LOMBARD ODIER: 'IDENTIFICATION OF COMMON VOLATILITY DRIVERS IN A MULTI-ASSET UNIVERSE'

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Contents

1 Introduction

A crucial factor that shapes the direction of prices on the market is the news. Our society is more interconnected than ever, and news spreads worldwide in real time. All the more so in times of geopolitical turmoil like the ones we live in, bad news is a crucial source of risk that needs to be taken into account while studying the financial market. What makes these events particularly interesting and dangerous from a risk management perspective on a portfolio is that it is well known that the correlation structure of different assets changes during periods of high market volatility. For this reason, even a portfolio that is well diversified in the traditional sense will experience significant concentration of risk during turmoil periods, as even originally weakly correlated assets will tend to co-move, exposing the portfolio to significant risk. Therefore, the paper is interested in measuring the impact of extreme events that influence all assets in a well-diversified portfolio. To explore these crucial scenarios in portfolio management, the paper by Engle and Campos-Martins (2023) [4] introduces the COVOL (common volatility) model. This is a single common factor fitted to unexplained volatility of the returns. As we are interested in a factor that explains volatility that is common to all asset classes, the portfolio we consider in this context contains, for instance, bonds, stocks from different sectors and countries. This model has a variety of interesting features: its interpretation is straightforward and in line with our expectation: it allows us to measure the impact of these extreme events on all asset types. It also enables us to estimate which type of assets are more exposed to the common volatility induced by these tail events and, on the other hand, which assets are more robust to it (this consideration is given by the different common factor's weights). Finally, it allows us to forecast the risk of extreme volatility events through statistical models, particularly by estimating the conditional variance of global COVOL and constructing tail risk measures like Geopolitical Value at Risk (GVaR). Practical implementation and real-world applications were conducted in partnership with Julien Royer (researcher at *Lombard & Odier*).

2 COVOL framework

This section introduces the COVOL (Co-Volatility) framework designed to capture time-varying, *common* variance shocks across multiple assets. First, each asset's return series is modeled via an AR(1)-GARCH(1,1) process, ensuring we remove individual autocorrelation and volatility clustering effects. However, even after standardizing residuals with GARCH, we often observe that major market events induce synchronized volatility surges across assets, pointing to a shared, global factor. Hence, the COVOL approach introduces a latent factor x_t representing *overall co-volatility* and asset-specific loadings s_i indicating each asset's sensitivity to the global shocks. By iteratively estimating x_t and s_i, we can quantify the extent of cross-asset variance dependence that standard GARCH alone cannot explain. Empirically, we verify this via a Global Co-Volatility Test, which checks residual cross-correlation in the squared standardized returns. A strongly significant test suggests the presence of a global variance factor. Applications of this framework, show that identifying and tracking x_t can improve *risk management* and *hedging strategies*, especially during large-scale market events (e.g., major policy announcements, commodity shocks, or climate-related transitions). The following sections detail the AR-GARCH setup, the estimation of the co-volatility factor, and practical uses of the model in portfolio construction and event-driven analysis.

2.1 Model

We have a database $\mathbf{R} \in \mathbb{R}^{T \times N}$, where each column corresponds to an asset's return series, $R_{t,i}$ ($t = 1, \ldots, T$, $i = 1, \ldots, N$) with T is the number of time periods and N is the number of assets. For each asset i, the time series $R_{t,i}$ is fitted with an AR(1)-GARCH(1,1) model.

2.1.1 AR(1) Model

$$R_{t,i} = \phi_i \, R_{t-1,i} + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim \mathcal{N}(0, \sigma_{t,i}^2), \tag{1}$$

where ϕ_i is the autoregressive parameter and $\epsilon_{t,i}$ is the innovation (residual). To ensure a stationary AR(1) process for each asset, we impose

$$|\phi_i| < 1 \quad \text{for each } i.$$

This condition prevents divergence and ensures a finite long-run variance of $R_{t,i}$.

2.1.2 GARCH(1,1) Model

The conditional variance of $\epsilon_{t,i}$ is modeled as:

$$\sigma_{t,i}^2 = \omega_i + \alpha_i \, \epsilon_{t-1,i}^2 + \beta_i \, \sigma_{t-1,i}^2, \tag{2}$$

where $\omega_i > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and the following stationarity condition ensures that the volatility does not explode over time and that a long-run variance exists

$$\alpha_i + \beta_i < 1 \quad \text{for each asset } i.$$

Combining these models allows us to capture linear dependence in $R_{t,i}$ via AR(1) and account for volatility clustering via GARCH(1,1). Once the model is fitted for asset i, we obtain the conditional variances $\sigma^2_{t,i}$ and define the *standardized residuals*:

$$z_{t,i} = \frac{\epsilon_{t,i}}{\sigma_{t,i}}.$$

2.2 Estimation of the Global Co-Volatility Factor

Even after GARCH standardization, residuals may still exhibit a *common* time-varying variance factor across assets. We therefore introduce a global latent factor x_t (for $t = 1, \ldots, T$) representing overall co-volatility and factor loadings $s_i \in [0, 1]$ (for $i = 1, \ldots, N$) that quantify each asset's sensitivity to x_t.

2.2.1 Model Assumption

We suppose the squared standardized residuals $z^2_{t,i}$ follow

$$\mathbb{E}\big[z^2_{t,i} \mid x_t, s_i\big] = g(s_i, x_t),$$

where

$$g(s, x) \;=\; s\,(x - 1) \;+\; 1 \tag{3}$$

and we impose $x_t > 0$ throughout the estimation. Hence, if $x_t = 1$, then $g(s_i, 1) = 1$. If x_t deviates from 1, an asset with higher s_i sees a greater (or lesser) shift.

2.2.2 Block Estimation Procedure

We define the negative log-likelihood (up to additive constants) for the random variables $\{z_{t,i}\}$, assumed $\mathcal{N}(0, g(s_i, x_t))$:

$$\mathrm{NLL}(x, s) = \frac{1}{2} \sum_{t=1}^{T} \sum_{i=1}^{N} \Big[\ln\!\big(g(s_i, x_t)\big) + \frac{z^2_{t,i}}{g(s_i, x_t)} \Big]. \tag{4}$$

noting $z^2_{t,i}$ is the squared standardized residual from the AR(1)-GARCH(1,1) step.

Steps:

1. **Initialization:**
   - Set $x_t = 1$ for all t.
   - Randomly initialize $s_i \in [0, 1]$ (e.g. uniform) and optionally normalize them.
2. **Update of x_t (fixing s_i):**
   For each t, minimize (4) w.r.t. x_t alone:
   $$\mathrm{NLL}(x_t) = \frac{1}{2} \sum_{i=1}^{N} \Big[\ln\!\big(s_i(x_t - 1) + 1\big) + \frac{z^2_{t,i}}{s_i(x_t - 1) + 1} \Big].$$
3. **Update of s_i (fixing x_t):**
   With $\{x_t\}$ fixed, minimize
   $$\mathrm{NLL}(s) = \frac{1}{2} \sum_{t=1}^{T} \sum_{i=1}^{N} \Big[\ln\!\big(s_i(x_t - 1) + 1\big) + \frac{z^2_{t,i}}{s_i(x_t - 1) + 1} \Big],$$
   subject to $0 \leq s_i \leq 1$.
4. **Iteration and Convergence:**
   Alternate between updating $\{x_t\}$ and $\{s_i\}$ until changes in all variables are below a tolerance ϵ.

Resulting Estimates: $\hat{x}_t$ the global co-volatility factor over time and $\hat{s}_i$ the loadings indicating each asset's exposure to the global factor.

2.3 Global Co-Volatility Test

After fitting, a statistical test can check whether the *centered* squared standardized residuals $(z_{t,i}^2 - 1)$ exhibit significant cross-correlation.

1. Calculation of the Statistic ξ

$$\xi = \sqrt{\frac{N\,T}{\frac{N-1}{2}}}\;\frac{\sum_{i=1}^{N}\sum_{j=i+1}^{N}\sum_{t=1}^{T}(z_{t,i}^2 - 1)\,(z_{t,j}^2 - 1)}{\sum_{i=1}^{N}\sum_{t=1}^{T}(z_{t,i}^2 - 1)^2}. \tag{5}$$

2. p-Value

Under appropriate assumptions (e.g. no cross-correlation of squared standardized residuals under the null), ξ is approximately $\mathcal{N}(0,1)$. Hence, the two-sided p-value is:

$$p = 2\left[1 - \Phi\big(|\xi|\big)\right].$$

where Φ is the standard normal CDF.

2.4 Practical use cases and References

Once the co-volatility factor $\{\hat{x}_t\}$ and factor loadings $\{\hat{s}_i\}$ are estimated, they can be employed in a variety of investment or hedging strategies that aim to account for common shifts in volatility across assets. Recent contributions in the literature emphasise the importance of such global factors:

- **Campos-Martins and Hendry (2024) [2]** highlight how the *global carbon transition* can induce *common volatility shocks* across multiple asset classes. In periods of substantial regulatory or technological change related to carbon emissions, numerous markets can experience synchronized volatility bursts. Such events are naturally captured by a global factor x_t, which may spike when carbon policy or climate-related news triggers simultaneous uncertainty in equities, bonds, commodities, or exchange rates.
- **Engle and Campos-Martins (2023) [4]** propose methods to identify the key events ("shocks that shake our world") and measure the global co-volatility they induce. They further discuss how to implement hedging solutions by exploiting the factor loadings of individual assets relative to the global factor. The $\hat{s}_i$ coefficients in our model provide a way to quantify how sensitive each asset is to the co-volatility shocks captured by $\hat{x}_t$.

From a *portfolio management* standpoint, one can use the estimated factor $\hat{x}_t$ to:

1. **Identify high co-volatility regimes.** When $\hat{x}_t$ deviates significantly from 1 (e.g., it spikes above a certain threshold), it signals a market-wide increase in volatility that impacts most assets simultaneously. This helps in *real-time* monitoring of systemic risk.
2. **Construct hedging strategies.** Assets with high factor loadings $\hat{s}_i$ are more vulnerable to these global shocks, while those with lower loadings are less affected. A simple hedging approach might involve underweighting assets with high $\hat{s}_i$ (or shorting them) and overweighting those with low $\hat{s}_i$ during periods of elevated $\hat{x}_t$. By doing so, the portfolio becomes less exposed to global volatility spikes.

Illustrative Example. As suggested in Engle and Campos-Martins (2023) [4], suppose an asset manager tracks a basket of equities, commodities, and currencies. After estimating the AR(1)-GARCH(1,1) for each instrument and extracting standardized residuals, they fit our COVOL model to obtain $\hat{x}_t$ and $\hat{s}_i$. A jump in $\hat{x}_t$ around a major *carbon emission regulation* announcement would reveal a market-wide volatility shock. The manager could then *rebalance* positions by scaling down exposure to high-$\hat{s}_i$ assets and temporarily shifting capital into lower-$\hat{s}_i$ positions or other hedging instruments. This approach mirrors the logic of "hedging global events" described by Campos-Martins and Hendry (2024) [2], with the difference that the COVOL factor $\hat{x}_t$ provides a real-time or ex-post measure of how large and pervasive the shock is.

