GENERALI ASSET MANAGEMENT

Core Matters

Relative Value Opportunities in Euro Credit

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October 5th, 2026

Our Core Matters series provides thematic research on macro, investment, and insurance topics

- We model corporate bonds using a stochastic mean-reverting approach applied to the residual yields of iBoxx EUR Corporate Investment Grade (IG) bonds. Our investment universe comprises iBoxx EUR Investment Grade (IG) corporate bonds spanning the 2008-2026 period. Residual yields are obtained by subtracting, from the bond's observed yield, the yield interpolated at the issuer's subsector and seniority level using the Nelson-Siegel-Svensson (NSS) parametric framework.
- The benchmark consists of a market value-weighted allocation, rebalanced on the first business day of each month. Portfolio weights are determined based on market values at the rebalancing date and adjusted using z-scores derived from an Ornstein-Uhlenbeck stochastic model with a 21-day investment horizon. As volatility is clustered around crisis periods, we model non-constant volatility by adding a GARCH(1,1) layer. To prevent any look-ahead bias, portfolio investments are implemented with a one-day lag.
- Our relative value strategy typically outperforms the benchmark by ~25 basis points (bps) per year with an information ratio (IR) of 0.7. We also adjust for duration with a hedging layer using EUR 5y swaps. The resulting strategy has a slightly lower information ratio of 0.6, but it is almost beta-neutral, and its excess return is less correlated with the benchmark. Finally, we compare our strategies with a naïve z-score allocation which underperforms in risk-adjusted metrics.
- Two points stand out. First, most of the value added does not come from broad top-down positioning: when we test the excess return for a sectoral bias, sector allocation accounts for only a limited share of performance, while the bulk of the signal comes from intra-sector relative value. Second, the strategy is not regime agnostic. It tends to add more value when markets are stressed or adjusting to a new equilibrium, as dispersion widens and relative mispricing become more visible.
- We recommend the hedged variant: it provides similar outperformance while slightly reducing beta and correlation to the benchmark.

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1. Introduction

Corporate bond markets are characterised by persistent inefficiencies arising from liquidity constraints, benchmark-driven investor behaviour, and the heterogeneous nature of credit instruments. We therefore believe that corporate bond spreads frequently deviate from their equilibrium value for extended periods before reverting, creating exploitable signals for investors.

This paper proposes a relative-value strategy for IG corporate bonds, grounded in the Ornstein-Uhlenbeck (OU) process, a continuous-time mean-reverting stochastic model. Our approach proceeds in two stages. First, we model the term structure of credit yields for each sector-seniority bucket using the Nelson-Siegel-Svensson (NSS) framework. The residual yield, i.e. the difference between a bond's observed yield and its NSS-fitted theoretical value, serves as a measure of relative attractiveness within its peer group. Second, we fit an OU model to each bond's historical yield residual series on an expanding out-of-sample basis, extracting the speed of mean reversion, the long-run mean, and the volatility parameter.

These parameters allow to construct a forward-looking z-score signal. The resulting signal drives a systematic portfolio construction engine that tilts weights away from a market-value-weighted benchmark, subject to active risk budgets and deviation constraints at individual bond level. Portfolio performance is evaluated against the benchmark on a net-of-transaction-cost basis, with out-of-sample diagnostics including Information Ratio, Tracking Error, and Hit Rate.

2. Methodology

2.1 Investment Universe

The investment universe consists of iBoxx EUR Investment Grade (IG) corporate bonds covering the period from January 2008 to September 2026. The universe is segmented along two dimensions: subsector, defined at iBoxx Level 4, and seniority, defined at iBoxx Seniority Level 2. Non-financial subordinated bonds are treated as a single aggregate group. For each resulting segment, a daily yield curve is estimated at market close across effective maturities measured as time to workout date.

2.2 Residual Yield Construction

For each segment and each trading day, the yield curve is interpolated using the Nelson-Siegel-Svensson (NSS) parametric framework. Each bond's residual yield is defined as the deviation of its observed market yield from the segment-level NSS interpolated yield:

$$r_{it} = y_{it} - \hat{y}(m_{it})$$

Where y_{it} is the is the bond's street yield on date t and $\hat{y}(m_{it})$ denotes the NSS yield evaluated at the bond's time to workout date within its subsector-seniority segment *i*. By construction, r_{it} strips out the systematic curve component common across the segment and isolates bond-specific deviations that may be attributed to idiosyncratic mispricing, liquidity, or credit differentiation.

