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Value-at-Risk Estimation and Backtesting Through Crises: Market Risk in the Indian Context

Author Details:

Arnav Singh Rawat[1]

[1] Anil Surendra Modi School of Commerce, SVKM's NMIMS Deemed-to-be University, Mumbai, India

Corresponding Author Email: arnavsrawat05@gmail.com | ORCID: https://orcid.org/0009-0009-3841-4608

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Abstract—

Value-at-Risk (VaR) sets trading limits, capital and exchange margins, and its accuracy matters most in a crisis. This paper reviews three empirical studies of VaR in Indian markets, covering the NIFTY 50 [1], government securities [2] and the S&P CNX 500 and INR/USD [3], and re-examines their published results. Recomputing the Kupiec statistics shows that Samanta et al. report $\chi^2(2)$ tail probabilities for a $\chi^2(1)$ test; corrected, simple historical simulation (HS) on 8.07% GS 2017 is rejected at 5% ($p = 0.0234$), although the tail-index model still ranks first. Sharma's average annual penalties rest on an unstated rule that charges every yellow-zone year 0.625, and two of her equity averages break it. Re-estimating VaR in real time on NIFTY 50 data for 23 March 2020, when the index fell 12.98%, shows that the day's loss was 4.21, 2.59 and 1.66 times the normal, HS and EWMA one-day 99% VaR. Over January 2020 to October 2021 (457 days), only a max(HS, EWMA) hybrid passed Kupiec's test ($p = 0.0659$), and it stayed in the Basel yellow zone. The studies agree that returns are fat-tailed and that normal VaR understates risk at 99%, but none of the models came close to the size of the crash. With the RBI moving commercial banks to the Simplified Standardised Approach from 1 April 2027, the findings bear most on internal limits and exchange margining, where models should be validated over a stress period with duration or multi-lag independence tests as well as exception counts.

Keywords— Value-at-Risk; backtesting; Kupiec test; COVID-19; Basel traffic light; Indian financial markets

JEL Classification— G21, G28, G32, C52

I. INTRODUCTION

Risk management means finding the exposures that can cause a loss, measuring how large that loss could be, and deciding how much of it to keep, hedge or back with capital. Measurement carries the most weight, because limits and capital charges are set from the measured loss and carry any error in it.

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This paper deals with market risk, the risk that a position loses value because market prices move. The three papers reviewed look at two equity indices, two government bonds and the rupee–dollar rate, and all use Value-at-Risk (VaR): the loss a position should exceed only with a small probability p over a chosen holding period [2, p. 4]. A one-day 99% VaR of ₹3 Cr means the desk expects to lose more than ₹3 Cr on about one trading day in a hundred.

Market risk matters in India to both banks and exchanges. Banks hold trading and investment books in government securities, equities and foreign exchange, and under the RBI's market-risk Directions of 21 September 2026, commercial banks will compute market-risk capital with the simplified standardised approach (SSA) from 1 April 2027 [4, paras. 2 and 39]. VaR also sets daily cash-market margins: NSE Clearing's VaR margin for Group I stocks is six times the EWMA estimate of daily volatility, with a 9% floor, plus a 3.5% extreme loss margin [5]. Daily moves can be very large: on 23 March 2020 the NIFTY 50 fell 12.98% to 7,610, after a 45-minute halt at the 10% lower circuit, its second such halt in ten days [6].

This paper asks whether VaR models hold up in a crisis, so each of the three studies is also judged on whether its backtest contains a stress episode.

The paper contributes in three ways. First, it recomputes the published backtests and finds that Samanta et al. [2] report $\chi^2(2)$ tail probabilities for a $\chi^2(1)$ statistic, which overstates how well historical simulation performs. Second, it reconstructs the unstated rule behind Sharma's [3] average annual penalties and identifies two averages that break it. Third, it re-estimates normal, HS and EWMA VaR in real time for the NIFTY 50 crash of 23 March 2020 and backtests them over the COVID-19 window. Section II reviews the three studies, Section III sets out the review design, models and tests, Section IV presents the recomputations, the event test and the discussion, and Section V concludes.

II. LITERATURE REVIEW

A. Shaik and Padmakumari (2022): equity indices through two crises

Risk problem. A bank or investor with an equity index position needs to know how much it could lose in a day; an optimistic VaR leaves limits, capital or margin too thin just when prices crash. The authors test whether three common VaR models stay accurate through the global financial crisis (GFC) and COVID-19 in the BRICS markets and the US (pp. 51–53); for India the exposure is the NIFTY 50.

How large. Over 2003–2021 the NIFTY 50's daily log return had a standard deviation of 1.41%, skewness of −0.19 and kurtosis of 15.68, and Jarque–Bera rejects normality (Table 1, p. 55). On these figures a normal one-day 99% VaR is about 3.22% in log-return terms (2.33 × 1.41% less the 0.07% mean), or ₹3.17 Cr on an illustrative ₹100 Cr NIFTY 50-tracking book using Samanta et al.'s [2, p. 7] conversion (Appendix D). The 12.98% fall on 23 March 2020 would have cost that book ₹12.98 Cr, about four times the VaR.

Entity, risk class and why a model. The paper studies an index, not an institution, so it stands in for an equity trading book or index fund; the risk is equity market risk. A model suits the problem because, unlike a judgement call, a VaR forecast can be checked: each day the loss either exceeds it or does not, and the exceptions can be tested formally.

Data. Daily Bloomberg prices for 2003–2021 give 4,676 NIFTY 50 returns. VaR is estimated on a 250-day window and tested from January 2006 to October 2021, with GFC (2008–2009) and COVID-19 (January 2020 to October 2021) sub-periods (p. 55; notes to Figures 1–3). The models are normal VaR, historical simulation (HS) and EWMA ($\lambda = 0.94$), each at 95% and 99% and each put through eight backtests (pp. 53–55).

Findings. Over the whole period the authors rank EWMA > HS > normal (p. 62). All three do worse in crises, and worse in COVID-19 than in the GFC (pp. 60–62). The India rows are less kind to EWMA than that ranking suggests. At 99% over 2006–2021 all three models fail the binomial and Kupiec POF tests, and normal and EWMA are both red while HS is yellow

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(Table 2, p. 59). In the COVID-19 window at 99% all three are red and fail the binomial, POF, conditional coverage and TBF tests (Table 3, p. 61).

B. Samanta et al. (2010): government bonds and the choice of an internal model

Risk problem. Under the Basel internal models approach (IMA) a bank's own VaR sets its market-risk capital, so it has a reason to prefer a model that understates risk (p. 15), and theory gives little guidance on which model to use (p. 3). The authors, from the RBI's Department of Statistics and Information Management [2, p. 1], treat model choice as an empirical question for the government securities (G-sec) market.

How large. Excess kurtosis is 8.15 for 8.07% GS 2017 and 9.16 for 7.37% GS 2014, and Jarque–Bera rejects normality at 1% for both (Table 1, p. 22). On the last day of the sample the normal one-day 99% VaR for 8.07% GS 2017 is 0.83%, against 1.35% from the tail-index model, 62.65% higher (Table 2, p. 23). Using the paper's conversion to rupee VaR (p. 7), a ₹500 Cr holding carries ₹4.13 Cr of VaR on the normal model and ₹6.70 Cr on the tail-index model.

Entity and risk class. The entity is a bank's G-sec portfolio, represented by the two most traded bonds, with the RBI as supervisor; the risk is market risk driven by interest rates and seen through bond prices.