Overall, incorporating the global factor $\hat{x}_t$ and asset loadings $\hat{s}_i$ allows one to detect, measure, and mitigate *common volatility* shocks across markets—whether driven by the global carbon transition or other major systemic events.

3 Descriptive Statistics and first application

Before detailing the application of our co-volatility model, we present a descriptive overview of the dataset. The sample spans a wide range of asset classes (commodities, interest rates, equity indices, etc.) from 2000 to 2024. We highlight several major macro-financial events (the 2008 Financial Crisis, the European Sovereign Debt Crisis, the COVID-19 pandemic, the Russia-Ukraine war, etc.), given their pronounced impact on market dynamics.

3.0.1 Price Evolution (2000–2024)

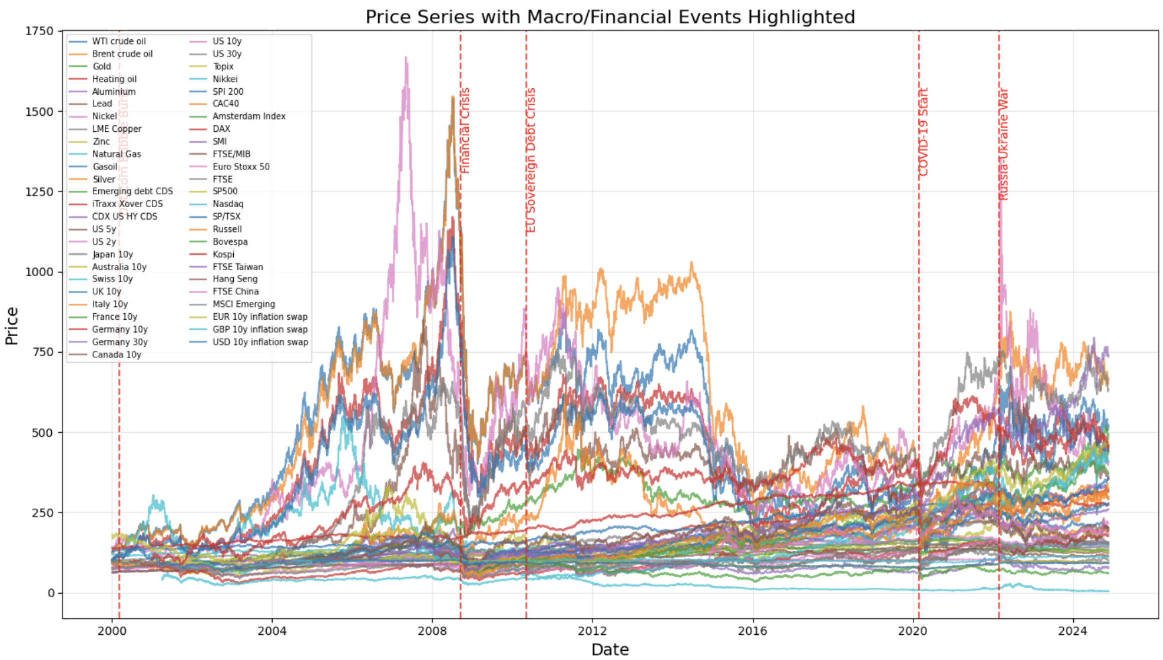


Figure 1: Price series for various assets, with key crisis events (*Financial Crisis*, *EU Sovereign Debt Crisis*, *COVID-19 Start*, and *Russia-Ukraine War*) highlighted by red vertical lines. We observe notable divergences across asset classes, but also synchronized up- or down-movements during systemic shocks.

Figure 1 depicts the nominal (index) prices of the assets over time. The spike around the 2008 Financial Crisis is particularly evident for commodities (oil, metals), yet other assets (equities, long-term bonds) also experience sizable volatility. Further, we see high price levels and fluctuations in some post-crisis intervals, reflective of persistent economic uncertainty.

3.0.2 Analysis of Daily (Log) Returns

To better capture underlying dynamics for GARCH-type models, we use *logarithmic returns* rather than raw returns. Figure 2 shows the magnitude of fluctuations around each highlighted event. The 2008 Financial Crisis exhibits a pronounced increase in volatility, and similarly the onset of COVID-19 in early 2020 and the Russia-Ukraine conflict in 2022. These *systemic* shocks suggest the presence of a *common volatility component* that affects multiple assets simultaneously, motivating the latent co-volatility factor (x_t) described in the following sections.

3.0.3 Correlation of Rolling Volatilities

Figure 3 illustrates a *correlation matrix* for volatilities computed with a rolling window (e.g., 60 days). Certain asset clusters (global equity indices, CDS, energy commodities) exhibit high mutual correlations in periods of stress, indicating that a global factor (e.g., macro-financial conditions or geopolitical shocks) may jointly influence their individual volatilities. Other assets (notably certain sovereign bonds) show more specific patterns, yet they too can be swept up by common volatility waves during crises.

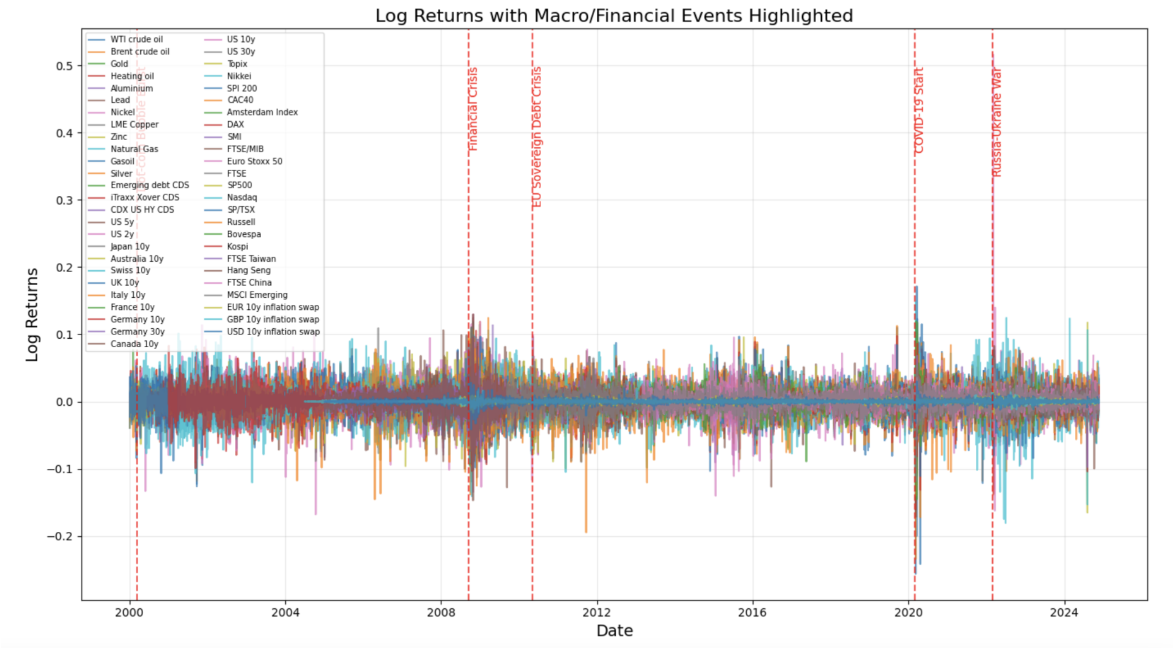


Figure 2: Daily log-returns of each asset, with the same macro-financial events indicated. Large spikes in volatility typically align with major global disruptions.

In summary, these descriptive analyses highlight the presence of common shocks and synchronized volatility patterns in the sample. This supports the introduction of a *latent co-volatility factor* to model and better understand these dynamics. The next subsection details how we implement and apply our *COVOL Model* to the data presented here.

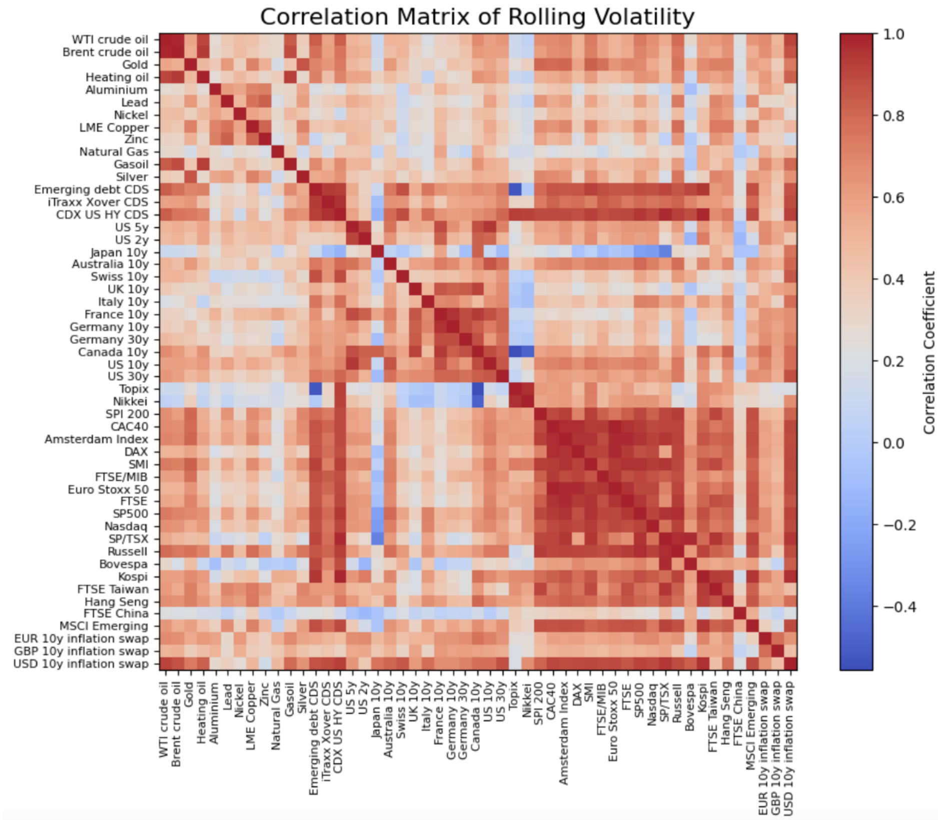


Figure 3: Correlation matrix of rolling volatilities across assets. Warmer (red/orange) colors indicate stronger positive correlation, whereas cooler (blue) tones signal weaker or negative correlation.

