ACHIEVING EFFECTIVE RISK GOVERNANCE BY A COMPREHENSIVE FILTERED HISTORICAL SIMULATION TOOL

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Abstract

Growing regulatory demands require financial institutions to improve risk governance beyond traditional market and credit risk measures. This paper proposes an enhanced filtered historical simulation (FHS) framework to support comprehensive risk management and capital assessment. The methodology combines a global risk factor inventory with generalized autoregressive conditional heteroskedasticity (GARCH)-type volatility filtering, bootstrap resampling, and scenario rescaling to generate coherent profit-and-loss distributions for value at risk (VaR) and expected shortfall (ES). Extensive backtesting across multiple asset classes and market regimes shows that the proposed long-term FHS approach improves tail-risk capture, maintains dependency structures, and achieves regulatory compliance. Finally, it avoids excessive capital conservatism.

1. CONTEXT

Regulators demand comprehensive risk management beyond market and credit risk, emphasizing governance and organization-wide awareness. Institutions must set appetite and tolerance limits versus current profiles, a task complicated by data gaps and silos. This study shows that a robust risk factor inventory with filtered historical simulation (FHS) generates structured scenarios for extreme losses. Studies stress expanding risk categories and refining measurement. Ielasi (2012) notes broader risk maps under Basel II, while Chockalingam et al. (2017) advocate simulation-based frameworks — underscoring adaptive, holistic risk management.

2. CAPITAL AND RISKS IN THE BANKS

A comprehensive risk management process involves four steps: identify, assess, manage via avoidance, transfer, hedging, or limits, and monitor continuously. For banks and insurers, the principle is clear:

$$own\ funds\ \geq\ risks \tag{1}$$

While own funds are simple to measure, risk estimation is complex — requiring factor selection, stochastic modeling, and judgment for unobservable events. Regulators demand holistic capital allocation across diverse risk types, yet blurred boundaries, data gaps, and methodological limits make robust economic capital quantification uncertain, underscoring the need for innovation.

3. THE PROPOSAL: COMPREHENSIVE FILTERED HISTORICAL SIMULATION

The aforementioned problems can be addressed by developing a global repository for all risk factors and simulating them effectively. This entails considering the natural frequency of time series, implementing data quality and filling tools, selecting absolute versus relative returns for each risk-class, accounting for time-varying volatility, and managing dependencies among risk factors. Classical approaches, such as the Gaussian parametric model (GPM), Monte Carlo simulation (MCS) and historical simulation (HS), show several weaknesses:

Table 1. Limitations of classical risk quantification approaches

GPM	MCS	HS
Assumes normality, ignoring fat tails and skewness	Accuracy depends on model specification	Relies on past data, assuming history repeats
Fails to capture volatility clustering and regime shifts	Computationally expensive for tail risk	Cannot account for unprecedented shocks
Sensitive to variance-covariance estimation errors	Calibration errors can distort results	Results depend heavily on window length
Poor representation of extreme market shocks	Underestimates risk if stress scenarios are missing	Ignores conditional volatility dynamics
Static unless extended with dynamic models	Sensitive to distributional assumptions	Biased in periods of abnormal stability or turbulence

To overcome limitations that underestimate front-office risk, Barone-Adesi et al. (1999) introduced FHS, offering more robust value at risk (VaR) estimates than standard bootstrapping. FHS combines historical simulation with volatility adjustment, generating scenarios from past data and current conditions without a variance-covariance matrix. Dependencies among risk factors remain intact, while non-stationary volatility is addressed through normalization and rescaling. Building on Boudoukh et al. (1998) and Hull and White (1998), FHS incorporates prevailing market conditions into joint return distributions for VaR and expected shortfall.

1. *Filtering*

Obtain standardized *i.i.d.* residuals from a generalized autoregressive conditional heteroskedasticity (GARCH)-type model for each risk factor $j = 1, \dots, N$ and simulation run $s = 1, \dots, S$:

$$\{ z_h^j \} \ for \ h \ = \ 1, \dots, T \tag{2}$$

with $E[z_h^j] \approx \ 0$ and $Var[z_h^j] \approx \ 1$, where, T is the sample size.

2. *Bootstrap*

Sample *i.i.d.* residuals for risk metric holding period k:

$$Z_h^* = \left(Z_h^{1*}, \dots, Z_h^{N*} \right)^T \tag{3}$$

to preserve cross-sectional dependence.