2.3 OU Signal Construction

The residual yield series r_{it} for each bond is modelled as a continuous-time Ornstein-Uhlenbeck (OU) process:

$$dr_t = \theta(\mu - r_t)dt + \sigma\, dW_t$$

where $\theta > 0$ is the mean-reversion speed, μ is the long-run mean, σ is the diffusion coefficient, and W_t is a standard Brownian motion.

Estimation. The continuous-time model is discretised exactly on a trading-day clock ($\Delta t = 1/252$) as an AR(1):

$$r_{t+\Delta t} = a\, r_t + b + \varepsilon_t$$

with $a = e^{-\theta \Delta t}$, $b = \mu(1-a)$, and the variance of the innovation term $q = \frac{\sigma^2}{2\theta}(1-a^2)$.

GARCH(1,1) Volatility Extension. Financial time series exhibit volatility clustering, particularly during crisis episodes. To capture time-varying conditional volatility, we augment the OU residuals with a GARCH(1,1) specification: $\varepsilon_t \mid \mathcal{F}_{t-1} \backsim \mathcal{N}(0, h_t)$.

With $h_t = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, h_{t-1}$. The parameter vector $\lambda = (a, b, \omega, \alpha, \beta)$ is estimated by Gaussian QMLE by maximizing the following Gaussian log-likelihood function up to the observation date:

$$\mathcal{L}(\lambda) = \frac{1}{2}\sum_{t=1}^{T}\left[\log(2\pi h_t) + \frac{{\varepsilon_t}^2}{h_t}\right].$$

For forecasting, we propagate GARCH(1,1) conditional variances h_t over the investment horizon and aggregate them through the AR(1)/OU transition dynamics to obtain the predictive standard deviation. Parameters are then mapped to the triplet (θ, μ, σ).

2.4 Portfolio Construction

Benchmark. The benchmark is a market-value-weighted portfolio, rebalanced on the first business day of each calendar month.

Active Overlay. On each rebalancing date, we compute active deviations $\delta_i = w_i^{\text{strat}} - w_i^{\text{bm}}$ by allocating a fixed L_1 active budget symmetrically between overweight and underweight positions, in proportion to each bond's absolute z-score. The allocation is subject to: (i) a per-bond deviation and liquidity cap; (ii) long-only constraints; (iii) full investment and (iv) a minimum amount for a trade to be implemented. We also introduce duration hedging using 5y EUR swap contracts. To avoid look-ahead bias, we apply a one-day lag to rolling positions at the monthly rebalance.

2.5 Transaction Costs and Liquidity

Transaction costs and liquidity are two central considerations when executing credit trades on behalf of clients and when assessing the deliverability of a systematic strategy. We model their magnitude using a dual approach that combines a bid-ask spread cost with a market impact component, as follows:

$$c_{i,t} = f(\sigma_t)\, s_{i,t} \left|\Delta w_{i,t}\right|$$

Where $\Delta w_{i,t}$ is the position variation, $s_{i,t}$ the effective half-spread relative to mid, $Y \in [0,1]$, $f(\sigma_{i,t})$ a scaling function of the market's volatility. We relied upon Bloomberg's liquidity model to build a simple profile (regime-aware step function) for f.

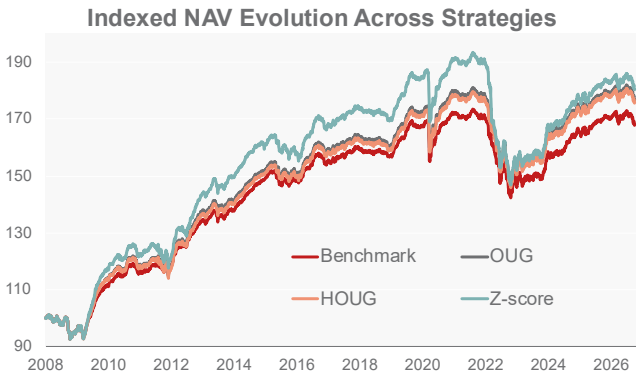
For illustration the notional is set at EUR 1 billion, while the strategy's capacity (the maximum notional that preserves a positive active return over the historical sample) is estimated at a few billion euro under this transaction costs model. This result is broadly consistent, although strategy design differs, with Ivashchenko and Kosowski (2024), who show that reversal or liquidity corporate-bond strategies have a capacity up to USD 10 billion. Beyond this point, market impact outweighs the benefits of the relative-value or liquidity signals.