3.1 Model Results

In this section, we present the outcomes of the AR(1)-GARCH(1,1) estimation for each asset, followed by the co-volatility factor (x_t) obtained from our COVOL model. We highlight key diagnostic checks, such as the stationarity of the AR and GARCH components and the significance of the global co-volatility factor.

3.1.1 AR(1) and GARCH(1,1) Parameter Estimates

Table 1 shows the AR(1) coefficients (ϕ_i) as well as the GARCH(1,1) parameters ($\omega_i, \alpha_i, \beta_i$) for each asset. The two rightmost columns check the usual stationarity constraints. Across all assets, we observe that $|\phi_i| < 1$ and $\alpha_i + \beta_i < 1$, indicating stable AR-GARCH processes without explosive volatility dynamics.

Table 1: AR(1) Parameters and GARCH(1,1) Estimates for Each Asset. The rightmost columns check stationarity conditions: $|\phi_i| < 1$ for AR(1) and $\alpha_i + \beta_i < 1$ for GARCH(1,1).

Asset	ϕ_i	ω_i	α_i	β_i	$\alpha_i + \beta_i$	$|\phi_i| < 1$?	$\alpha_i + \beta_i < 1$?
Gasoil	0.0254	5.82e-06	0.10	0.88	0.96	True	True
Gold	-0.0559	1.99e-06	0.05	0.93	0.95	True	True
Aluminium	-0.0192	1.15e-06	0.05	0.93	0.97	True	True
Nasdaq	-0.0815	3.49e-06	0.10	0.88	0.98	True	True
Emerging debt CDS	0.0042	2.37e-07	0.20	0.78	0.93	True	True
Euro Stoxx 50	0.0135	1.80e-06	0.10	0.88	0.97	True	True
Russell	-0.0478	3.93e-06	0.10	0.88	0.96	True	True
US 5y	-0.0128	9.87e-08	0.10	0.88	0.96	True	True
US 2y	-0.0118	1.44e-07	0.20	0.78	0.97	True	True
Germany 10y	0.0191	9.70e-08	0.05	0.93	0.98	True	True
DAX	0.0414	2.92e-06	0.10	0.88	0.98	True	True
SP500	-0.0964	2.35e-06	0.10	0.88	0.96	True	True
Nikkei	-0.0169	3.49e-06	0.10	0.88	0.98	True	True
MSCI Emerging	-0.0699	3.48e-06	0.10	0.88	0.95	True	True
USD 10y infl. swap	0.0479	1.89e-07	0.10	0.88	0.98	True	True
Natural Gas	-0.0495	1.81e-05	0.10	0.88	0.97	True	True
Zinc	0.0057	2.51e-06	0.05	0.93	0.92	True	True

3.1.2 Global Co-Volatility Test Results

Table 2: Global Co-Volatility Test Statistic ξ and p-Value. If $p < 0.05$, we reject H_0 (no cross-correlation in squared standardized residuals), implying significant co-volatility.

Statistic	ξ	p-value
Global Co-Vol Test	108.8814	0.0

In Table 2, we report the **Global Co-Volatility Test** statistic (ξ). Its large magnitude (108.88) and near-zero p-value confirm that the standard GARCH(1,1) modeling of each asset alone does not fully capture common variance across assets. Hence, a latent factor approach is warranted.

3.1.3 Estimated Conditional Variances and Latent Factor

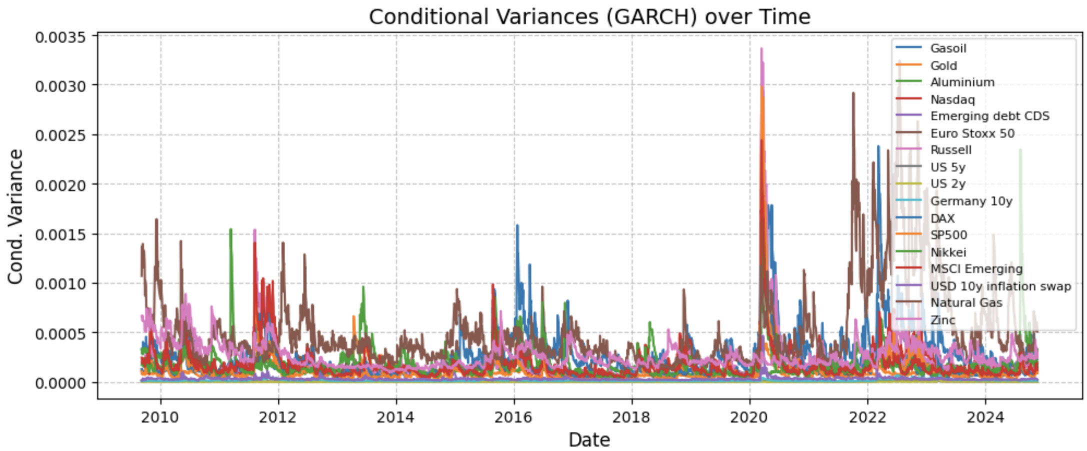


Figure 4: Estimated conditional variances $\sigma^2_{t,i}$ from the univariate GARCH(1,1) models for each asset over time. Peaks coincide with major market disruptions.

Figure 4 presents the conditional variances, showing how different assets' volatility spikes often align in time, reflecting common market shocks.

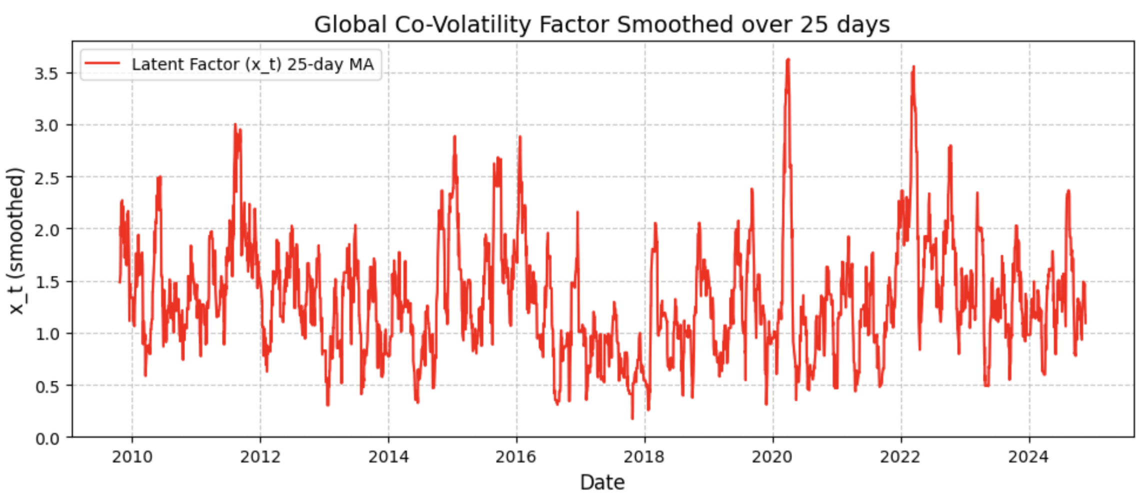


Figure 5: The global co-volatility factor x_t smoothed over 25 days. Higher values signal stronger common volatility.

Finally, in Figure 5, we depict the latent co-volatility factor $\{x_t\}$. Sharp increases typically align with known events, demonstrating that *common* volatility shocks are shared across multiple assets.

3.1.4 Factor Loadings

The estimated factor loadings $\{s_i\}$ quantify each asset's exposure to the global co-volatility factor. Intuitively, higher $\hat{s}_i$ indicates that asset i experiences greater volatility shifts in response to the common factor x_t, while lower values imply more idiosyncratic variance.

In Figure 6, we see substantial variation across assets. Equities (e.g., *S&P500*, *Nasdaq*, *Euro Stoxx 50*) often exhibit relatively high loadings, reflecting their sensitivity to widespread market turbulence. Certain fixed-income or commodity instruments (like *Germany 10y* or *Natural Gas*) may show lower or more moderate values, possibly indicating a weaker response to the same global volatility impulses. Notably, the magnitude of these loadings has implications for hedging strategies (e.g., overweighting lower-s_i assets during volatile periods) and for understanding the cross-asset impact of major events such as macroeconomic announcements or geopolitical tensions

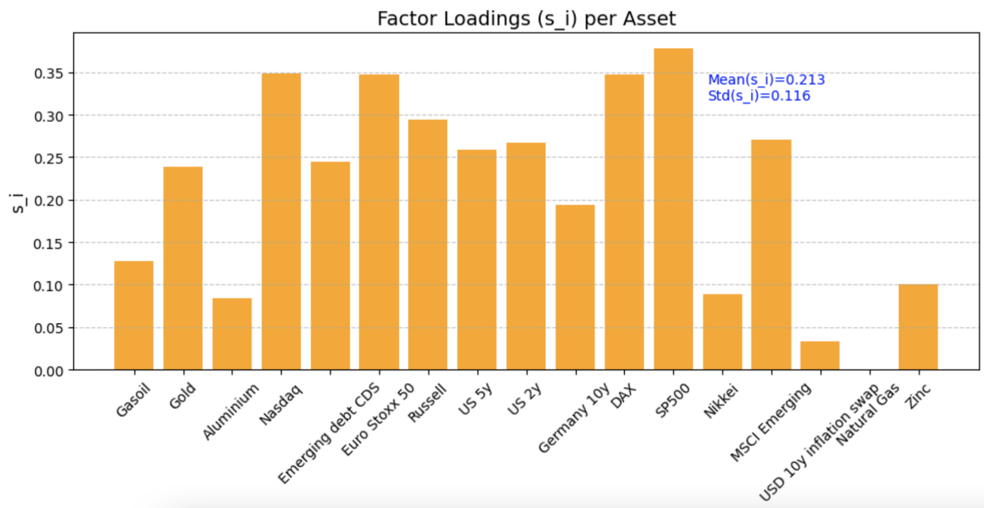


Figure 6: Estimated factor loadings s_i for each asset. The mean and standard deviation of $\{s_i\}$ are reported in the legend. Assets with higher loadings are more sensitive to common shocks.

4 Extensions and Improvements

In the following sections, we present our results and considerations that leverage COVOL and extends the original work of the paper and our replication. In Section 4.1 we show how the Global COVOL latent-factor series can be merged with a text-based indicator of market tone extracted from central-bank policy statements using FinBERT, thereby allowing us to test directly whether the language of monetary authorities tracks, or predicts, day-to-day swings in global volatility. In Section 4.2 we put forward our results and considerations on utilizing COVOL to implement an hedging strategy against extreme events that generate high volatility across the market.