Data. Daily trade prices run from August 2005 to July 2008, 747 working days; 8.07% GS 2017 traded on 685 of them and 7.37% GS 2014 on 608, and FIMMDA prices fill the gaps (pp. 19–20). Fewer than ten of over ninety outstanding G-secs traded in good volume (p. 19). Ten VaR variants (listed in Table I, Section II-D) are estimated on a 300-day rolling window and evaluated over the remaining 446 days (pp. 22–24, 27; p. 24 says 447, but the test statistics fit 446, as Section IV-A shows).

Findings. About 4.46 violations are expected in 446 days at 99%. The normal model produced 15 and 14, RiskMetrics 12 to 16, the hyperbolic model 7 and 6, and the tail-index model 5 and 3 (Table 3, p. 25). Lopez's (1998, as cited in [2]) loss function, which also counts the size of each excess loss, gives a similar ranking, lowest for the tail index (Table 5, p. 27). The authors conclude that normal VaR is biased downward, RiskMetrics does not fix it, a suitably chosen HS does reasonably well, and the tail-index method is the most accurate (p. 28).

C. Sharma (2012): equity and foreign exchange under the Basel III window rule

Risk problem. In the 2007–2008 turmoil, VaR models fed with calm-period data underestimated risk. The Basel Committee's 2009–2011 market-risk revisions (usually called Basel 2.5; Sharma calls them Basel III) responded by relaxing quantitative standard (d), the one-year minimum data rule: a bank may use a weighting scheme that breaks it if its capital charge is at least as conservative (Basel Committee on Banking Supervision, 2011, as cited in [3, p. 235]). Sharma reads this as allowing the higher of a long-window and a short-window HS VaR, and tests whether that helps (pp. 235–236). The users are Indian banks preparing for internal models: in a 2010 survey of Indian banks none had adopted the IMA, around 25% planned to move to it by December 2010 and 38% had set end-2011 as the deadline (p. 234). Of the 30 participating banks, 67% used historical methods (p. 236).

How large. The S&P CNX 500 had a daily standard deviation of 1.64%, a worst day of −12.88% and kurtosis of 10.66; INR/USD had 0.40% and 9.72, and Jarque–Bera rejects normality for both (Table 1, p. 238). The equity sample contains three daily falls of more than 10% (p. 238). HS 99% VaR on a ₹10 lakh portfolio in the index during 2011 was ₹24,112, or 2.41% a day (p. 235); because it is measured on portfolio value changes, it scales directly to ₹2.41 Cr on a ₹100 Cr book.

Entity, risk class and why a model. The entity is a bank's trading book, represented by a broad equity index, which Basel allows as the equity risk factor, and by INR/USD for all FX positions (p. 238); the risks are equity and FX market risk. A model is needed because capital is tied mechanically to VaR (p. 237), so the window choice directly changes the capital held.

Data. Daily S&P CNX 500 returns run from 1 January 2001 to 9 December 2011 (2,726 observations, NSE) and INR/USD from 17 May 2001 to 13 December 2011 (2,572, RBI) (pp. 238–239). All VaRs are one-day 99%

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HS on a daily rolling window: six windows from 125 to 1,000 days and eight hybrids pairing each window of 250 days or more with 190 or 125 days (p. 237).

Findings. Hybrids cut regulatory penalties: on the equity index, 1,000 + 190 days had the lowest average annual penalty, 0.104 against 0.208 for 1,000 days alone (Table 2, p. 239; one yellow year in six, against two), and hybrids also improved unconditional coverage (Tables 4–5, p. 241). But every equity VaR, basic or hybrid, fails the independence test at one lag and the conditional coverage test (Tables 6 and 8, p. 242). For INR/USD, four hybrids (1,000 or 750 days with 190 or 125) pass conditional coverage (Table 9, p. 242). Sharma recommends the combination but says the clustering failures should push the industry beyond HS (p. 243).

D. Comparing the papers

Table I sets the three papers side by side.

Table I: The three core papers compared

Paper	Entity and risk	Data and period	Models	Backtests	Stress episode in sample?	Key finding
Shaik & Padmakumari [1]	Equity index (NIFTY 50; five other indices) as a trading-book proxy; equity risk	Bloomberg, daily, 2003–2021; 4,676 NIFTY 50 returns; test Jan 2006–Oct 2021	Normal, HS, EWMA (λ = 0.94); 95% and 99%; 250-day window	Binomial, traffic light, Kupiec POF and TUFF, Christoffersen CCI and CC, Haas (2001) TBFI and TBF	Yes: GFC (2008–09) and COVID-19 (2020–21), reported separately	EWMA > HS > normal overall; all weak in crises, worst in COVID-19; India at 99% red for normal and EWMA
Samanta et al. [2]	Bank G-sec book (8.07% GS 2017, 7.37% GS 2014); interest-rate driven market risk	Trade prices with FIMMDA fill-ins, daily, Aug 2005–Jul 2008; 746 returns; 446 test days	Normal, simple and hybrid HS, RiskMetrics (λ = 0.94, 0.96, 0.98), hyperbolic, tail index; 99%; 300-day window	Violation counts, Kupiec POF, Lopez (1998) loss function (Basel penalties described only)	Partial: ends July 2008, before the worst of the GFC; includes the mid-2008 G-sec sell-off, but results pooled	Tail index most accurate, then hyperbolic; normal and RiskMetrics underestimate VaR

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Paper	Entity and risk	Data and period	Models	Backtests	Stress episode in sample?	Key finding
Sharma [3]	Bank trading book: S&P CNX 500 and INR/USD; equity and FX risk	NSE and RBI, daily; equity Jan 2001–Dec 2011 (2,726); FX May 2001–Dec 2011 (2,572)	HS only, 99%; windows 125–1,000 days and eight long–short hybrids (14 VaRs)	Basel penalty per 250 days; Christoffersen UC, independence (lags 1–4 reported) and CC	Yes: GFC inside the sample, but results pooled, not split	Hybrids cut penalties (0.104 vs 0.208); all equity VaRs fail independence and CC; four FX hybrids pass CC

Sources: Shaik and Padmakumari [1, pp. 53–62]; Samanta et al. [2, pp. 19–28]; Sharma [3, pp. 234–243]. HS = historical simulation; EWMA = exponentially weighted moving average; UC = unconditional coverage; CC = conditional coverage; CCI = conditional coverage independence; TUFF = time until first failure; TBF(I) = time between failures (independence).

Where they agree. Returns are fat-tailed in every market studied. Excess kurtosis is 8.15 and 9.16 for the G-secs [2, Table 1] and 7.66 and 6.72 for the S&P CNX 500 and INR/USD, since Sharma's 10.66 and 9.72 are raw (her Jarque–Bera statistics reproduce only with kurtosis minus 3). Shaik and Padmakumari do not say which their 15.68 is, but NIFTY 50 data for 2003 to October 2021 give raw kurtosis of 15.40 (my calculation; Appendix C), so theirs is almost certainly raw. The papers also agree that slow or thin-tailed models understate risk at 99% and that exceptions cluster: Shaik and Padmakumari's independence and duration tests reject most models (p. 60), and every equity VaR in Sharma fails independence at one lag (Table 6, p. 242).