3. Results

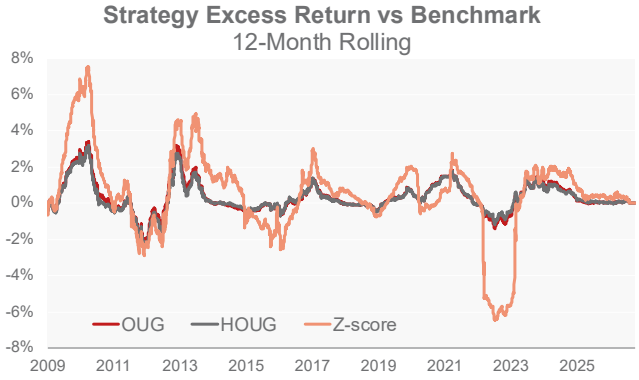
We study OUG (see definition below) as the baseline strategy. However, the conclusions also hold for the duration-hedged variant.

3.1 Strategy Performance

We evaluate the Ornstein-Uhlenbeck strategy with a GARCH layer (OUG) against a "naïve" z-score strategy (Z-score) and a benchmark. We also consider a duration-hedged variant (HOUG). Over the full period, OUG delivers a positive excess return relative to the market-value benchmark with superior risk-adjusted performance. HOUG preserves the outperformance while materially reducing beta and correlation to the benchmark. By contrast, Z-score delivers higher returns, but a lower information ratio, suggesting that OU-based calibration improves the economic quality of the signal.



Source: iBoxx, Bloomberg, GenAM own calculations



Source: iBoxx, Bloomberg, GenAM own calculations

Overall Metrics	*OUG*	*HOUG*	*Z-score*	*Benchmark*
Annual return	3,10%	3,07%	3,22%	2,83%
Volatility (ann.)	3,1%	3,1%	3,4%	3,0%
Sharpe Ratio	1,00	1,00	0,95	0,94
Excess return				
Annual return	0,26%	0,23%	0,39%	
Volatility (ann.)	0,39%	0,39%	0,91%	
Information Ratio	0,69	0,59	0,43	
Alpha	0,23%	0,22%	0,18%	
Beta	0,01	0,00	0,07	
Correlation	8,5%	2,0%	24,7%	

Indeed, even though the Z-score strategy offers higher total returns, it shows poorer risk-adjusted metrics, as well as higher correlation with the benchmark. The outperformance is driven by more risky bets rather than well-calibrated relative value allocation. Overall, the stochastic model is more resilient during crisis, as it recalibrates volatility and remains flexible enough to capture post-crisis dispersion decline.

3.2 Statistical Validation

Our framework was tested under a single hyperparameter-constraint configuration for the stochastic model. Moreover, the long-only and budget constraints leave only one

back-test parameter free to vary, the z-score entry threshold, for which we evaluated two configurations. This limited search materially reduces the likelihood of overfitting.

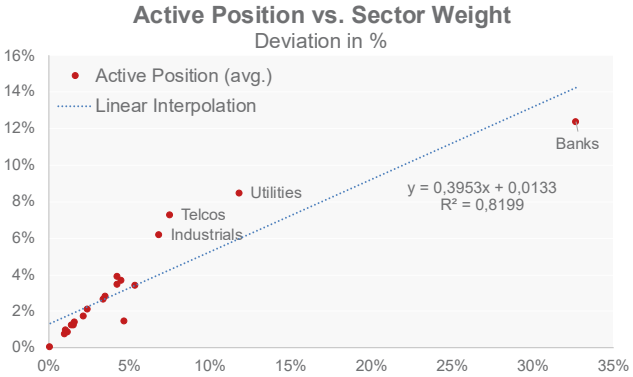
To assess whether each strategy delivers a genuinely positive edge, we test the null hypothesis that the mean active daily return is zero using a Student t-test; for both strategies we obtain a p-value of 0.01, rejecting the null at the 95% confidence level.

Furthermore, to avoid imposing parametric distributional assumptions and to consider the autocorrelation of the returns, we also employ a moving block bootstrap. We resample the daily active return series using overlapping blocks of 35 trading days thereby preserving short-run dependence in the data.[1] The estimated probability of obtaining a bootstrap mean return at or below zero is around 0.05 for both strategies. This tests yields a slightly lower confidence while remaining conclusive.