4.1 Does Rhetoric Move Risk? A Daily COVOL - Sentiment Test

Recent commentary in financial media has revived a long-standing debate over whether equity markets sometimes drift away from economic fundamentals. Early empirical classics such as, Schwert (1981) [8], Pearce and Roley (1985) [6], Cutler, Poterba and Summers (1989) [3], document that stock returns and volatility react sharply to macro news, implying that prices are anything but detached from incoming information. Subsequent work, beginning with McQueen and Roley (1993) [5], refined that view by showing the state of the economy shapes how strongly markets respond: when conditions are weak, good news about output or employment boosts equities more because the central bank is unlikely to tighten; when the economy is strong, the same news can be muted, or even reverse-signed, because investors fear an offsetting rate hike. All of these studies, however, look at individual asset classes or specific rate surprises. None asks whether the words of the central bank itself reverberate through the common component of volatility that spans global markets.

That question has become feasible only recently. Engle and Campos-Martins (2023) [4] introduced global COVOL, a latent factor that captures volatility shocks affecting many assets at once, and in late 2022 released a daily COVOL series. If all major asset classes reprice almost immediately to monetary-policy surprises, then a meaningful shift in the tone of a policy statement should, in principle, register in that factor, just as geopolitical shocks do in the Engle-Campos-Martins framework. We therefore ask whether central-bank rhetoric itself has the power to “shake the world.”

To investigate, we scraped every policy statement issued by the Federal Reserve, the European Central Bank and the Bank of Japan from their public archives, stripped out formal boiler-plate and fed the remaining text through FinBERT, a transformer model trained on financial language. Averaging the positive-sentiment probabilities by date and institution produced three daily series of central-bank tone. We then merged those sentiment series with the newly released daily COVOL index and flagged the top decile of COVOL observations as high-uncertainty days.

In doing so, we extend Engle and Campos-Martins’s framework into the realm of textual analysis and pioneer a method to assess, at the daily frequency, whether central banks lean into market fear or whether markets react with a lag to central-bank tone. By leveraging state-of-the-art sentiment extraction on recently released daily COVOL data, we explore the interplay between words and risk at an unprecedented temporal resolution.

The kernel-density curves Figure **7** reveal striking differences in how each central bank "sounds". Fed statements cluster almost entirely at the upper end of the scale, hence the blue curve forms a tall with a narrow spike around 0.93, and only a faint shoulder near 0.48. This indicates that the 42 observations of FOMC statements are almost uniformly positive in FinBERT's vocabulary, leaving very little variation to explain movements in market uncertainty. The ECB, by contrast, supplies more than 2 100 statements, and its curve shows a broad, bimodal distribution (orange). One mode sits close to 0.42, reflecting the more cautious language the Governing Council deploys during macro strain, while a second, flatter hump appears between roughly 0.65 and 0.75, capturing moderately upbeat tone. The sheer width of the orange curve underscores how heterogeneous ECB messaging can be as the institution balances nineteen member economies. BoJ statements occupy the middle ground (green). With only 39 releases, the curve is smoother but shows two gentle peaks: one near 0.70 and a larger one around 0.90. In other words, the Bank of Japan alternates between fairly positive and very positive language, but unlike the Fed, we can still notice a amount of neutral or guarded assessments remarks.

Because each density is normalised to integrate to one, a higher peak does not signal a larger sample; it signals a tighter spread. The Fed's towering spike therefore reflects an extremely compressed sentiment range, not a bigger dataset. This compression helps explain why Fed tone shows almost no statistical link to global COVOL: there is simply not enough day-to-day variation to covary with volatility shocks. Conversely, the ECB's wide, two-humped profile offers plenty of variation, yet its centre-of-mass still lies in mildly positive territory. This explains why even pronounced swings in COVOL register only weak correlations. Finally, the BoJ's modest sample produces a smooth but low-amplitude curve; the limited number of high-uncertainty days in Japan means any apparent association with COVOL cannot be viewed as robust. Overall, the plot underscores a key empirical takeaway: differences in the dispersion of tone across central banks and the stark discrepancy in available press-release counts, rather than the absolute level of positivity, largely determine how much information their words can convey about global market risk.

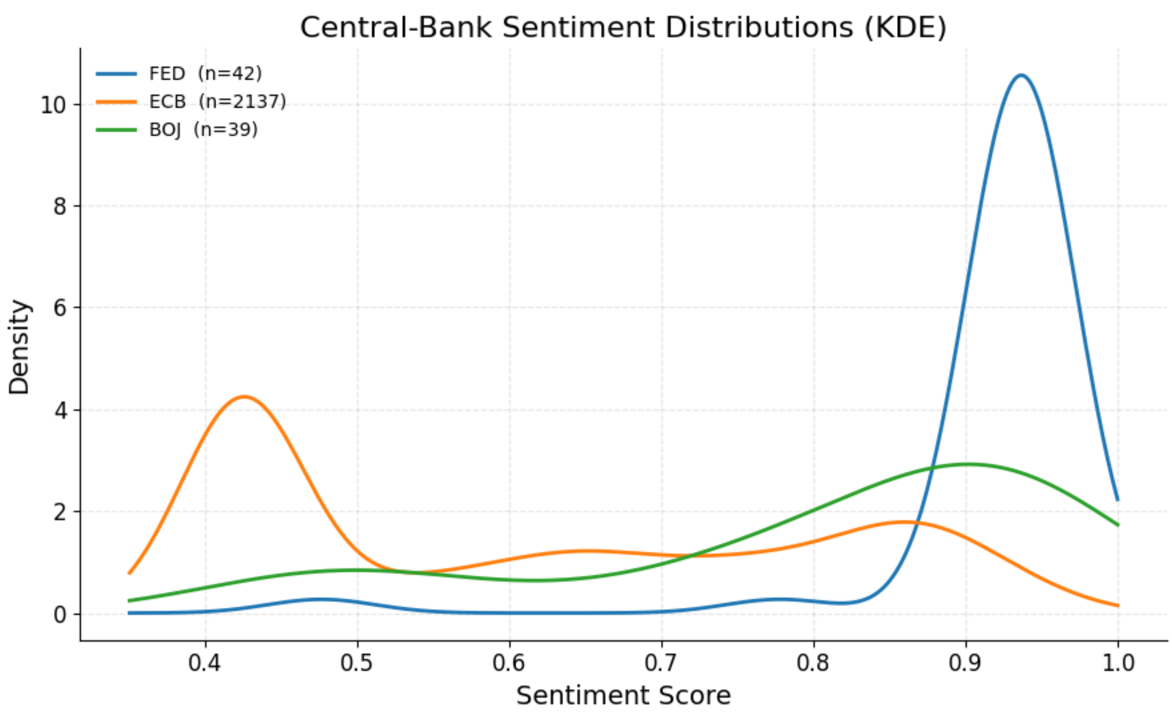


Figure 7: Kernel Density of FinBERT-Based Sentiment Scores for Fed, ECB, and BoJ Policy Statements

Figure 8 overlays the two usable series in our sample on a common set of axes. The hexagonal cells depict the ECB statements: the density gradient shows that almost every Governing-Council meeting occurred when global COVOL was below 3, and only a handful of observations sit above 10. The dashed orange LOWESS line slopes only marginally upward, in line with the negligible contemporaneous correlation we report for the ECB ($\rho \approx +0.01$). In other words, even sizeable daily swings in worldwide volatility leave the average tone of ECB communiqués essentially unchanged.

Super-imposed blue circles represent Fed press releases. They cluster tightly around a sentiment score of 0.93 and COVOL values under 5. The dashed blue LOWESS curve tilts gently downward, reflecting the modest negative correlation ($\rho \approx -0.19$). The narrow vertical spread of the Fed cloud underscores why this correlation lacks economic punch: with only 42 observations with almost all uniformly positive, there is little variation in tone that could covary with volatility shocks.

We exclude the BoJ from this plot. The Bank of Japan archive yields only 39 statements in the daily-COVOL window, and just one of those coincides with a non-missing COVOL reading; including that solitary point would add no statistical insight while stretching the x-axis. The figure therefore concentrates on the two central banks whose sample sizes allow a meaningful visual appraisal of the tone–volatility relationship.

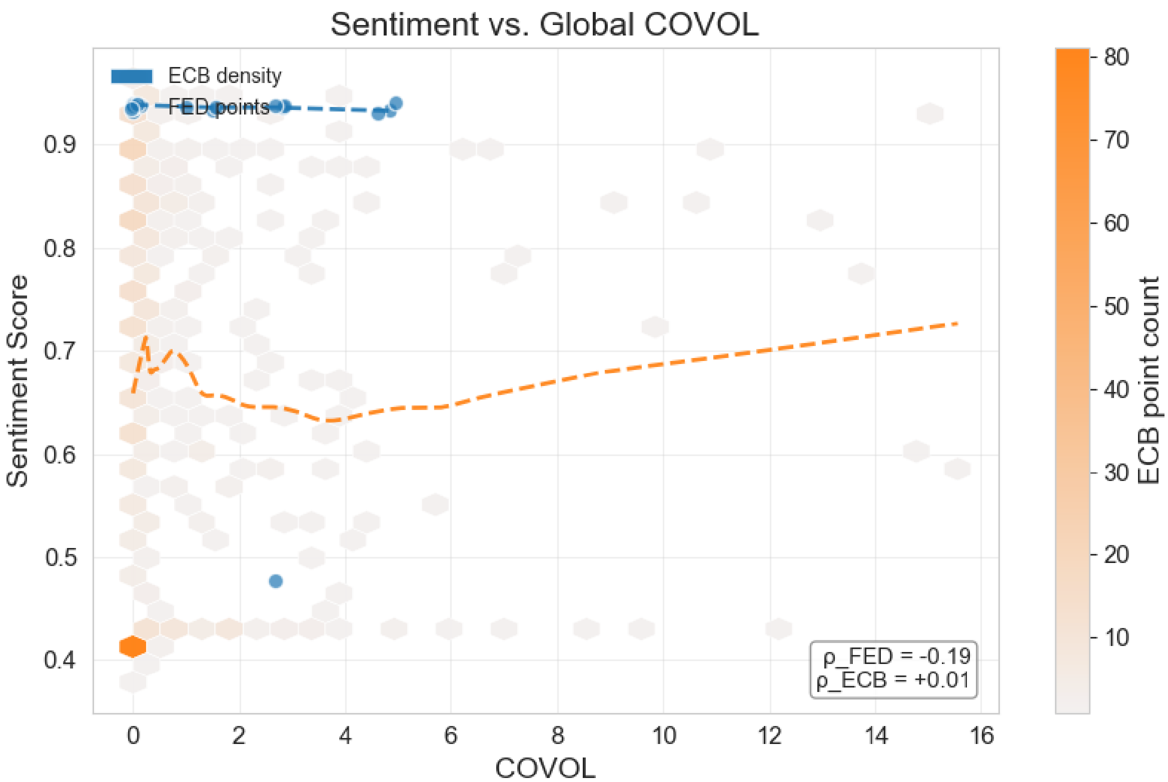


Figure 8: Kernel Density of FinBERT-Based Sentiment Scores for Fed, ECB, and BoJ Policy Statements

