Embrechts evaluation
BS	9.37%	Red	564.2 (0.00)	2.1 (0.15)	1.38	-0.78	0.60	0.0600
SV	3.26%	Red	70.5 (0.00)	0.0 (0.83)	0.53	-0.95	-0.42	0.0479
SVJ	0.69%	Green	2.4 (0.12)	0.2 (0.65)	0.31	-0.99	-0.68	0.0267
SVCJ	0.51%	Green	6.6 (0.01)	0.1 (0.74)	0.64	-0.99	-0.35	0.0398
h=14								
BS	23.28%	Red	2325.8	554.4 (0.00)	3.23	-0.01	3.22	0.2276
SV	10.30%	Red	657.0 (0.00)	733.8 (0.00)	0.42	-0.85	-0.43	0.1786
SVJ	7.85%	Red	414.5 (0.00)	613.8 (0.00)	0.39	-0.89	-0.50	0.1699
SVCJ	2.22%	Red	24.1 (0.00)	234.2 (0.00)	-0.13	-0.98	-1.11	0.0389
h=28								
BS	27.06%	Red	2880.3	941.9 (0.00)	3.80	0.31	4.11	0.2811
SV	16.18%	Red	1337.3	1181.8	0.59	-0.74	-0.14	0.2341
SVJ	13.34%	Red	990.8 (0.00)	1082.9	0.52	-0.80	-0.28	0.2230
SVCJ	5.35%	Red	202.8 (0.00)	617.5 (0.00)	-0.13	-0.95	-1.08	0.0889

Conclusion

- Estimation window with $H = 30$ produces more accurate VaR estimation, compared wit $H = 90$
- As the holding periods increases (e.g., $h = 14$ or 28), the SVCJ model outperforms others in predicting VaR.
- As the holding periods increases (e.g., $h = 14$ or 28), the SVJ and SVCJ models outperforms others in predicting ES.



Tail risk in Bitcoin under the Basel framework

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