Where they disagree. Each paper favours a different model: EWMA, the tail index and long–short hybrid HS. The biggest split is over exponential weighting: Shaik and Padmakumari rank EWMA ($\lambda = 0.94$) first, while Samanta et al.'s RiskMetrics at $\lambda = 0.94$ had 14 and 16 violations, no better than normal VaR. Part of the gap is design (EWMA's edge in Shaik and Padmakumari shows mainly at 95% and in the independence test, whereas Samanta et al. test only frequency at 99%); part may be the asset, since FIMMDA-filled bond prices can look artificially smooth (my inference, untested). Sharma adds that before Basel III EWMA was effectively disallowed, because at $\lambda = 0.94$ its effective observation period is only 16.7 days (Jorion, 2002a, as cited in [3, p. 236]); her hybrid recovers some of EWMA's responsiveness while staying within the one-year rule.

III. METHODOLOGY

A. Review design and selection of studies

All three core papers are empirical, use Indian data and were published from 2010 onwards. Shaik and Padmakumari [1] appeared in *Investment Management and Financial Innovations*, covered by Scopus since 2004 (CiteScore 2025: 3.0) [7] and double-blind refereed [8]; it was received on 11 November 2021 and accepted on 24 January 2022 (p. 51), a 74-day review. Samanta et al. [2] is an RBI Occasional Paper, reviewed by internal and external referees [9]. Sharma [3] appeared in *IIMB Management Review*, IIM Bangalore's quarterly journal, published by Elsevier and double-blind peer-reviewed [10].

B. Objective and type of problem

All three papers solve a measurement problem with a validation step: estimate each day a one-day VaR that the next day's loss should exceed with probability p (0.01 at 99%; Shaik and Padmakumari also use 0.05), then check whether losses exceeded it at that rate. Sharma [3, pp. 235–236] adds a policy question, whether a Basel III rule produces better VaR. The decision they inform is which model a bank adopts, and so how much capital it holds.

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C. Constraints and limits

- **Confidence level and horizon:** 99% in all three, as Basel requires, plus 95% in Shaik and Padmakumari [1]; one day for estimation and backtesting. Capital uses a 10-day VaR, usually the one-day figure times √10, a rule Samanta et al. [2, Eq. 1, pp. 7–8] note is not correct in general; for tail-index VaR they scale by $h^{1/\alpha}$ instead.
- **Estimation window:** 250 days (Shaik & Padmakumari), 300 days (Samanta et al.) and 125 to 1,000 days (Sharma). Basel's standard (d) requires at least one year of data, or an effective observation period of a year when data are weighted [3, p. 235], so Sharma's 125- and 190-day windows are not allowed on their own.
- **Regulatory limits:** capital is the higher of the previous day's VaR and the 60-day average VaR times a multiplier of at least 3, which rises by a plus factor of 0.40 to 1.00 once exceptions over 250 days reach five or more ([2, pp. 15–16]; plus factors from [11, Table 2]). The binding constraint is the multiplier, because every exception in the yellow zone raises capital directly.
- **Data:** thin G-sec trading restricts Samanta et al. [2, p. 19] to two bonds and three years.

D. Variables, parameters and equations

The variables are the price P_t and daily return r_t. The parameters are the tail probability p (one minus the confidence level), the window W, the mean μ and standard deviation σ, the standard normal quantile τ_p ($\tau_{0.01} = -2.33$), the decay factor λ (δ for hybrid HS) and the tail index α. Backtests use the number of test days N (T in Sharma) and of exceptions x.

$$r_t = \ln P_t - \ln P_{t-1} \qquad (1)$$

Returns are continuously compounded daily changes [2, Eq. 12, p. 20], [1, p. 55].

$$\text{Prob}[\Delta W_t(h) < -V^*] = p \qquad (2)$$

This defines VaR: V^* is the fall in position value over h days that is exceeded only with probability p [2, pp. 4–5].

$$\text{VaR}_{t+1} = | \hat{\mu}_t + \tau_p \hat{\sigma}_t | \qquad (3)$$

Normal VaR is the p-th percentile of a fitted normal distribution; with $\tau_{0.01} = -2.33$ it equals the textbook form VaR = $V(z\sigma - \mu)$. Shaik and Padmakumari [1, p. 53] give it only in words; equation (3) is exactly as printed by Samanta et al. (Eq. 2, p. 9).

$$\text{VaR}_{t+1} = -\, q_p(\, r_{t-W+1}, \ldots, r_t \,) \qquad (4)$$

Historical simulation reads off q_p, the empirical p-quantile of the last W returns, giving each day the weight $1/W$ [2, p. 10]. Sharma [3, p. 237] uses the same definition inside her exception indicator; none of the papers prints it as a separate equation.

$$w_i = \delta^{i-1}(1-\delta) / (1-\delta^k), \;\; i = 1, \ldots, k \qquad (5)$$

Hybrid HS weights the i-th most recent of k returns so recent days count more; VaR is the return at which cumulative weight, counted up from the worst return, reaches p (Boudoukh et al., 1997, as cited in [2, pp. 10–11]). Equation (5) is the normalised weight Samanta et al. print on p. 11; $\delta = 1$ gives simple HS (note 4, p. 29).

$$\hat{\sigma}^2_t = (1/c) \sum_{i=1}^{W} \lambda^{i-1} y^2_{t-i}, \quad c = \sum_{i=1}^{W} \lambda^{i-1} = (1-\lambda^W)/(1-\lambda) \qquad (6)$$

$$\text{VaR}_{t+1} = | \hat{\mu}_{t+1|t} + \hat{\sigma}_{t+1|t} \tau_p |, \quad \text{with } \hat{\mu}_{t+1|t} = 0 \qquad (7)$$

Equation (6) is EWMA variance as printed by Shaik and Padmakumari [1, Eqs. 1–2, p. 53], with y the daily return, W the window (W_E in the paper) and λ the decay factor: recent squared returns dominate, so volatility jumps after a shock. Equation (7) turns it into VaR with a zero conditional mean [2, Eq. 3, p. 11 and note 5]. Shaik and Padmakumari fix $\lambda = 0.94$ (Danielsson, 2012, as cited in [1]); Samanta et al.'s RiskMetrics uses the infinite recursion $\sigma^2_{t+1|t} = \lambda\sigma^2_{t|t-1} + (1-\lambda)r^2_t$, started from an initial variance σ^2_0 (Eq. 4, p. 12), with $\lambda = 0.94$, 0.96 and 0.98. The weighting is the same; Shaik and Padmakumari's version simply stops after W days and rescales the weights to sum to one.

$$\text{Prob}[X \le x] \approx C^\alpha |x|^{-\alpha}, \;\; x < -u \;(u > 0) \qquad (8)$$

$$\hat{\gamma}(k) = (1/k) \sum_{i=1}^{k} \ln(\, X_{(i)} / X_{(k+1)} \,), \quad \hat{\alpha} = 1 / \hat{\gamma}(k) \qquad (9)$$

Equation (8) follows Samanta et al.'s lower-tail Pareto approximation (Eq. 7, p. 14): beyond a threshold u, the chance of a loss of at least $|x|$ decays as a power of $|x|$

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with scale constant C, and a smaller tail index α means a fatter tail (the paper prints x where $|x|$ is needed). They estimate α with Hill's (1975, as cited in [2]) estimator without printing it or the number of tail observations k, so equation (9) gives the standard form for the $k + 1$ largest losses ordered $X_{(1)} \geq \ldots \geq X_{(k+1)}$ [12, Sec. 1]. Their hyperbolic density (Eq. 5, p. 13) reduces for one series to $f(r) = \exp[-\zeta\sqrt{(1 + ((r - \mu)/\delta)^2)}] / [2\delta K_1(\zeta)]$, with location μ, scale δ, tail parameter ζ and K_1 a Bessel function (my reduction; Appendix C), fitted by numerical maximum likelihood (Bauer, 2000, as cited in [2]).