Table 3: COVOL coefficients across alternative specifications

Specification	$\hat{\beta}_{\text{COVOL}}$	z (or t)	p-value	Fit[1]
OLS with bank dummies, cluster SEs	0.0006	1.09	0.278	$R^2 = 0.085$
OLS with bank dummies and COVOL×bank, HC3	0.0083	0.06	0.953	$R^2 = 0.086$
OLS with month fixed effects†, HC3	0.0055	0.04	0.972	$R^2 = 0.366$
Mixed effects, random bank intercept	−0.0023	−0.61	0.540	$\ell = 233.18$
Mixed effects, random bank intercept & slope	−0.0028	−1.05	0.301	$\ell = 233.29$

†The month dummies absorb calendar variation that would otherwise be captured by a rolling window. Our empirical exercise links 515 daily observations of policy-statement tone that we extracted with FinBERT for the Federal Reserve, and the European Central Bank to the daily global COVOL series of Engle and Campos-Martins (2023). The first three rows of Table 3 show progressively richer ordinary least squares specifications. In the benchmark model, which

[1]For the OLS specifications the column reports R^2; for mixed effects models it reports the maximum log-likelihood.

controls only for bank-level differences and clusters standard errors by institution, the COVOL coefficient is 0.0006, its z-statistic is 1.09, and the associated p-value is 0.28. Allowing the slope on COVOL to vary across banks leaves that coefficient effectively unchanged and renders the interaction terms themselves highly insignificant.

The third specification introduces a full set of month fixed effects. Doing so mimics a twelve-month rolling window in the sense that it nets out any common seasonal drift in sentiment, thereby forcing the identification of the COVOL effect to come from within-month fluctuations. Although this time fixed-effect structure lifts the adjusted R^2 to 0.366, the estimate of $\hat{\beta}_{\text{COVOL}}$ remains economically tiny at 0.0055 and statistically negligible with a p-value of 0.97. Put differently, once we account for systematic calendar patterns, patterns that a rolling window would also remove, the purported link between tone and global volatility all but disappears.

The final two rows report mixed-effects results. A random intercept specification lets each central bank have its own unconditional mean tone, while the random slope extension also permits heterogeneous responsiveness to COVOL. Neither framework alters the substance of the findings: point estimates hover around -0.002, the corresponding z-statistics stay well below conventional significance thresholds, and likelihood improvements are trivial.

Overall, our findings close the empirical loop we set out to explore. Even after stripping out each bank's characteristic tone, purging seasonality through month fixed effects (the statistical analogue of a twelve month rolling window), and allowing for random heterogeneity in both intercepts and slopes, the COVOL coefficient stays numerically trivial and nowhere near significance. In plain language, the day-to-day flow of global market anxiety leaves no audible trace in the words of the world's three major central banks, nor do those words foreshadow such anxiety a few days ahead. Within the high-frequency framework we pioneered, FinBERT scores matched to the newly available daily COVOL index-central bank rhetoric and the common component of volatility move on separate tracks. The story that emerges is therefore unambiguous: at the daily horizon, global markets appear to listen to actions, not to the tone of policy statements.

4.2 Mitigation COVOL

As we explained in *Introduction*, global financial markets are increasingly vulnerable to geopolitical risks and macroeconomic shocks that trigger widespread volatility across asset classes. Traditional diversification strategies, which rely on the assumption of low correlation between assets, often fail to provide adequate protection during periods of global common volatility because global shocks tend to propagate across markets and asset classes simultaneously. Indeed, macroeconomic shocks like global recessions, political instability, or major policy shifts often introduce a surge in correlated volatilities across seemingly uncorrelated assets, rendering traditional diversification less effective.

That is the reason why, inspired by Engle and Campos-Martins (2023) [4], we introduce a novel criterion for portfolio optimisation aimed at mitigating exposure to these global shocks, namely global COVOL mitigation. This approach leverages the insight that assets load differently on global volatility shocks, allowing portfolio managers to strategically underweight assets with high global COVOL exposure and overweight those with lower sensitivity. The intuition behind this strategy is that, during global volatility events, not all assets are equally affected. Some markets may act as volatility amplifiers while others might serve as stabilizers (or safe havens), thereby presenting an opportunity for selective rebalancing that minimises overall portfolio risk.

In theory, global COVOL mitigation effectively extends the concept of risk diversification to account not just for idiosyncratic risks but also for common volatility shocks that traditional models tend to overlook, adding a new constraint to the typical Markowitz optimisation problem. By rebalancing the portfolio in a manner that accounts for differential exposure to these global shocks, the strategy enhances resilience against market-wide turbulence. This is particularly crucial during crises where the correlation structure of asset returns can change abruptly, leading to unexpected spikes in portfolio risk.

Overall, the goal of this section is to provide the synthesis for that setting from the paper and, later, demonstrate how it works in practice, with its limits and achievements. At the end, there will be room for comments, extensions and ideas to develop it further.

To formalize this risk-aware strategy, we propose an optimisation problem that maximises portfolio returns while constraining both total variance and exposure to global financial risk. This optimisation problem is defined as:

$$\max \; w'\mu \tag{6}$$

subject to constraints on idiosyncratic and global COVOL induced risks:

$$
\begin{aligned}
w' \left[\operatorname{diag}(\sigma_j^2)\beta' + \operatorname{diag}(\sigma_j^2)\right] w \le \theta_1 \quad &\text{(Total variance)} \\
w' \left[\operatorname{diag}(\tilde{s}_j)\beta' + \operatorname{diag}(\tilde{s}_j)\right] w \le \theta_2 \quad &\text{(Global COVOL)}
\end{aligned}
\tag{7}
$$

where β represents the factor loadings, σ_j^2 the unconditional variance of idiosyncratic risks, and $\tilde{s}_j$ the variance weighted global COVOL loadings. This optimisation framework is designed to enhance portfolio resilience by systematically reducing exposure to assets that are disproportionately affected by global shocks, offering a robust mechanism for navigating volatile market conditions.

Intuitively, this strategy works because it recognizes that not all volatility is purely local or idiosyncratic. During global financial distress, shocks tend to spread across multiple asset classes, even those traditionally thought to be uncorrelated. Mitigating exposure to global COVOL reduces the portfolio's sensitivity to these extreme events, effectively smoothing out returns and maintaining stability when it is most needed. This marks a shift from merely spreading risk across assets to actively managing exposure to systemic shocks, a concept that becomes critical in a highly interconnected global economy.

Nevertheless, in practice, there are some problems to be addressed. The optimisation process was conducted by leveraging the Python class previously introduced and an appropriate optimisation function for mitigating exposure to global COVOL. The primary objective of this optimisation is to construct a portfolio that maximises expected returns while satisfying two critical constraints from (7). The constraints were initially set arbitrarily as $\theta_{\text{var}} = 10^{-3}$ and $\theta_{\text{covol}} = 10^{-4}$, reflecting a tight control on both variance and exposure to common global volatility shocks.

The resulting optimal portfolio weights are displayed in the bar plot in Figure 9, illustrating the asset allocation that achieves maximum expected return under the imposed risk constraints.

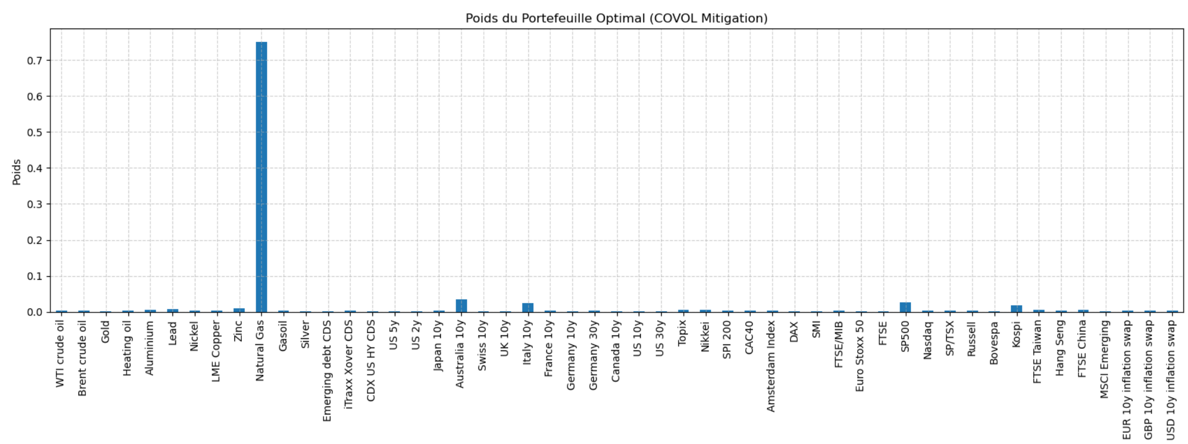


Figure 9: Portfolio Weights for the Optimal COVOL Mitigation Portfolio between 5/3/2013 and 19/11/2024

Beyond the positivity of all weights, even in the absence of explicit non-negativity constraints, the most striking outcome of the optimisation is the overwhelming allocation to Natural Gas, which accounts for over 70% of the total portfolio composition. This outcome suggests that, under the optimisation framework, Natural Gas appears to offer a highly attractive return-to-risk profile when adjusted for global COVOL shocks. This dominant position may be explained by the optimisation logic, where the asset's low co-movement with other financial instruments under global volatility conditions allows it to effectively hedge against global shocks, thereby reducing the overall exposure to COVOL. Moreover, its historical return characteristics, combined with the estimated betas, seem to favour its inclusion as a major component of the risk-mitigated portfolio. However, such a heavy concentration introduces significant concerns such as the concentration risk, as the portfolio is highly reliant on the performance of a single commodity. In practice, this may lead to excessive sensitivity to idiosyncratic shocks specific to energy markets, particularly geopolitical tensions, regulatory changes, or abrupt shifts in supply and demand dynamics. This over-exposure is particularly alarming given the inherent volatility of natural gas markets, which are known for sharp price fluctuations. Meanwhile, this reasoning aligns with similar findings of Baur and McDermott (2009) [1] and Ranaldo and Söderlind (2010) [7], who provide evidence that during periods of crisis, certain robust assets tend to decouple from the co-movement observed among various asset classes. Notably, assets such as gold and foreign currencies, like the Yen, have historically demonstrated strong resilience, acting as safe havens during market turmoil, including the recent T-Day of 2nd of April 2025, where these assets outperformed both the US and the international markets. Furthermore, the results raise questions about the stability of the optimisation model. If the parameter estimations $(\mu, \beta, \sigma_i^2, s_i)$ are overly sensitive to sample variations or window selections, the dominant weight assigned to Natural Gas could easily shift to another asset under slightly different conditions. This sensitivity undermines the robustness of the optimisation and calls for further investigation into parameter stability across different time horizons.