3. *Rescaling*

Propagate conditional volatility forecasts $\sigma_{\{t+h\}}^j$ through the selected process and reconstruct shocks:

$$\Delta y_{\{t+h\}}^{j*} = \ \sigma_{\{t+h\}}^j \times \ Z_h^{j*} \tag{4}$$

for $h \ = \ 1, \dots, k$.

4. *Scenario profit-and-loss distribution (PnL)*

Compute portfolio scenario *PnL* using the evaluation function $V(\cdot)$:

$$PnL_{\{t+k\}}^s = \ V\left(\theta_{\{t+k\}}^s\right) - \ V\left(\theta_{\{t\}}^s\right), \tag{5}$$

where, $\theta_{\{t\}}^s$ is the portfolio's valuation state (i.e., the key inputs required for the valuation: market parameters, instrument structure, etc.) at the compute-date, while $\theta_{\{t+k\}}^s$ is the updated state after applying simulated shocks over the holding period.

5. *VaR and expected shortfall (ES)*

Repeat the bootstrap procedure *S* times (e.g., 100k) to obtain the scenario *PnL*, and compute:

$$VaR_{\alpha}^{(k)} := -quantile_{1-\alpha}(PnL) \tag{6}$$

$$ES_{\alpha}^{(k)} := E\left[PnL \middle| PnL \leq -VaR_{\alpha}^{(k)}\right] \tag{7}$$

Table 2. How FHS addresses canonical risk quantification methodologies limitations

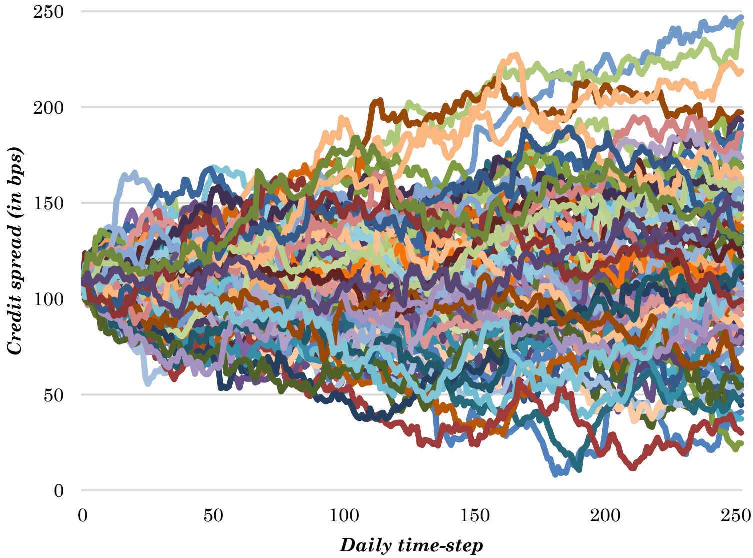
Limitation	***GPM***	***MCS***	***HS***	***FHS response***
Fat tails & skewness	Assumes normality	Depends on the chosen distribution	Preserves empirical distribution but unscaled	Rescales historical residuals with a volatility filter, preserving heavy tails
Volatility clustering & regime shifts	Ignores conditional dynamics	Requires complex modeling	Ignores conditional volatility	Incorporates a GARCH-type filter to capture time-varying volatility
Extreme market shocks	Poor representation	Needs explicit stress scenarios	Limited to observed history	Retains historical shocks but adjusts for current volatility
Static nature	Static unless extended	Adaptive but model-driven	Fully static	Adaptive through dynamic volatility filtering
Model risk	Parametric assumptions	High dependence on model specification	Minimal assumptions but rigid	Combines empirical residuals with parametric volatility, reducing model risk
Window length sensitivity	Sensitive to covariance estimation	Sensitive to calibration	Strongly dependent on the sample window	Mitigates by rescaling older shocks to the current volatility regime

We propose long-term FHS (LT-FHS), extending traditional FHS into a risk-type-sensitive framework for large portfolios and evolving regulations. LT-FHS introduces:

- rigorous return metric selection — absolute or relative — aligned with risk taxonomy and market conventions;
- scenario-rescaling for long-horizon metrics assuming constant volatility, ensuring convergence and robustness;
- dynamic control rules enforcing plausible bounds based on historical minima and maxima, adjusted for realized volatility, while capturing tail risk;
- an efficient bootstrap algorithm for generating 1-month and 1-year scenarios;

• a robust mechanism linking market scenarios with portfolio positions to compute PnL for VaR and ES.