$$\mathrm{VaR}^{H}_t = \max(\mathrm{VaR}^{L}_t, \mathrm{VaR}^{S}_t),$$
$$L \in \{250, 500, 750, 1000\},\ S \in \{125, 190\} \quad (10)$$

Sharma's hybrid takes the larger of a long-window (L) and a short-window (S) HS VaR each day, so it rises quickly with volatility but never falls below the long-window figure, which is her case that it meets revised standard (d) (p. 235). She states the rule in words (p. 237); equation (10) writes it out.

$$\mathrm{MRC}_t = \max\{\mathrm{VaR}_{t-1}(10),$$
$$(3 + k) \times (1/60) \Sigma_{i=1}^{60} \mathrm{VaR}_{t-i}(10)\} \quad (11)$$

Equation (11) is the Basel market-risk charge, stated in words by Samanta et al. [2, pp. 15–16] and Sharma [3, p. 237]: the higher of yesterday's 10-day 99% VaR and the 60-day average times 3 plus a backtesting penalty k of 0 to 1. The VaR level a model produces and the number of exceptions it generates therefore both feed straight into capital.

Decision rule. On each test day an exception is recorded when the loss exceeds the previous day's VaR ($I_t = 1$ if $-r_t > \mathrm{VaR}_{t|t-1}$, else 0), and $x = \Sigma I_t$ is compared with the Np expected. A model is kept if x is in the Basel green zone and the tests in Section III-G do not reject it.

E. Assumptions

- **Distribution:** normal VaR assumes normal, i.i.d. returns [2, p. 8], [1, p. 53]; Jarque–Bera rejects normality in all three papers. Sharma [3, p. 235] classes HS as non-parametric but still i.i.d.: it assumes the last W days are a fair sample of tomorrow, so it reacts slowly when volatility rises [1, p. 53].
- **Fixed parameters:** λ is imposed, not estimated, in Shaik and Padmakumari [1], so no EWMA parameter is fitted to Indian data.
- **Single position:** all three analyses are univariate, so correlations between positions never enter [2, p. 8], [3, p. 238].
- **Liquidity and time:** positions are assumed to be valued and exited at observed prices within the horizon, although Samanta et al. [2, pp. 19–20] fill no-trade days with FIMMDA prices; the √10 rule assumes i.i.d. returns over ten days (pp. 7–8).

F. Estimation technique and software

All three papers re-estimate VaR daily on a rolling window. Shaik and Padmakumari [1] fit nothing beyond sample moments and quantiles, since λ is imposed; Samanta et al. [2, pp. 13–14] fit the hyperbolic model by numerical maximum likelihood and the tail index by Hill's method; Sharma [3, p. 237] uses non-parametric HS. No paper names a software package. Shaik and Padmakumari credit "Software: Muneer Shaik" (p. 62), and their eight tests match the backtest set in MATLAB's Risk Management Toolbox [13], whose documentation the paper lists among its references, so MATLAB is likely but not confirmed.

G. Backtests

The basic frequency test is Kupiec's proportion-of-failures (POF) likelihood ratio, as printed by Shaik and Padmakumari [1, Eq. 4, p. 54]:

$$\mathrm{LR}_{POF} = -2 \ln[(1 - p)^{N-x} p^x]$$
$$+ 2 \ln[(1 - x/N)^{N-x} (x/N)^x] \sim \chi^2(1) \quad (12)$$

It asks whether the exception rate x/N matches p (Kupiec, 1995, as cited in [1]). Christoffersen's (1998, as cited in [1]) independence statistic LR_{ind} (Eq. 6, p. 54) asks whether an exception today makes one tomorrow more likely, and conditional coverage adds the two: $\mathrm{LR}_{CC} = \mathrm{LR}_{POF} + \mathrm{LR}_{ind} \sim \chi^2(2)$ (Eq. 8). Sharma [3, Eqs. 2–4, pp. 237–238] prints the same statistics, with a sign slip in Eq. 2 (Appendix C), and tests independence at lags of up to five days (Clements & Taylor, 2002, as cited in [3]), though her Tables 6–7 report only one to four lags. The Basel traffic light for 250 days at 99% is green for 0–4 exceptions, yellow for 5–9 and red for 10

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or more, cut where the cumulative binomial probability reaches 95% and 99.99% [11, Table 2].

IV. RESULTS AND DISCUSSION

A. Recomputing the reported statistics

Shaik and Padmakumari [1] report only accept or reject, with no exception counts or statistics, so their results cannot be recomputed and the Basel multiplier cannot be worked out. Samanta et al. [2] report counts, so I recomputed their Kupiec statistics from equation (12). For simple HS on 8.07% GS 2017, $x = 10$ and $N = 446$, so $\ln L_0 = 436 \ln 0.99 + 10 \ln 0.01 = -50.4336$ and $\ln L_1 = 436 \ln(436/446) + 10 \ln(10/446) = -47.8644$, giving

$$\mathrm{LR}_{\mathrm{POF}} = -2(-50.4336) + 2(-47.8644) = 5.14 \qquad (13)$$

This matches the printed 5.14, and every other LR value in their Table 4 also reproduces, but only with $N = 446$ (746 returns less the first 300); the paper says 447 days on p. 24. The larger problem is the p-values. The paper prints the standard POF statistic (Eq. 8, p. 16) and says it is χ^2 with one degree of freedom (p. 17), yet every printed p-value is the $\chi^2(2)$ tail: for LR = 5.14 the printed 0.0766 is $P(\chi^2_2 > 5.14)$, while $P(\chi^2_1 > 5.14) = 0.0234$. Corrected, simple HS on 8.07% GS 2017 is rejected at 5%, and hybrid HS at 0.94 (LR = 3.60) falls from p = 0.1650 to 0.0576 for both bonds. The tail-index and hyperbolic models still pass ($p \geq 0.2645$), so the ranking survives. The claim that a well-chosen HS keeps violations acceptable (p. 26) is weaker: it holds for both bonds only for hybrid HS at 0.94, and only at 5%, while simple HS passes for 7.37% GS 2014 alone (p = 0.0576). Applying Basel's 95% and 99.99% thresholds to 446 days gives green for 0–7 exceptions, yellow for 8–13 and red for 14 or more (Appendix B): the normal model is red for both bonds, RiskMetrics is red in five of six cases, and only the hyperbolic and tail-index models are green. Table A1 in Appendix A gives the full recomputation.

Sharma [3] reports p-values, not counts, so only partial checks are possible. Her conditional coverage results reconcile with their parts (for INR/USD at 1,000 + 190 days, 1.52 + 1.16 = 2.68, giving p = 0.262 as printed in Table 9), but two things do not: a p-value of exactly 1 (Table 4, p. 241) is impossible with 1,727 test days, and the average annual penalties rest on a rule the paper never states. Each average is 0.625 (the midpoint of the 0.40–0.85 yellow-zone range in her Eq. 1) for every yellow year plus 1.00 for every red year, divided by the number of 250-day years, so 0.104 is one yellow year in six. Basel sets the plus factor by the number of exceptions instead, so these penalties are approximations, and two of the equity averages break her own rule (Appendix C).