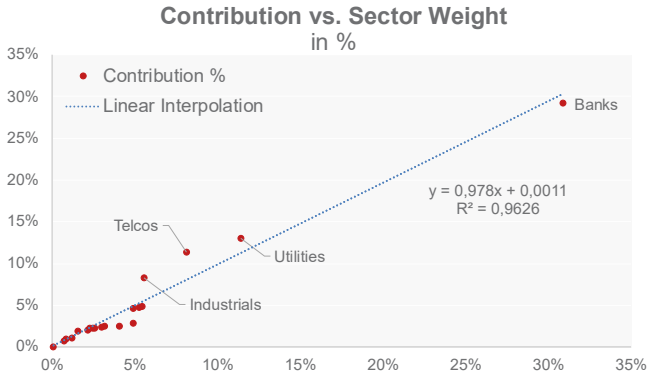
3.3 Performance Drivers

Because our strategies retain exposure to several factors, the observed (out)performance warrants further scrutiny. In particular, OUG is neither duration-hedged nor sector-neutral (note that preserving sector weighting performs similarly, with a 0.6 IR overall). Since we previously showed that the duration contribution to returns was minimal (see section 3.1), we turn to analysing sector contribution.

P&L Contribution and Sector Positioning for OUG. Contribution is largely proportional to benchmark sector weights, without indicating excessive concentration. This suggests that the portfolio's net sector exposure mainly reflects the benchmark opportunity set and the need for portfolio breadth, rather than a deliberate source of alpha. This is supported by the limited role of duration reported above, the similar performance of the sector-preserving specification, and the attribution results below.



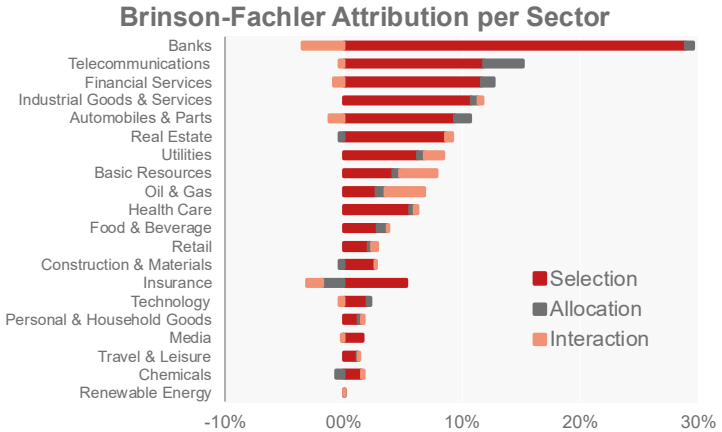
Source: iBoxx, GenAM own calculations



Source: iBoxx, GenAM own calculations

[1] The block length is chosen to reflect the optimal bias-variance trade-off in block bootstrap inference for dependent data. It accounts in this case for the data's observed autocorrelation (see Lahiri, S. N.).

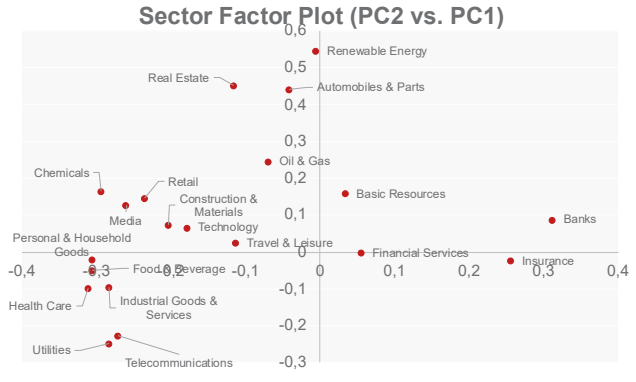
Brinson-Fachler attribution. Over the full back-test period, the selection effect (intra-sector bond picking) accounts for 92.4% of the total excess return, while the allocation effect (sector over/underweighting) contributes 5.7%. This means that virtually all of the strategy's value added originates from identifying relatively cheap and rich bonds within each sector, rather than from top-down sector bets. Banks and Telcos are the two largest alpha contributors, consistent with these sectors offering deep liquidity and higher beta.



Source: iBoxx, GenAM own calculations

Principal component analysis of sector factors. To further characterise the structure of returns, we regress OUG's excess daily returns on sector excess returns. We apply a PCA to the standardised daily excess returns of the 19 sectors. The first two components explain approximately 45% of total variance.

The first principal component (PC1) loads positively on financial sectors, but negatively on more defensive sectors such as Utilities, Telecommunications, Health Care, and Food & Beverage, consistent with a broad risk-on / risk-off factor. The second component (PC2) captures a distinct cross-sectional dimension, with strong positive loadings for Renewable Energy, Automobiles & Parts, and Real Estate, and negative loadings for Utilities, Telecommunications, and Industrial Goods & Services. This suggests that PC2 reflects a rotation between more cyclical or asset-sensitive sectors and traditional defensives.