Figure 1. Simulation of annual paths of the Italian government 10Y credit spread risk factor



Note: $k = 252$. The credit spread as of $t_0 = 31/12/2024$ is equal to 108.15 basis points (bps), while the value of the parameter $\hat{\sigma}_{ITA-10Y}$ is estimated to be equal to 2.89 bps per day.

The backtesting covered over 15 years of data (March 2010–April 2025, 183 months), spanning multiple market regimes. Analysis focused on a one-month holding period (21 business days), aligned with regulatory standards for long-term risk. Four VaR models were tested: LT-FHS, standard (STD) FHS, STD HS, and weighted HS (λ-HS) (exponentially weighted, $\lambda = 0.99$). Tests included key risk classes — EUR interest rates, global equities, and Italy country risk — at confidence levels of 95%, 97.5%, 99%, and 99.9%, with emphasis on 99% for regulatory capital.

Backtesting used hypothetical portfolios representing interest rate, credit, and equity risk. Interest rate and credit portfolios were built with uniform sensitivities of -1000 €/bps: the former on standardized euro short-term rate (ESTR) curve positions (0.25–30 years), the latter on Italian government bonds mapped to Bloomberg Valuation Service (BVAL) BVIS0575 (1–30 years). Equity exposures were set at €1,000,000 per position, diversified across major indices and sector baskets.

Table 3. Equity portfolio composition

FTSE MIB Index
EURO STOXX 50
S&P 500 Index
MSCI Europe Consumer Discretionary Index
MSCI Europe Consumer Staples Index
MSCI Europe Energy Index
MSCI Europe Financials Index
MSCI Europe Industrials Index
MSCI Europe Communication Services Index
MSCI Europe Utilities Index
MSCI IT Consumer Discretionary Sector
MSCI IT Energy Sector
MSCI IT Financials Sector
MSCI IT Industrials Sector
MSCI IT Telecommunication Services Sector
MSCI IT Utilities Sector

Portfolio composition remained fixed during backtesting, isolating the effects of market movements and model dynamics. This approach ensures transparent, consistent VaR performance comparisons across asset classes and metrics.

Table 4. Standard Bootstrap Historical Simulation — Kupiec backtesting performances

Confidence level	***Risk class***	***Obs.***	***Breach***	***Kupiec p-value***	***Result***
99.90%	Credit	183	2	1.47%	Rejected
	Interest	183	3	0.08%	Rejected
	Equity	183	1	18.39%	Passed
99.00%	Credit	183	3	42.61%	Passed
	Interest	183	6	1.43%	Rejected
	Equity	183	1	49.99%	Passed

Table 5. Lambda-Decaying Bootstrap Historical Simulation — Kupiec backtesting performances

Confidence level	***Risk class***	***Obs.***	***Breach***	***Kupiec p-value***	***Result***
99.90%	Credit	183	2	1.47%	Rejected
	Interest	183	2	1.47%	Rejected
	Equity	183	2	1.47%	Rejected
99.00%	Credit	183	3	42.61%	Passed
	Interest	183	7	0.34%	Rejected
	Equity	183	4	16.35%	Passed

Table 6. Standard Filtered Historical Simulation —
Kupiec backtesting performances

Confidence level	***Risk class***	***Obs.***	***Breach***	***Kupiec p-value***	***Result***
99.90%	Credit	183	1	18.39%	Passed
	Interest	183	0	99.99%	Passed
	Equity	183	1	18.39%	Passed
99.00%	Credit	183	3	42.61%	Passed
	Interest	183	3	42.61%	Passed
	Equity	183	1	49.99%	Passed

Table 7. Long-Term Filtered Historical Simulation —
Kupiec backtesting performances

Confidence level	***Risk class***	***Obs.***	***Breach***	***Kupiec p-value***	***Result***
99.90%	Credit	183	3	0.08%	Rejected
	Interest	183	0	99.99%	Passed
	Equity	183	1	18.39%	Passed
99.00%	Credit	183	3	42.61%	Passed
	Interest	183	5	5.23%	Passed
	Equity	183	1	49.99%	Passed

At 99%, LT-FHS passes across all risk classes, including interest rate risk with 5 breaches ($p = 5.23\%$), while STD HS and λ-HS fail decisively (6 breaches, $p = 1.43\%$; 7 breaches, $p = 0.34\%$). For global equity risk, LT-FHS shows near-perfect alignment (1 breach, $p \approx 50\%$), whereas λ-HS records 4 breaches ($p \approx 16\%$). Credit risk is non-discriminatory, with all models at 3 breaches ($p \approx 42.6\%$).