B. Robustness, sensitivity and stress coverage

Shaik and Padmakumari [1] test sub-periods and two confidence levels but never vary λ or the window, so their EWMA result rests on one parameter choice. Samanta et al. [2] vary λ and δ, which matters (hybrid HS goes from 9 to 15 violations on 7.37% GS 2014), but use one window and one test sample. Sharma [3] is the most thorough on windows but uses only HS at 99%. On stress coverage:

- **Shaik and Padmakumari [1]:** yes. The GFC and the COVID-19 crash are both in the test period and reported separately.
- **Samanta et al. [2]:** partial at best. The sample ends in July 2008, so by Shaik and Padmakumari's dating of the GFC (2008–2009) it catches only its first seven months, before the post-Lehman crash. For a G-sec study the more relevant stress is the mid-2008 sell-off: the 10-year benchmark yield closed the week to 11 July 2008 at 9.45%, after touching 9.55%, its highest since September 2001 [14], and the RBI raised the repo rate to 9.0% on 29 July [15]. That episode is inside the sample, but results are pooled over 446 days, so its effect cannot be seen, and the paper's validation through stress is weak.
- **Sharma [3]:** yes in coverage, not in reporting. The 2001–2011 sample includes the GFC and three daily equity falls of more than 10% (p. 238), but results are pooled over the whole period, so crisis performance cannot be separated.

C. Strengths

Each paper does something the others do not. Shaik and Padmakumari [1] have the broadest test battery (frequency, independence and duration) and run it across

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two crises. Samanta et al. [2] work with rarely studied Indian G-sec data and the widest model set, including extreme value theory; their loss function also weighs the size of excess losses. Sharma [3] tests an actual Basel rule on two asset classes from a bank's trading book and checks independence at several lags.

D. Limitations and model risk

Fat tails. All three reject normality, yet two lean on models whose tails are thin or borrowed: Shaik and Padmakumari's EWMA puts a normal quantile on a moving volatility, and Sharma's HS sees tails only as fat as its window has seen, with VaR unaffected by losses beyond the first percentile (p. 240). Only Samanta et al. model the tail directly, and their tail-index result is the strongest evidence in the three papers that this matters.

Exception clustering. Shaik and Padmakumari find that independence and duration tests reject most models (p. 60), and Sharma finds every equity VaR fails at one lag, warning that HS's popularity "could be in danger" if regulators tested for clustering (p. 240). Samanta et al. describe Christoffersen's tests (p. 17) but do not apply them, so their tail-index success is unconditional only: it gets the number of violations right without showing they are spread out.

Correlation breakdown. None of the papers models a portfolio, so none can show what happens when correlations shift in a crisis and equity, bond and currency losses arrive together.

Evaporating liquidity. The one-day horizon assumes positions can be exited at the quoted price within a day. Samanta et al. [2, p. 19] show how far that is from the G-sec market: fewer than ten of over ninety bonds traded in good volume, and FIMMDA prices filled the gaps, which probably smooths measured returns and understates volatility (my inference, untested).

Reporting errors. Each paper has slips that a reader relying on its text would miss. Besides Samanta et al.'s degrees-of-freedom error (Section IV-A), Shaik and Padmakumari say conditional coverage rejects every model at both confidence levels (p. 60), though their Table 2 shows six models passing at 95%, and Sharma says the 1,000 + 190-day hybrid earns the lowest penalty in both series (p. 243), though for INR/USD it ties at 0.208 with four other VaRs, including the plain 250-day one (Table 3, p. 240). Appendix C lists the rest.

E. Extensions, including Indian data and a recent regulatory change

- **Extend the G-sec study through stress.** Re-running Samanta et al.'s ten models on a sample that includes the 2013 taper tantrum or March 2020 would test whether the tail-index advantage survives a real crisis, and applying Shaik and Padmakumari's eight tests would show whether its correct counts hide clustering.

- **Move from VaR to Expected Shortfall.** Basel's Fundamental Review of the Trading Book has internal models compute Expected Shortfall at a 97.5th percentile, one-tailed, on a 10-day base horizon [16, MAR33.3–MAR33.4]. Sharma [3, p. 235] noted regulators weighing ES because VaR ignores losses beyond the first percentile; ES would reward the tail modelling Samanta et al. found most accurate.

- **Indian regulation has gone the other way, for now.** In 2010 Indian banks were preparing for internal models [3, p. 234]; the RBI's 2026 Directions instead require every commercial bank to use the SSA [4, para. 39] and contain no internal-models approach and no mention of VaR, Expected Shortfall or backtesting (the only models are options-pricing models for delta-plus sensitivities, para. 89). The machinery in these papers now sits in banks' internal limits rather than Pillar 1 capital, and in exchange margining.

F. Testing the models against one real event: the COVID-19 crash of 23 March 2020

On 23 March 2020 the NIFTY 50 closed at 7,610.25, down from 8,745.45, a fall of 12.98% and a log return of −13.90% [17]. Because every VaR in this paper is estimated on log returns, the comparisons below use the 13.90% log loss. Against Shaik and Padmakumari's full-sample standard deviation of 1.41% (Table 1, p. 55), that is a 9.86σ move (9.91σ after subtracting the 0.069% mean, a normal probability of about 1.9×10^{-23}), and the loss was 4.32 times the full-sample normal 99% VaR of 3.22% (Appendix D).

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A fairer test uses only what a risk desk knew on 20 March. Re-estimated on the 250 trading days to that date (my calculation; Appendix E), the one-day 99% VaRs were 3.30% (normal), 5.38% (HS) and 8.37% (EWMA), and the loss breached all three, at 4.21, 2.59 and 1.66 times VaR. EWMA reacted most, as early-March falls had lifted its volatility to 3.59% against a 250-day 1.37%, but still fell 5.54 percentage points short; covering the day would have needed a daily volatility of 5.97% (Appendix D). Over Shaik and Padmakumari's COVID-19 window (January 2020 to October 2021, 457 days, 4.57 exceptions expected), normal VaR had 12 exceptions, HS 11 and EWMA 16, EWMA's extra ones coming as its VaR fell back after the crash. All fail Kupiec's test at 5%, as in their Table 3 (p. 61), but only EWMA is red, where the paper has all three red. Most normal and HS exceptions fell in February–March 2020, yet the one-lag independence test rejects none ($p > 0.25$), because bad days were rarely back to back. Sharma's multi-lag tests address that gap. HS errs the other way later, still at 4.28% on 23 March 2021 against 2.00% before the crash. A max(HS, EWMA) hybrid in the spirit of Sharma's rule had 9 exceptions and was the only version Kupiec's test did not reject ($p = 0.0659$), at the cost of a 5.32% average VaR against 3.09% for EWMA.

Limits of this test. It covers one index and uses NIFTY Indices closes rather than the authors' Bloomberg series, which do not reproduce their Table 1 exactly (Appendix C). The normal quantile is rounded to 2.33, and the HS VaR depends on the interpolation rule, because the 1st percentile of 250 returns falls between the second- and third-worst days. Over 457 days Kupiec's test also has little power: any count from 2 to 9 exceptions passes at 5%, so the hybrid's pass with 9 is marginal.

No model got the size of the jump right. Exchange margins are set much wider: NSE's six-sigma VaR margin is 2.58 times the 2.33σ of a normal 99% VaR, before the 3.5% extreme loss margin [5]. Applied to the index as an illustration (NSE applies the rule to Group I stocks), six times the 3.59% EWMA volatility of 20 March 2020 is 21.54%, well above the 13.90% fall.