Source: iBoxx, GenAM own calculations

Regressing the strategy's excess return on these principal components yields an adjusted R^2 of 0.39, while the intercept (alpha) remains highly statistically significant. Overall, sector factors explain a meaningful share of return variation, yet a substantial non-sector component persists, consistent with alpha originating primarily from the intra-sector relative-value signal.

3.4 Market regimes and signal efficacy

The OUG strategy's active return is regime dependent (see table below). Performance is primarily generated during stressed or transitional market environments when benchmark volatility is elevated and cross-sectional opportunities tend to widen, despite higher transaction costs. The strategy typically underperforms at the onset of crisis episodes but subsequently adapts as dispersion increases and thus participates in the rebound. By contrast, in low-volatility trending bull markets typical of late-cycle phases, alpha compresses to almost zero.

Regime	Duration (days)	Excess return (ann., bps)	TE (bps)	IR	Max DD (bps)
Euro Sovereign Debt Crisis (mid 2011 -- mid 2012)	283	-61.3	88.4	-0.69	-159,4
Draghi QE / Spread Compress. (mid 2012 -- end 2015)	885	+15.2	29.9	+0.51	-69,6
Late-Cycle / Low-Vol (2016 -- 2019)	1035	+28.5	24.8	+1.15	-35,1
COVID Crisis (H1 2020)	128	+108.7	42.9	+2.54	-11,6
Post-COVID Recovery (H2 2020)	395	+52.7	13.1	+4.01	-22
Inflation / Rate Hiking (2022 -- 2023)	526	+15.6	38.5	+0.41	-122
Normalisation (2024 -- today)	698	+15.9	10.6	+1.49	-8,1

4. Conclusion

The results suggest that relative value in EUR investment-grade credit can be captured in a systematic and disciplined way. Using NSS residual yields and an Ornstein-Uhlenbeck framework, the OUG strategy delivers consistent excess return over the benchmark, with better risk-adjusted performance than a simple z-score approach. Moreover, execution is key, as corporate credit remains less liquid than other asset classes. The electronification of credit markets, coming with decreasing bid-ask spreads, represents an opportunity to implement relative value signals.

Two points stand out. First, most of the value added does not come from broad top-down positioning: sector allocation accounts for only a limited share of performance, while the bulk of the signal appears to come from intra-sector relative value. Second, the strategy is not regime agnostic. It tends to add more value when markets are stressed or adjusting to a new equilibrium, as dispersion widens and relative mispricing becomes more visible.

In that sense, this is less a directional credit strategy than a systematic way of harvesting dislocations within the market. Accordingly, we recommend HOUG: it provides similar outperformance while slightly reducing beta and correlation to the benchmark. OUG should be viewed as a slightly higher-exposure option suited to investors who deliberately accept residual credit directional risk.

5. References

Bloomberg L.P. (2026). Bloomberg Liquidity Assessment. *Bloomberg Professional Services*. https://professional.bloomberg.com/products/risk/lqa/

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*. https://doi.org/10.1016/0304-4076(86)90063-1

Brinson, G. P. & Fachler, N. (1985). Measuring Non-US Equity Portfolio Performance. *The Journal of Portfolio Management*. https://doi.org/10.3905/jpm.1985.409005

Ivashchenko, A., & Kosowski, R. (2024). Transaction Costs and Capacity of Systematic Corporate Bond Strategies. *Financial Analysts Journal, 80*(4). https://doi.org/10.1080/0015198X.2024.2360390

Lahiri, S. N. (2003). Resampling methods for dependent data. *Springer. Chap. 2,5,7.*

Nelson, C. R., & Siegel, A. F. (1987). Parsimonious Modeling of Yield Curves. *Journal of Business*. https://doi.org/10.1086/296409

Svensson, L. E. O. (1994). Estimating and Interpreting Forward Interest Rates: Sweden 1992-1994. *NBER Working Paper No. 4871*. https://doi.org/10.3386/w4871

Uhlenbeck, G. E., & Ornstein, L. S. (1930). On the Theory of the Brownian Motion. *Physical Review*. https://doi.org/10.1103/PhysRev.36.823

Vasicek, O. (1977). An Equilibrium Characterization of the Term Structure. *Journal of Financial Economics*. https://doi.org/10.1016/0304-405X(77)90016-2

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