At 99.9%, critical for economic capital (ECAP) under the supervisory review and evaluation process, LT-FHS remains robust: interest rate risk — 0 breaches ($p \approx 99.99\%$), equity — 1 breach ($p \approx 18.4\%$), and credit — 3 breaches ($p = 0.08\%$, borderline conservatism). In contrast, STD HS and λ-HS fail systematically with multiple breaches and p-values $< 2\%$, confirming their inability to capture extreme tails.

LT-FHS outperforms classical HS approaches, delivering statistical validity under stress and extreme quantiles, ensuring compliance for both regulatory VaR and ECAP while maintaining prudential robustness without excessive conservatism.

Figure 2. EUR interest rate risk — Backtesting VaR at 99% confidence level

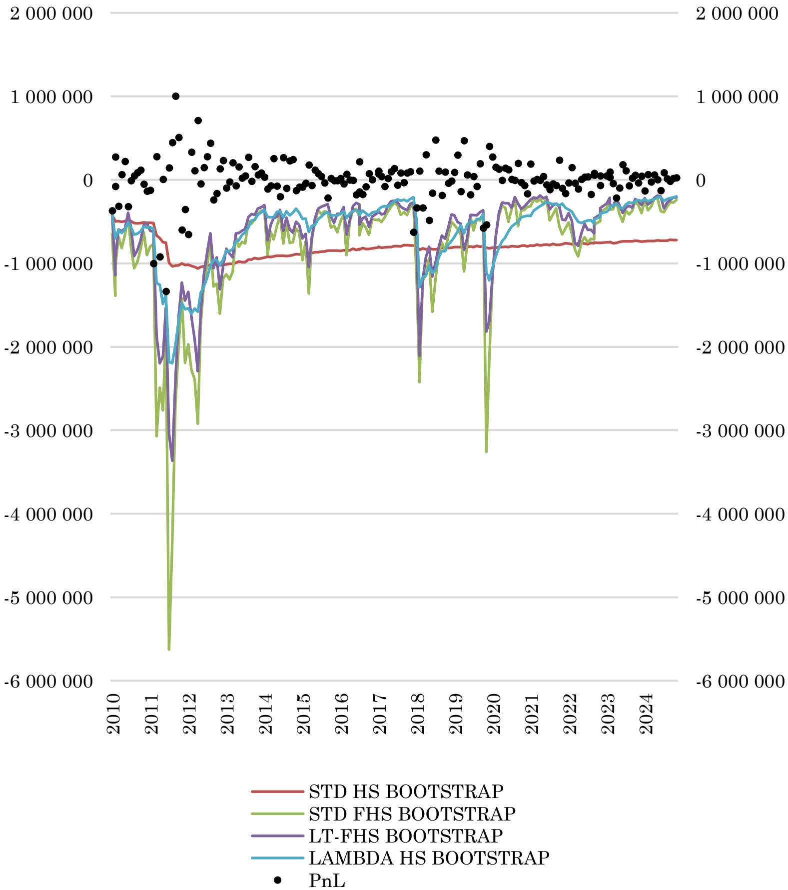


Figure 3. Italy country risk — Backtesting VaR at 99% confidence level

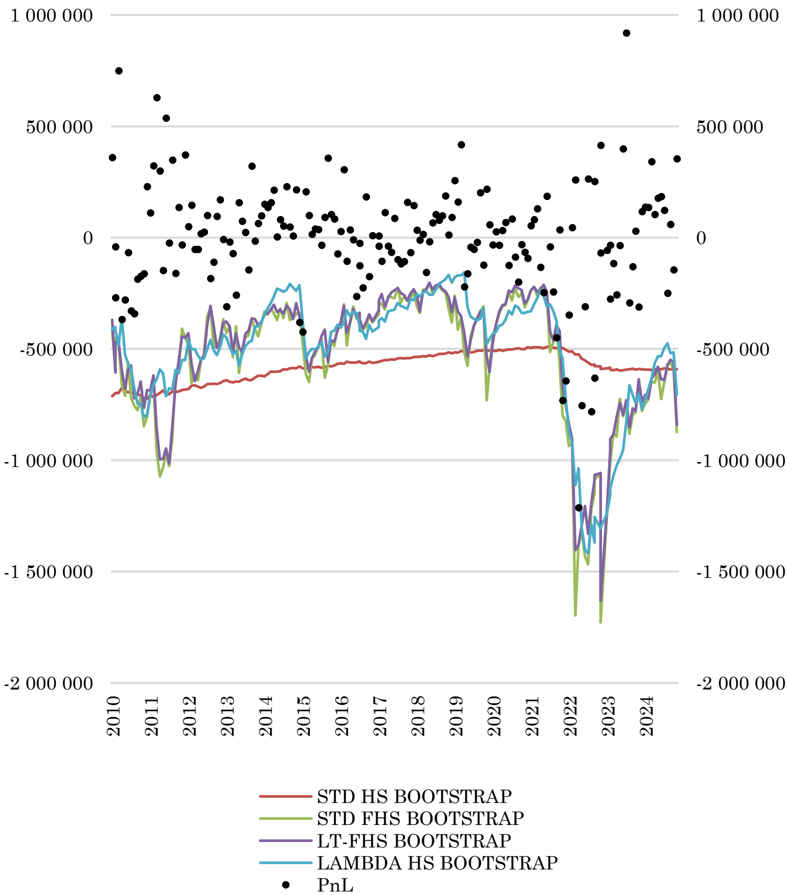