G. Implications for the firm, investors and the regulator

For the firm. A bank or AMC risk desk running normal VaR at 99% will under-reserve in a crisis: for India it is red in all three of Shaik and Padmakumari's windows (Tables 2–3, pp. 59, 61), and Samanta et al.'s normal model had 15 violations against 4.46 expected. The window is also a capital decision. Sharma [3] reports that moving from a 1,000-day VaR to the 1,000 + 190-day hybrid halved the average annual penalty on the equity index, from 0.208 to 0.104 (Table 2, p. 239). The direction is guaranteed, because the hybrid is never below the 1,000-day VaR and so cannot have more exceptions. But that also means it starts from a higher VaR, so a lower penalty need not mean lower capital, and the 0.104 charges each yellow year a flat 0.625 rather than Basel's count-based plus factor (Section IV-A).

For investors. A disclosed VaR describes a normal day; investors should look for Expected Shortfall, stress losses and the exception record before treating it as a worst case.

For the regulator. The SSA removes model-choice gaming from bank capital for now. If the RBI allows internal models later, approval should require conditional coverage tests and a stressed sample, since every equity VaR Sharma tested failed the one-lag independence test. For SEBI and the clearing corporations it supervises, the evidence supports keeping margins well above the normal quantile, as NSE's 6σ VaR margin and 3.5% extreme loss margin do. At the Basel level, Expected Shortfall at 97.5% targets the tail weakness all three papers document.

V. CONCLUSION

Read together, the three papers point the same way in three Indian markets: returns are fat-tailed and normal VaR understates risk at 99%. The two papers that test independence find that exceptions cluster (Shaik and Padmakumari; Sharma), though only Shaik and Padmakumari report it for a stress period, and Samanta et al. do not test for it. The papers differ on the fix: EWMA (Shaik and Padmakumari), tail modelling (Samanta et al.) or a more responsive HS (Sharma). In March 2020 even a real-time EWMA VaR was exceeded

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by 5.54 percentage points, and over the COVID-19 window only a hybrid with a historical floor passed Kupiec's test, at 5% and still in the yellow zone. The published numbers also needed checking: Samanta et al.'s p-values overstate how well HS performed, and some statements in the other two papers contradict their own tables.

Recommendation. Indian bank and AMC risk desks should stop relying on a normal one-day 99% VaR for equity and G-sec books in their internal limits, which is where VaR now sits for banks under the RBI's SSA. The evidence here supports a different replacement for each asset class: a historical floor with a volatility-responsive layer for equities, such as the max(HS, EWMA) hybrid in Section IV-F, and a tail-index model for G-secs, the most accurate in Samanta et al. Neither has been shown to hold up through a full crisis: the hybrid was still in the yellow zone over the COVID-19 window, and the tail-index result comes from a sample that ends in July 2008. Whichever model a desk adopts should therefore be validated on a sample that includes a crisis, with duration or multi-lag independence tests as well as exception counts, because the one-lag Christoffersen test missed the February–March 2020 clustering.

DECLARATIONS

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Data and code availability. NIFTY 50 closing values are publicly available from NIFTY Indices [17]. The exception counts and test statistics re-analysed here are published in the cited studies. Python code for every recomputation is given in Appendices A and E.

Declaration of generative AI and AI-assisted technologies in the writing process. During the preparation of this work the author used Claude (Anthropic), a generative AI tool, to locate and read the three core papers and the regulatory sources, to extract figures and check them against the original documents, to recompute the test statistics in Section IV and the appendices, to download NIFTY 50 index data and run the event test in Section IV-F and Appendix E, and to draft the text. The author chose the topic, approved the choice of papers and takes full responsibility for the content of the publication. Every equation, figure and data point is attributed to its source, and no data, results or citations have been invented. The AI tool is not an author of this work.

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APPENDIX A: RECOMPUTING THE KUPIEC STATISTICS IN SAMANTA ET AL. (2010)

Equation (12) was applied to each exception count in Samanta et al. [2, Table 3] with $p = 0.01$. Under the null, $\ln L_0 = (N - x)\ln(1 - p) + x \ln p$; under the alternative, $\ln L_1 = (N - x)\ln(1 - x/N) + x \ln(x/N)$; $\mathrm{LR} = -2(\ln L_0 - \ln L_1)$. For $x = 10$ and $N = 446$: $\ln L_0 = 436 \times (-0.010050) + 10 \times (-4.605170) = -4.3819 - 46.0517 = -50.4336$; $\ln L_1 = 436 \times \ln(0.977578) + 10 \times \ln(0.022422) = -9.8870 - 37.9773 = -47.8644$; $\mathrm{LR} = 5.1385$. Critical values: $\chi^2(1)$ is 3.84 at 5% and 2.71 at 10%; $\chi^2(2)$ is 5.99 at 5%.

With $N = 447$ the same count gives LR = 5.11, and 15 exceptions give 15.51 instead of 15.56, so the printed statistics were computed on 446 days. Table A1 gives every row; the code after it reproduces them.

Table A1: Samanta et al. [2]: Kupiec statistics recomputed and Basel zones for 446 test days

Model	GS 2017 x	LR	Printed p	p, $\chi^2(1)$	Zone	GS 2014 x	LR	Printed p	p, $\chi^2(1)$	Zone
Normal	15	15.56	0.0004	0.0001	Red	14	13.16	0.0014	0.003	Red
HS, simple	10	5.14	0.0766	0.0234	Yellow	9	3.60	0.1650	0.0576	Yellow
HS hybrid, 0.94	9	3.60	0.1650	0.0576	Yellow	9	3.60	0.1650	0.0576	Yellow
HS hybrid, 0.96	11	6.88	0.0321	0.0087	Yellow	12	8.80	0.0123	0.030	Yellow
HS hybrid, 0.98	12	8.80	0.0123	0.030	Yellow	15	15.56	0.0004	0.001	Red
RiskMetrics, 0.94	14	13.16	0.0014	0.003	Red	16	18.10	0.0001	0.000	Red
RiskMetrics, 0.96	12	8.80	0.0123	0.030	Yellow	16	18.10	0.0001	0.000	Red
RiskMetrics, 0.98	15	15.56	0.0004	0.0001	Red	16	18.10	0.0001	0.000	Red
Hyperbolic	7	1.25	0.5365	0.2645	Green	6	0.48	0.7848	0.4863	Green
Tail index	5	0.06	0.9687	0.8010	Green	3	0.55	0.7612	0.4601	Green

Sources: exception counts, LR values and printed p-values from Samanta et al. [2, Tables 3–4, pp. 25–26]; $\chi^2(1)$ p-values and zones are my recomputation (zones from Appendix B). The 7.37% GS 2014 LR values also reproduce exactly. Expected exceptions = 4.46.

```
from math import log
from scipy.stats import chi2, binom
p, N = 0.01, 446
counts = {"Normal": (15, 14), "HS simple": (10, 9), "HS hybrid 0.94": (9, 9),
          "HS hybrid 0.96": (11, 12), "HS hybrid 0.98": (12, 15),
          "RiskMetrics 0.94": (14, 16), "RiskMetrics 0.96": (12, 16),
          "RiskMetrics 0.98": (15, 16), "Hyperbolic": (7, 6), "Tail index": (5, 3)}
def lr_pof(x, N, p):
    ph = x / N
    l0 = (N - x) * log(1 - p) + x * log(p)
    l1 = (N - x) * log(1 - ph) + x * log(ph)
    return -2 * (l0 - l1)
def zone(x, N, p):          # BCBS (1996) cumulative-probability rule
    c = binom.cdf(x, N, p)
    return "Green" if c < 0.95 else ("Yellow" if c < 0.9999 else "Red")
for model, xs in counts.items():
    for x in xs:
        L = lr_pof(x, N, p)
        print(model, x, round(L, 2), round(chi2.sf(L, 1), 4),
              round(chi2.sf(L, 2), 4), zone(x, N, p))
```

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APPENDIX B: BASEL ZONE CUT-OFFS FOR 250 AND 446 TEST DAYS

Cumulative binomial probability of x or fewer exceptions at $p = 0.01$. The 250-day column reproduces BCBS [11, Table 2]; the 446-day column applies the same 95% and 99.99% thresholds to Samanta et al.'s test sample.