The construction of the efficient frontier on a grid for θ_{var} and θ_{covol} allowed us to identify two key portfolios of interest: the Tangent Portfolio, which maximises the Sharpe Ratio (the risk-free rate considered is the 3-Month Treasury Bill Secondary Market Rate obtained from the Federal Reserve Economic Data), and the Min-COVOL Portfolio, designed to minimise global COVOL exposure while achieving a specified minimum return threshold. The results are illustrated in *Figure 10*, which displays the efficient frontier with global COVOL exposure represented as a colour gradient. The Tangent Portfolio is marked with a red star, while the Min-COVOL Portfolio is marked with a blue triangle.

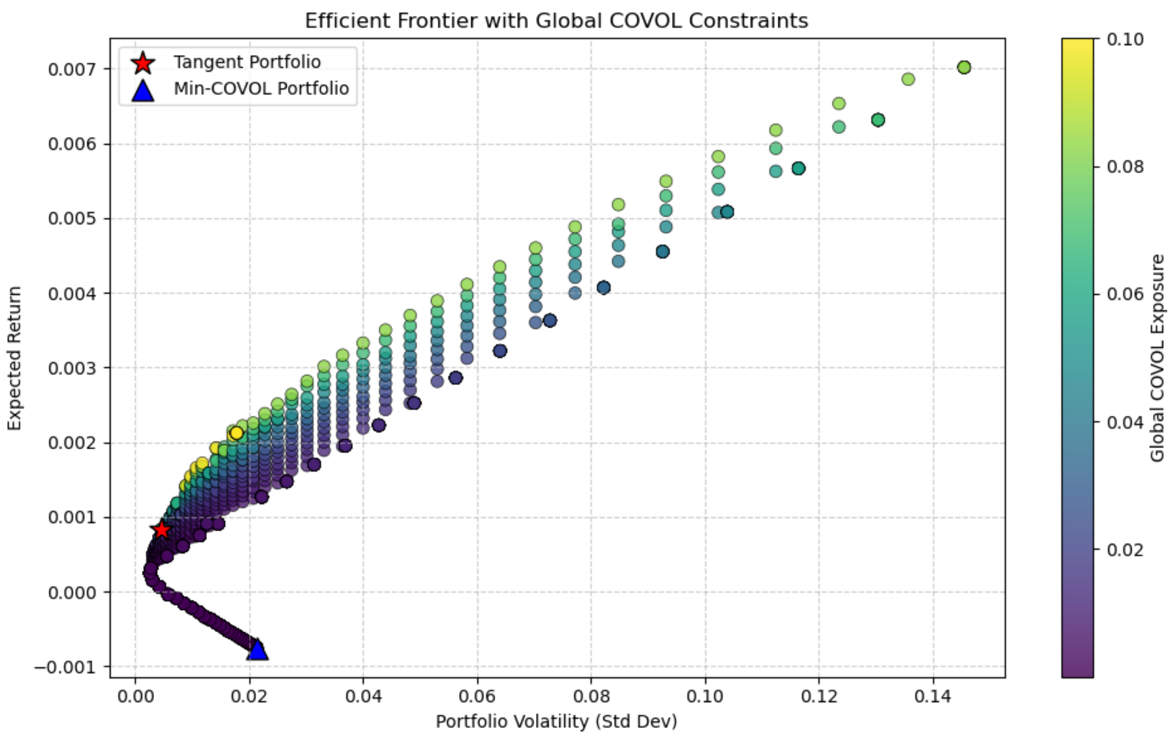


Figure 10: Efficient Frontier with Global COVOL Constraints, the Tangent portfolio and the portfolio with minimal global COVOL exposure

The cumulative performance of these portfolios is plotted in *Figure 11*, alongside an equal-weighted benchmark. The Tangent Portfolio significantly outperforms both the equal-weighted and the Min-COVOL portfolios in terms of cumulative returns over the studied period. This is expected, given its construction to maximise return per unit of risk. However, it is important to note the behaviour of the Tangent Portfolio during periods of high market stress, such as the COVID-19 pandemic. While the Tangent Portfolio experiences even larger drawdowns compared to the equal-weighted portfolio during these events, the Min-COVOL Portfolio remains remarkably stable. This stability highlights its effectiveness in reducing global volatility exposure, even if its general performance remains considerably lower, considering that the overall market has grown consistently in this 10-year time frame. Furthermore, we stress the considerably low impact of the Min-COVOL during Covid-19, remaining essentially stable without experiencing a sudden drop.

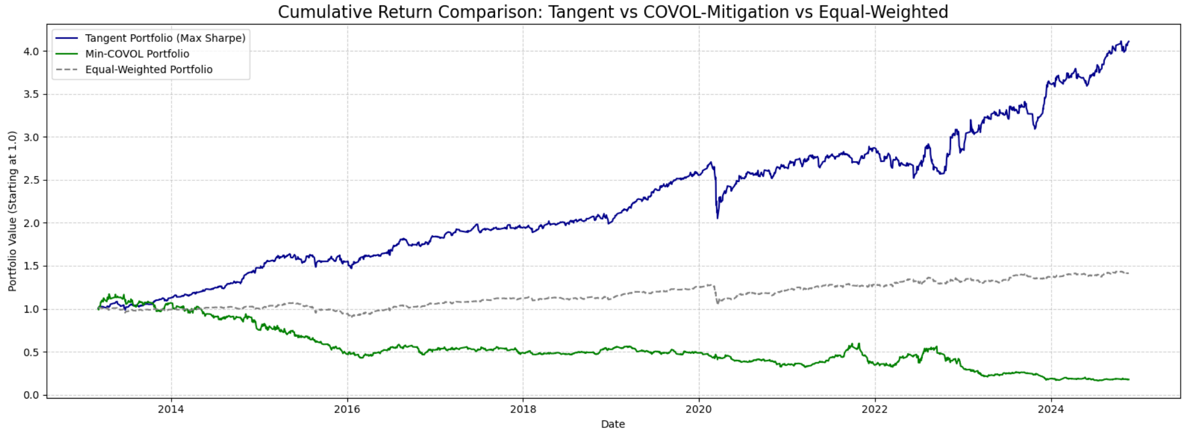


Figure 11: Cumulative Return Comparison: Tangent vs. COVOL-Mitigation vs. Equal-Weighted

The stability observed during significant global events is particularly noteworthy for the Min-COVOL Portfolio. Despite its weak performance and its apparent lack of growth, it maintains a certain robustness against global shocks. This behaviour is consistent with the core concept of COVOL mitigation: by reducing exposure to global common volatility factors, the portfolio is less sensitive to systemic risks. This comes, however, at the expense of substantial underperformance in normal market conditions, where global volatility is more subdued.

It is crucial to emphasise that the parameters for the Min-COVOL Portfolio optimisation were set to:

$$\theta_{\text{var}} = 5.18 \times 10^{-4}, \quad \theta_{\text{covol}} = 1.00 \times 10^{-5}$$

These values reflect a strict constraint on both total variance and exposure to common volatility, resulting in a portfolio allocation heavily skewed towards Natural Gas. Indeed, the optimised weights for the Min-COVOL Portfolio reached nearly 90% for Natural Gas alone, intensifying the concentration risk observed in earlier tests. This allocation indicates that, under the given optimisation constraints, Natural Gas is perceived as the most efficient vehicle for hedging against global COVOL.

The entirety of the analysis conducted in this section was purely in-sample, aiming solely to explore the theoretical effectiveness and the inherent limitations of the Mitigation COVOL approach. The empirical results were intended to provide a clearer understanding of how global COVOL exposure could be used to manage portfolio optimisation. Under the conviction of COVOL being utilised as a valuable indicator for volatility in the markets and for various asset classes from equities to commodities and bonds.

Discussing more from a practical standpoint, it is evident that maintaining the Min-COVOL Portfolio in a continuous, static fashion is neither realistic nor optimal. The design of the portfolio inherently focuses on mitigating risk during periods of extreme market stress or heightened global volatility. Hence, its primary utility would be as a defensive measure during specific periods when systemic risks are anticipated or when volatility signals reach critical thresholds. This opens the door for a more dynamic application, where the portfolio composition would switch to the Min-COVOL configuration around well-identified events that historically trigger market distress. For instance, preparing for volatility on the 2nd of April, an event which proved to have a significant negative impact on global markets, it could have been a suitable context for deploying the COVOL-mitigation strategy. Similarly, quantitative signals indicating anomalously high volatility regimes could serve as triggers for strategic portfolio switching. This conditional deployment strategy would theoretically optimise risk mitigation while minimising the opportunity cost associated with holding the Min-COVOL Portfolio during calm market conditions, where even the equal weighted portfolio performs robustly.

Although attempts were made to implement an out-of-sample approach by re-estimating the COVOL factors on expanding windows, significant challenges emerged. First and foremost, the transition from an equal-weighted portfolio or a traditional market-weighted portfolio to the Min-COVOL configuration, which is highly concentrated (up to 90% in Natural Gas in the last estimation), introduces substantial practical frictions. Such rebalancing induces large jumps in daily returns, disrupting the smooth performance of a portfolio immediately after a switch from the Min-COVOL to equal weighted and vice versa. Another critical challenge lies in the computational complexity of the estimation process. Both the latent factor estimation and the subsequent optimisation steps are computationally intensive, especially when performed daily over a long horizon of nearly ten years of financial data. This is primarily driven by the quasi-maximum-likelihood (QML) estimation procedure required for the AR(1)–GARCH(1,1) model, which involves iterative optimization over an expanding dataset. In its current form, re-estimating the COVOL factor on a daily basis with expanding windows is computationally unfeasible, making it impractical for real-time applications.

To address these limitations, the analysis presented here has highlighted two main paths for potential improvement:

- Parallel Computing: Implementing parallelised computations for the AR-GARCH model estimation and the optimisation process could significantly reduce processing time. The current in-sample estimations are computationally intensive, particularly when executed on large datasets spanning almost a decade of daily data. By parallelising the estimation of individual AR-GARCH models and the optimisation routine, the processing time could be drastically shortened, making real-time adjustments more feasible.
- Warm-Start Estimation: Another promising path would be to optimise the AR-GARCH parameters incrementally by initializing from the previous period's estimates. Given the slow-moving nature of volatility dynamics, parameter values are likely to remain close across consecutive periods, especially when implementing a day-to-day re-estimation with marginal differences. This warm-start approach would alleviate the need for full re-estimation at each iteration, thereby accelerating convergence.