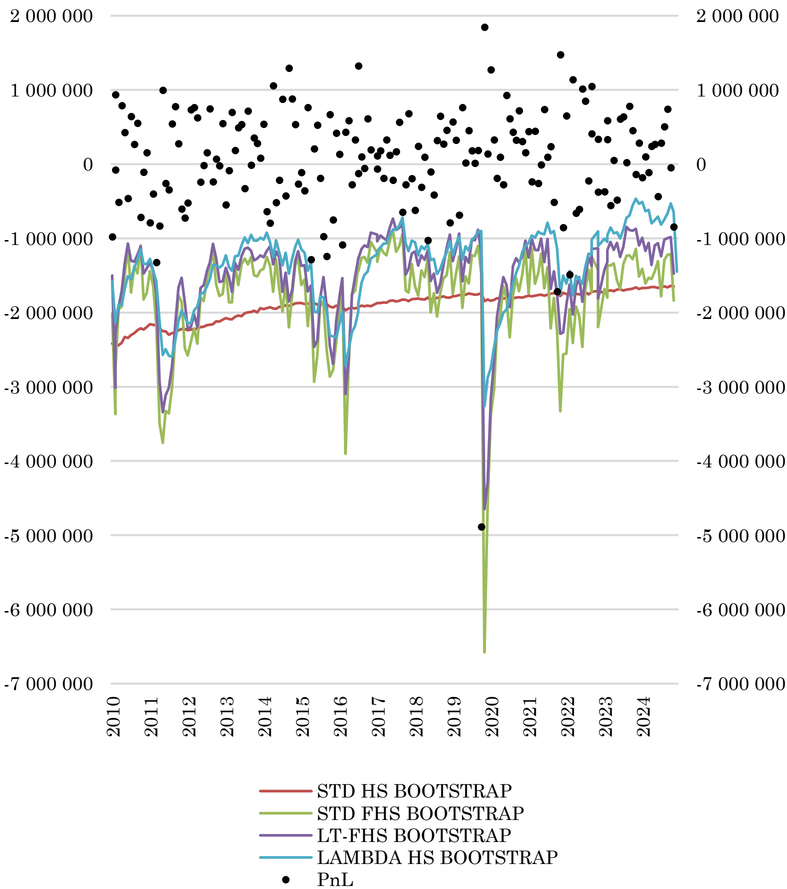


Figure 4. Global equity risk — Backtesting VaR at 99% confidence level



Backtesting confirms LT-FHS as highly robust under tail events and severe stress while requiring far less capital than standard historical simulation. Given the extensive empirical experiments we conducted, we conclude that this efficiency arises from our LT-FHS framework's design — dynamic volatility filtering, constant-volatility scenario rescaling, and control rules enforcing plausible risk-factor bounds. These features deliver economically consistent long-horizon risk estimates without excessive conservatism. LT-FHS supports Basel-compliant VaR and other metrics, enhancing precision, responsiveness, and regulatory compliance — strengthening resilience and adaptability in complex financial environments.

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