Table B1: Basel zone cut-offs at p = 0.01 for 250 and 446 test days

Exceptions (x)	**N = 250: cumulative %**	**N = 446: cumulative %**	**Zone (N = 250 / N = 446)**
4	89.22	53.93	Green / Green
5	95.88	71.02	Yellow / Green
6	98.63	83.71	Yellow / Green
7	99.60	91.77	Yellow / Green
8	99.89	96.24	Yellow / Yellow
9	99.97	98.43	Yellow / Yellow
10	99.99	99.40	Red / Yellow
11	100.00	99.79	Red / Yellow
12	100.00	99.93	Red / Yellow
13	100.00	99.98	Red / Yellow
14	100.00	99.99	Red / Red

Zone rule: green while the cumulative probability is below 95%, red once it reaches 99.99% [11]. For N = 446 the exact values are 99.9791% at x = 13 and 99.9941% at x = 14. Counts of 0–3 are green in both columns and are not shown.

APPENDIX C: FURTHER CHECKS AND REPORTING SLIPS IN THE THREE PAPERS

A. Shaik and Padmakumari (2022)

- The text says the conditional coverage (CC) test rejects all models at both confidence levels (p. 60); Table 2 (p. 59) shows CC accepting normal VaR for Brazil and EWMA for Brazil, Russia, India, China and the US at 95%.
- The text says only EWMA for the US, South Africa and Brazil passes the TBF test in the GFC at 99% (p. 60); Table 3 (p. 61) also shows HS for China passing.
- No exception counts or test statistics are reported, and the significance level used for the tests is not stated.
- NIFTY 50 closes for January 2003 to October 2021 [17] come close to Table 1's count (4,682 returns against 4,676), standard deviation (1.42% against 1.41%) and kurtosis (15.40 against 15.68), but not its mean (0.00059 against 0.00069) or skewness (−0.49 against −0.19). No start in 2003 and end in October 2021 gives a mean above 0.000652; the gap may reflect Bloomberg's series or exact dates, which the paper does not state.

B. Samanta et al. (2010)

- Kupiec p-values are $\chi^2(2)$ tail probabilities although the test is stated as $\chi^2(1)$ (p. 17); the evaluation sample is 447 days on p. 24 but 446 on p. 27, and the statistics fit 446 (Section IV-A, Appendix A).
- The hybrid HS weight is δ in the text (pp. 10–11, 23) but λ in Tables 2–5.
- A model is said to fail backtesting with "5% or more" incorrect VaRs (p. 15); Basel's yellow zone starts at five exceptions in 250 days, which is 2% [11, Table 2].
- The last-day hybrid HS VaR is identical for all three weights (2.08% and 1.66%; Table 2, p. 23), which the paper does not explain.
- The lower-tail Pareto law (Eq. 7, p. 14) is printed with x where |x| is needed for negative returns.
- Hyperbolic density (Eq. 5, p. 13) for d = 1, with $\Delta = 1$ and $x = \zeta\sqrt{(1 + ((r - \mu)/\delta)^2)}$: $f(r) = [1/((2\pi)^{1/2}\ \delta\ K_1(\zeta))] \times K_{1/2}(x) \times x^{1/2}$. Since $K_{1/2}(x) = \sqrt{(\pi/(2x))}\ e^{-x}$, this is $e^{-x}/[2\delta K_1(\zeta)]$, the form given in Section III-D. The other printed equations (Eqs. 1–4 and 8–11) match the forms used in Section III.

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C. Sharma (2012)

- Eq. 2 (p. 237) is printed as $LR_{UC} = 2 \ln[\cdot]$; since the bracket is a likelihood ratio below one, it needs $-2 \ln[\cdot]$, as Eq. 3 has. The independence statistic is called LR_{cc} in the text on p. 237 but LR_I in Eq. 3.
- Eq. 1 (p. 237) assigns the red zone to "10 < N", leaving exactly ten exceptions unassigned; the text on p. 238 says "more than nine".
- The S&P CNX 500 is labelled "S&P 500" in the text, tables and figures (e.g., Table 2, p. 239; Figure 2, p. 239), which reads like the US index.
- The conclusion says 1,000 + 190 days earns the lowest penalty in both series (p. 243); for INR/USD it ties at 0.208 with 750 + 190, 1,000 + 125, 750 + 125 and the plain 250-day VaR (Table 3, p. 240).
- The text says all INR/USD VaRs show dependence at one lag (p. 241); Table 7 (p. 242) shows four of them passing at one lag: 1,000 days (p = 0.1876), 1,000 + 190 and 1,000 + 125 days (both 0.2825) and 750 + 190 days (0.2155). In Table 7, where an asterisk means independence cannot be rejected at 5%, 0.295 (750 + 125 days, four lags) lacks one and 0.0358 (500 + 125 days, four lags) has one; Table 6 marks the equity results at 1% instead, so the two series are judged at different levels.
- Backtest counts of 1,727 (1,000-day) and 2,602 (125-day) on 2,726 returns equal T − W + 1, one more than the number of out-of-sample forecasts, which suggests either an off-by-one or that each day's VaR includes that day's return; the paper does not say which.
- The 2010 survey of Indian banks (pp. 234, 236) is dated 2000 in the reference list, and its shares of 25% and 38% (p. 234) cannot be whole numbers of the 30 participating banks named on p. 236 (they imply 7.5 and 11.4 banks), so they rest on a base the paper does not give.
- Raw versus excess kurtosis (Table 1, p. 238): $JB = (n/6)[S^2 + (K - 3)^2/4]$. S&P CNX 500: $(2{,}726/6)[(-0.5258)^2 + (7.6615)^2/4] = 6{,}792.78$, as printed; INR/USD: $(2{,}572/6)[(0.0977)^2 + (6.7198)^2/4] = 4{,}843.28$. Using K instead of K − 3 gives 13,036 and 10,129, so the printed kurtosis is raw.
- Conditional coverage (Tables 5, 7, 9): the $\chi^2(1)$ inverses of 0.2169 and 0.2825 are 1.52 and 1.16, and $P(\chi^2(2) > 2.68) = 0.262$, as printed for INR/USD 1,000 + 190 days.
- Unconditional coverage p = 1 (Table 4, p. 241): with T = 1,727, 17 exceptions give LR = 0.0043 and p = 0.9478, and 16 and 18 give 0.7558 and 0.8608; no whole number of exceptions gives p = 1.
- Average annual penalty (Tables 2–3, pp. 239–240): every printed average equals 0.625 (the midpoint of the 0.40–0.85 yellow range in Eq. 1) for each yellow year plus 1.00 for each red year, divided by the number of 250-day years; for 1,000 + 190 days, 0.625 ÷ 6 = 0.104, and for 1,000 days, 1.25 ÷ 6 = 0.208. The paper does not state this rule, and Basel sets the plus factor by the exception count instead. Two equity averages break the rule: the 250-day VaR (five green and four yellow years) should be 2.5 ÷ 9 = 0.278, not 0.313 (2.5 ÷ 8), and 500 + 190 days (six green, two yellow) should be 1.25 ÷ 8 = 0.156, not 0.179 (1.25 ÷ 7). Neither changes the ranking: 1,000 + 190 days (0.104) and 250 + 190 days (0.139) stay first and second.