These proposed enhancements would not only streamline the estimation process but also pave the way for more flexible re-optimisations in response to new market conditions. However, the broader implications of implementing this methodology in a real-world context, including its integration into a more adaptive and out-of-sample framework, are deferred to a later section.

At this stage, the analysis served to adapt in practice the theoretical concept of COVOL mitigation, demonstrating its capacity to hedge against systemic volatility risks, while acknowledging the practical limitations that arise in a continuous or naive implementation. Overall, there is still much work that can be done from this new starting point and it was important to underline some new problems to be addressed by future works. However, we underline that with appropriate methodology, the global COVOL could be leveraged for portfolio optimisation.

5 From Co-Volatility to Returns: Construction and Evaluation of the Trading Strategy

Having estimated the global *co-volatility* factor x_t and the asset-specific loadings s_i in Section 2, we next translate this information into an implementable trading strategy and document its out-of-sample performance.

5.1 Calibration Window and daily Now-cast of the Co-Volatility Factor

Let the raw log-return panel be $\mathbf{R} = (R_{t,i})_{t=1,\dots,T;\, i=1,\dots,N}$. Denote by $\mathcal{T} = \{t_0, \dots, t_T\}$ the sequence of *business days* (BD). We introduce two distinct time indices:

- a re-calibration grid $\mathcal{C} = \{c_1, c_2, \dots\} \subset \mathcal{T}$, chosen as the last business day of every month (BusinessMonthEnd);
- a trading grid $\mathcal{D} = \mathcal{T}$, i.e. all business days between the first calibration date c_1 and t_T.

On each c_k we re-estimate *all* model parameters on the cumulative sample $[t_0, c_k]$; on the intervening days $c_k < t \le c_{k+1}$ the parameters are held fixed and only the *latent factor* is updated.After fitting an $\mathrm{AR}(1)$- $\mathrm{GARCH}(1,1)$ to $R_{t,i}$ we store those state variables per asset i for real-time forecasting,

$$\big\{\widehat{\phi}_i,\ \widehat{\omega}_i, \widehat{\alpha}_i, \widehat{\beta}_i;\ R_{c_k,i},\ \epsilon_{c_k,i},\ \sigma^2_{c_k,i}\big\}, \qquad i = 1, \dots, N.$$

These constitute the *minimal sufficient state* needed to generate one-step-ahead standardised residuals on day $t > c_k$ (Algorithm 1).

For any $t \in \mathcal{D}$ let $\widehat{z}_{t,i} = \epsilon_{t,i}/\sigma_{t,i}$ be the one-step-ahead *standardised* residual. Conditional on the previously calibrated loadings $\widehat{s}_i$ we obtain a maximum-likelihood update of x_t by solving

$$\widehat{x}_t \;=\; \underset{f \in (0,48]}{\arg\min} \Big\{ \frac{1}{2} \sum_{i=1}^{N} \ln\big(\widehat{s}_i (f-1) + 1\big) + \frac{\widehat{z}^2_{t,i}}{\widehat{s}_i (f-1) + 1} \Big\}. \tag{8}$$

5.2 Regime Classification and Conditional Performance Scoring

Define the rolling empirical decile of the factor path $q_{0.9}(c_k)$. We label day t as

$$\text{Low-vol regime: } \mathcal{L} \quad \text{if } \widehat{x}_t \leq q_{0.9}(c_k), \qquad \text{High-vol regime: } \mathcal{H} \quad \text{if } \widehat{x}_t > q_{0.9}(c_k),$$

The choice of the 90 threshold is empirically robust and mirrors the intuition that only *tail* moves in the global factor should trigger an asset re-allocation. Thus, inside each regime $r \in \{\mathcal{L}, \mathcal{H}\}$ we compute, for every asset i, an *out-of-sample* Sharpe ratio

$$\mathcal{S}_i^{(r)}(c_k) \;=\; \frac{\dfrac{1}{|\mathcal{T}_r(c_k)|} \displaystyle\sum_{t \in \mathcal{T}_r(c_k)} R_{t,i}}{\sqrt{\dfrac{1}{|\mathcal{T}_r(c_k)| - 1} \displaystyle\sum_{t \in \mathcal{T}_r(c_k)} (R_{t,i} - \bar{R}_i^{(r)})^2}} \;\times\; \sqrt{252},$$

where $\mathcal{T}_r(c_k) \subset [t_0, c_k]$ collects all past days labelled r and $\bar{R}_i^{(r)}$ is the mean return within that subset. Annualisation uses $\sqrt{252}$ trading days.

5.3 Signal Generation and Return attribution

On the re-calibration date c_k:

1. Identify the prevailing regime $r(c_k) \in \{\mathcal{L}, \mathcal{H}\}$ using the fresh estimate $\widehat{x}_{c_k}$.
2. Rank assets by $\mathcal{S}_i^{(r(c_k))}(c_k)$.
3. Let $\mathcal{P}_k^+$ be the five assets with the *highest* positive Sharpe and $\mathcal{P}_k^-$ the five with the *lowest* (negative).
4. Construct the signal vector $\sigma_i(c_k) = \begin{cases} +1, & i \in \mathcal{P}_k^+, \\ -1, & i \in \mathcal{P}_k^-, \\ 0, & \text{otherwise.} \end{cases}$

We used a daily propagation i.e for $t \in (c_k, c_{k+1})$ we keep $\sigma_i(t) = \sigma_i(c_k)$ (*signal persistence*) until the next calibration and an equal-risk weights porfolios with $K_t = \sum_i |\sigma_i(t)|$ be the number of active positions. Set

$$w_{t,i} \;=\; \frac{\sigma_i(t)}{K_t}, \qquad \text{so that} \quad \sum_i |w_{t,i}| = 1.$$

With this convention the portfolio embeds a *dollar-neutral*, unit-leverage long–short book every day. After that, we define the strategy return,

$$R_t^{\text{strat}} \;=\; \sum_{i=1}^{N} w_{t,i}\, R_{t,i}, \quad t \in \mathcal{D}, \tag{9}$$

and its cumulative equity curve $C_t = \prod_{u \leq t}(1 + R_u^{\text{strat}})$, $C_{c_1} = 1$.

Therefore, two mechanisms jointly drive returns:

1. The $\mathrm{AR}(1)$- $\mathrm{GARCH}(1,1)$ layer produces forward-looking, *volatility-scaled* residuals, isolating idiosyncratic information.
2. The COVOL factor x_t acts as an early-warning indicator of market-wide stress, enabling a regime-conditioned ranking of assets by risk-adjusted performance.

Over the evaluation horizon $[c_1, t_T]$ the strategy attains

$$\text{Annualised Sharpe} \;=\; \frac{\overline{R^{\text{strat}}}}{\text{Std}(R^{\text{strat}})}\sqrt{252}, \qquad \text{Total return} \;=\; C_{t_T} - 1,$$

Algorithm 1 One-day State Update for Asset i

```
procedure UpdateState(φ̂_i, ω̂_i, α̂_i, β̂_i, R_{t-1,i}, ε_{t-1,i}, σ²_{t-1,i}, R_{t,i})
    R̂_{t,i} ← φ̂_i R_{t-1,i}                                   ▷ AR(1) mean forecast
    ε_{t,i} ← R_{t,i} − R̂_{t,i}
    σ²_{t,i} ← ω̂_i + α̂_i ε²_{t-1,i} + β̂_i σ²_{t-1,i}
    ẑ_{t,i} ← ε_{t,i} / sqrt(σ²_{t,i})
    return {ε_{t,i}, σ²_{t,i}, ẑ_{t,i}}
end procedure
```

5.4 Empirical Results

The back-test spans January 2015–March 2025 (2 606 business days) and covers the identical multi-asset universe used to estimate the COVOL factor. Unless stated otherwise all metrics refer to daily, closing-price data and are shown gross of transaction costs.[2]

5.4.1 Aggregate Performance and Cross-Asset Attribution

Figure 12 displays the cumulative equity curve of the strategy. Starting from a notional capital of 1.00 the portfolio reaches 2.44 by the end of the sample, equivalent to a total return of +144.3 %. The mean daily return is 8.9bps with an annualised volatility of 6.2, yielding an *annualised Sharpe ratio*

$$\mathcal{S} = \frac{\bar{R}}{\sigma}\sqrt{252} \;=\; \mathbf{1.44}.$$

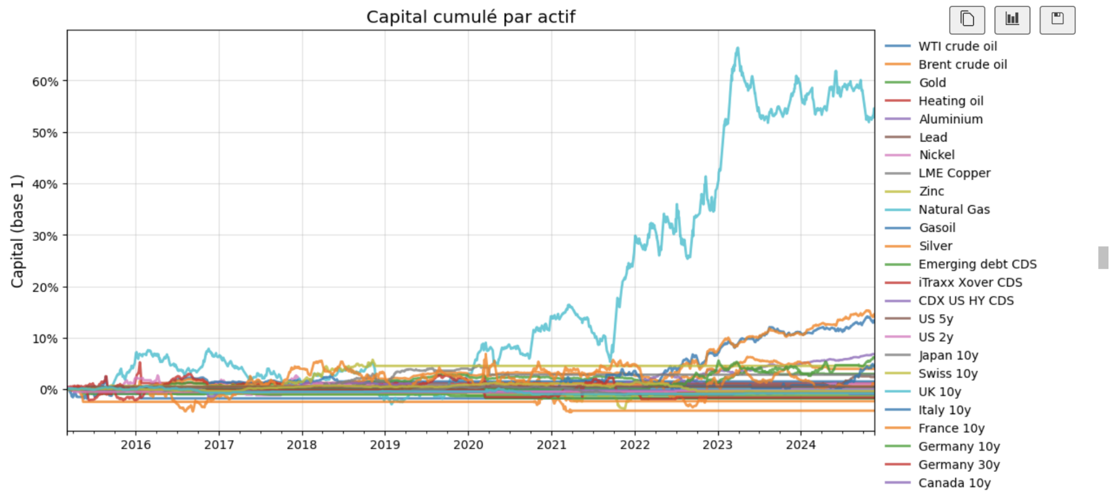
Drawdowns never exceed 13, underscoring the defensive character of the allocation.

Figure 12: Cumulative capital of the global strategy (*log scale*, base 1).