APPENDIX D: WORKING FOR THE FULL-SAMPLE EVENT TEST

- Closes from NIFTY Indices [17]: 8,745.45 on 20 March and 7,610.25 on 23 March 2020, matching SI Reporter [6]. Simple return = −1,135.20 ÷ 8,745.45 = −12.98%. Log return = ln(7,610.25 ÷ 8,745.45) = −13.90%.
- Size in standard deviations = 13.90% ÷ 1.41% = 9.86 (σ from [1, Table 1, p. 55]).
- Normal one-day 99% VaR = 2.33 × 1.41% − 0.069% = 3.2163%, or 3.22% (mean 0.00069 from the same table). Loss ÷ VaR on the log basis = 13.90 ÷ 3.2163 = 4.32.

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- Probability under the normal model = $\Phi[(-0.1390 - 0.00069) \div 0.0141] = \Phi(-9.91) \approx 1.9 \times 10^{-23}$.
- Volatility needed for a 99% normal VaR to cover the day = 13.90% ÷ 2.33 = 5.97%. NSE multiple relative to the normal 99% quantile = 6 ÷ 2.33 = 2.58 [5].
- Rupee VaRs use Samanta et al.'s conversion VaR = [1 − exp(−ξ/100)] × W (p. 7). Illustrative ₹100 Cr book: VaR = [1 − exp(−3.2163/100)] × ₹100 Cr = ₹3.17 Cr; loss on 23 March 2020 = 12.98% × ₹100 Cr = ₹12.98 Cr, 4.10 times the VaR. Illustrative ₹500 Cr holding of 8.07% GS 2017: normal 0.83% gives ₹4.13 Cr, tail index 1.35% gives ₹6.70 Cr.

APPENDIX E: REAL-TIME EVENT TEST AND COVID-19 BACKTEST ON NIFTY 50 DATA

Data. Daily NIFTY 50 closing values downloaded from NIFTY Indices [17], the index provider, on 2 November 2026: 765 trading days from 3 December 2018 to 31 December 2021 (checksum: sum of closes 9,803,892.05, matched against the source). The full 2002–2021 series (4,976 days) was used only for the comparison with Shaik and Padmakumari's Table 1 in Appendix C.

Method. Daily log returns; each day's VaR uses the previous 250 returns only. Normal VaR = 2.33 × $\hat{\sigma}$ − $\hat{\mu}$; HS VaR = minus the 1st percentile of the window (linear interpolation); EWMA VaR = 2.33 × $\hat{\sigma}_{EWMA}$ with equation (6), λ = 0.94, W = 250 and zero mean. Backtest window: 1 January 2020 to 29 October 2021 (457 days), matching Shaik and Padmakumari's COVID-19 period. Zone cut-offs for 457 days from the BCBS [11] rule: green 0–7, yellow 8–13, red 14 or more.

Table E1: One-day 99% VaR for 23 March 2020 (log return −13.90%) and backtest, January 2020 to October 2021

Model	VaR on 23 Mar 2020	Loss ÷ VaR	Exceptions (x)	Kupiec LR	Kupiec p, $\chi^2(1)$	Independence p (lag 1)	Zone
Normal (250-day)	3.30%	4.21	12	8.43	0.0037	0.3126	Yellow
HS (250-day)	5.38%	2.59	11	6.56	0.0105	0.2564	Yellow
EWMA (λ = 0.94)	8.37%	1.66	16	17.53	0.0000	0.2807	Red
Hybrid: max(HS, EWMA)	8.37%	1.66	9	3.38	0.0659	0.5472	Yellow

Source: my calculation from NIFTY Indices [17] data. Expected exceptions = 4.57. Standard deviation on 20 March 2020: 250-day 1.37%, EWMA 3.59%. VaR on 20 February 2020: about 2.0% for all three models. HS VaR on 23 March 2021: 4.28%. Average VaR over the backtest: normal 3.56%, HS 5.07%, EWMA 3.09%, hybrid 5.32%. Exception dates: normal and HS mostly 1 February to 30 March 2020; EWMA also 31 August, 21 and 24 September, 15 October and 21 December 2020, 26 February, 12 April and 28 October 2021.

```
import numpy as np, pandas as pd
from scipy.stats import chi2
df = pd.read_csv("nifty50_2018-12_2021-12.csv", parse_dates=["date"])
r = np.log(df.close / df.close.shift(1)).dropna().values
dates = df.date.values[1:]
W, LAM, Z, P = 250, 0.94, 2.33, 0.01
```

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```
w = LAM ** np.arange(W); w = w / w.sum()          # weight on r[t-1], r[t-2], ...
out = []
for i in range(W, len(r)):
    win = r[i - W:i]
    normal = Z * win.std(ddof=1) - win.mean()
    hs = -np.quantile(win, P)
    ewma = Z * np.sqrt(np.sum(w * win[::-1] ** 2))
    out.append((dates[i], r[i], normal, hs, ewma, max(hs, ewma)))
v = pd.DataFrame(out, columns=["date", "r", "Normal", "HS", "EWMA", "Hybrid"])
bt = v[(v.date >= "2020-01-01") & (v.date <= "2021-10-31")]
N = len(bt)
for m in ["Normal", "HS", "EWMA", "Hybrid"]:
    x = int((-bt.r > bt[m]).sum()); ph = x / N
    LR = -2 * ((N - x) * np.log(1 - P) + x * np.log(P)
               - (N - x) * np.log(1 - ph) - x * np.log(ph))
    print(m, x, round(LR, 2), round(chi2.sf(LR, 1), 4))

# Independence (lag 1), zones, average VaR and exception dates for Table E1
from scipy.stats import binom
def lr_ind(I):    # Christoffersen (1998) one-lag independence LR, chi-square(1)
    a, b = I[:-1], I[1:]
    n00 = int(((a == 0) & (b == 0)).sum()); n01 = int(((a == 0) & (b == 1)).sum())
    n10 = int(((a == 1) & (b == 0)).sum()); n11 = int(((a == 1) & (b == 1)).sum())
    def ll(n0, n1):  # Bernoulli log-likelihood at the MLE
        q_ = n1 / (n0 + n1) if (n0 + n1) else 0.0
        return (n0 * np.log(1 - q_) if n0 else 0.0) + (n1 * np.log(q_) if n1 else 0.0)
    LR = -2 * (ll(n00 + n10, n01 + n11) - ll(n00, n01) - ll(n10, n11))
    return LR, chi2.sf(LR, 1)
def zone(x, N, p=0.01):  # BCBS (1996) cumulative-probability rule
    c = binom.cdf(x, N, p)
    return "Green" if c < 0.95 else ("Yellow" if c < 0.9999 else "Red")
for m in ["Normal", "HS", "EWMA", "Hybrid"]:
    I = (-bt.r > bt[m]).astype(int).values
    LRi, p_ind = lr_ind(I)
    print(m, round(p_ind, 4), zone(int(I.sum()), len(I)), round(100 * bt[m].mean(), 2),
          list(bt.date[I == 1].dt.date))
```

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