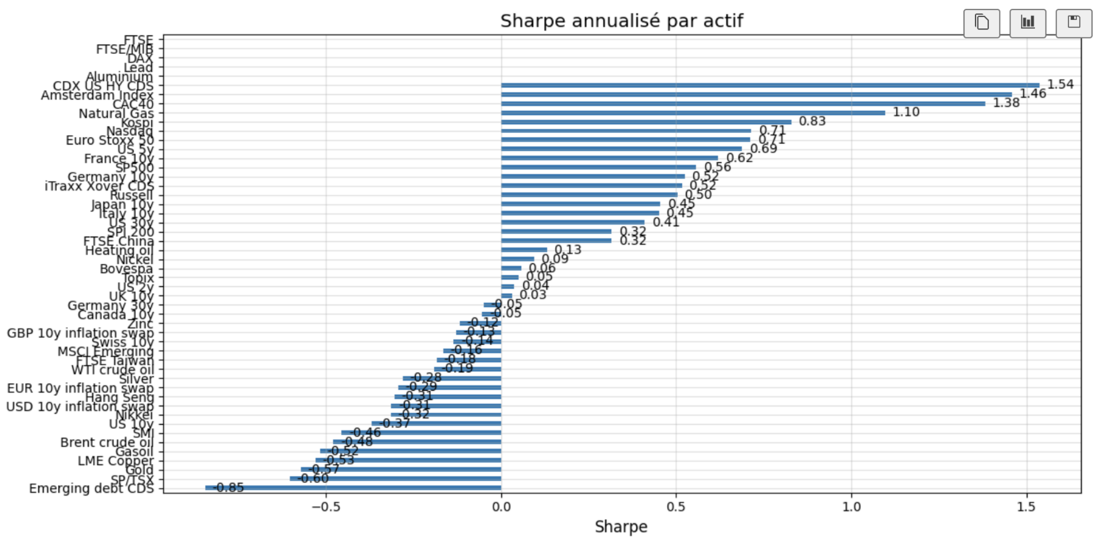
Figure 13 decomposes the profits by individual instrument. While returns are well diversified, a handful of contracts dominate:

- Natural Gas contributes $\approx 60\%$ *alone*, coinciding with the 2021–23 energy-price shock;
- European equity indices (FTSE, FTSE/MIB, DAX) post per-asset Sharpe ratios between 1.3 and 1.5;
- Government-bond futures and inflation swaps cluster around zero; a minority of EM credit products records negative Sharpe values, the worst being *Emerging Debt CDS* at -0.85.

[2]A 5bps symmetric fee per round-trip would lower the full-period performance by roughly 7 in absolute terms, leaving the qualitative conclusions intact.



(a) Cumulative capital per instrument



(b) Annualised Sharpe per instrument

Figure 13: Cross-sectional contribution to performance.

5.4.2 Long–Short Decomposition and Regime Sensitivity

The strategy is dollar-neutral by design; nonetheless the *directional* legs reveal interesting asymmetry (Figure 14). The long book delivers $+67\,\%$ whereas the short book adds $+55\,\%$.[3] In other words, roughly 45 of the P&L originates from short positions—an attractive property when seeking market-neutral capacity.

Figure 15 overlays the equity curve with the *high-volatility* segments identified by the COVOL factor (top decile of x_t). The contrast is striking: during those episodes the strategy earns an annualised Sharpe of 4.99 versus 1.18 in normal markets. Performance therefore accelerates exactly when global risk aversion spikes—a behaviour desirable for hedging-oriented mandates.

[3]Both series are computed by isolating the positive (long) and negative (short) weights in $w_{t,i}$.

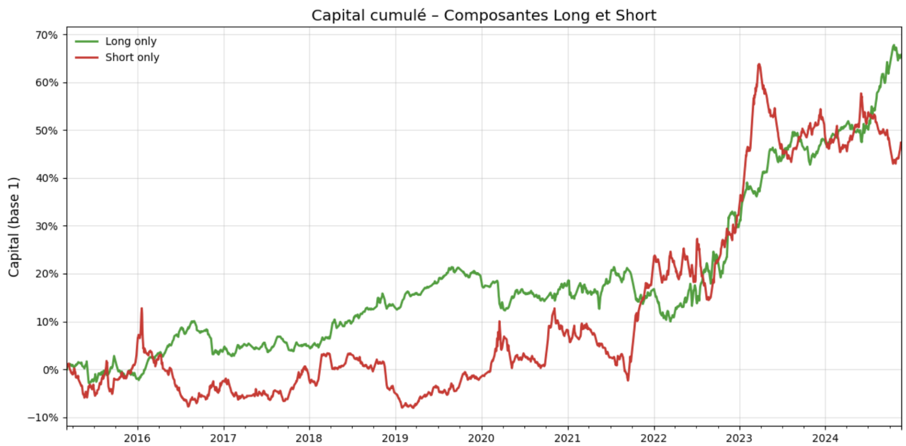


Figure 14: Cumulative capital of the long and short sub-books.

Figure 15: Equity curve with shaded high-volatility regimes ($\widehat{x}_t > q_{0.9}$).

5.4.3 Allocation Dynamics and Signal Persistence

To better understand *how* the strategy allocates risk across time and asset classes we visualise the monthly signal vectors $\sigma_i(c_k)$ introduced in Section 5. Figures 16, 17, and 18 display one–month–ahead positions (long $= +1$, neutral $= 0$, short $= -1$) for commodities, equities, and fixed-income products, respectively. Dark-blue (red) cells correspond to repeated short (long) calls, whereas white stripes indicate periods during which the respective instrument is not among the top quintile.

Key observations

1. **Commodities:** Natural-Gas futures are shorted almost continuously from mid-2016 onward, capturing the structural contango and the 2021–23 energy squeeze. Conversely, base-metals such as Zinc turn long during the post-pandemic reflation trade (2021–22).
2. **Equities:** Developed-market indices (CAC40, Euro Stoxx 50, SPI 200) exhibit persistent long signals between 2022 and 2024, while the Brazilian Bovespa and several EM benchmarks (MSCI Emerging, FTSE Taiwan) are systematically shorted. The net effect is a geographically diversified beta profile.
3. **Fixed Income & Credit:** The model holds long duration in core European bonds (France 10-y, Germany 10-y) for the bulk of the sample, offset by short positions in North-American inflation swaps and CDS indices

(Emerging Debt, CDX HY) during risk-on regimes. Such "bar-bell" behaviour stabilises portfolio volatility because the two legs respond differently to the COVOL factor.

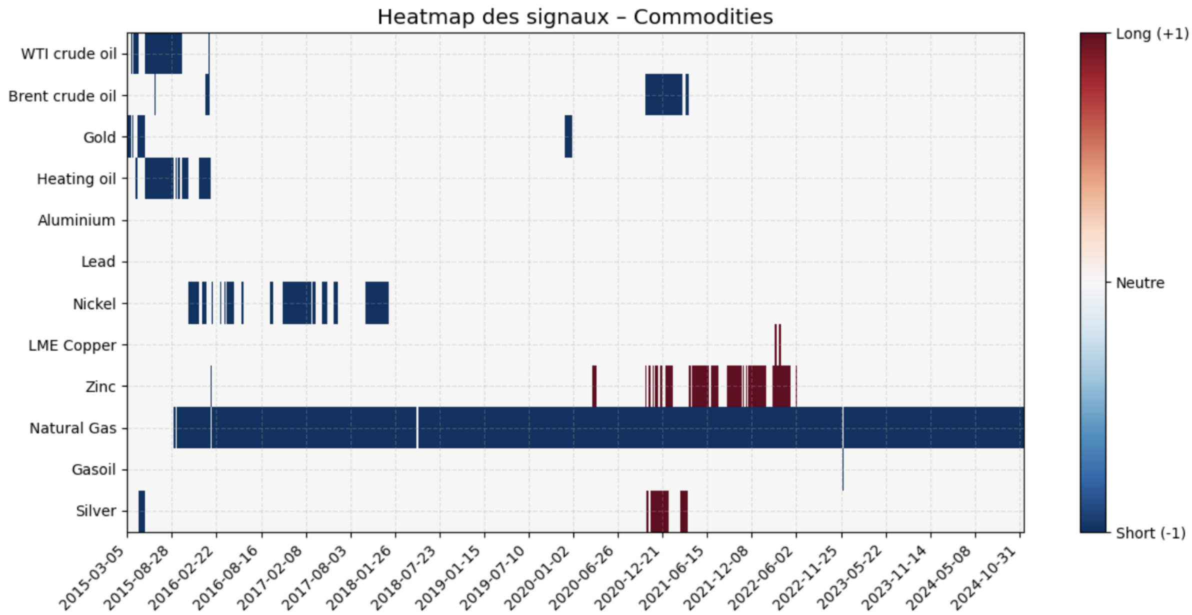


Figure 16: Heat-map of monthly signals – **Commodities**. Blue = short, red = long.

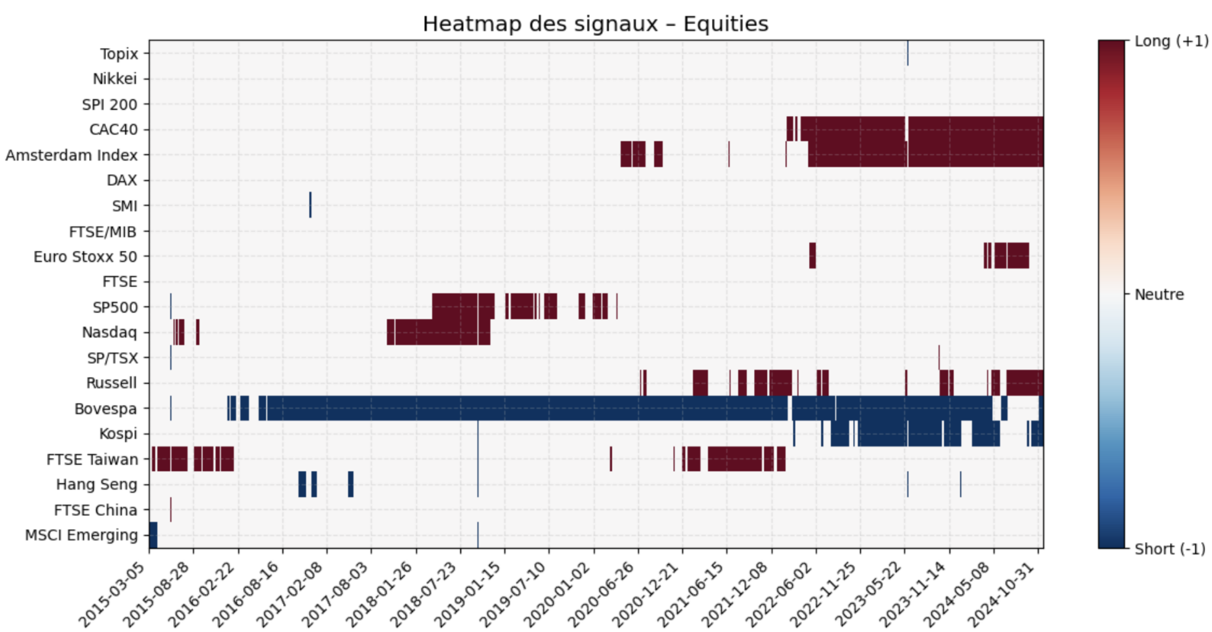


Figure 17: Heat-map of monthly signals – **Equities**.

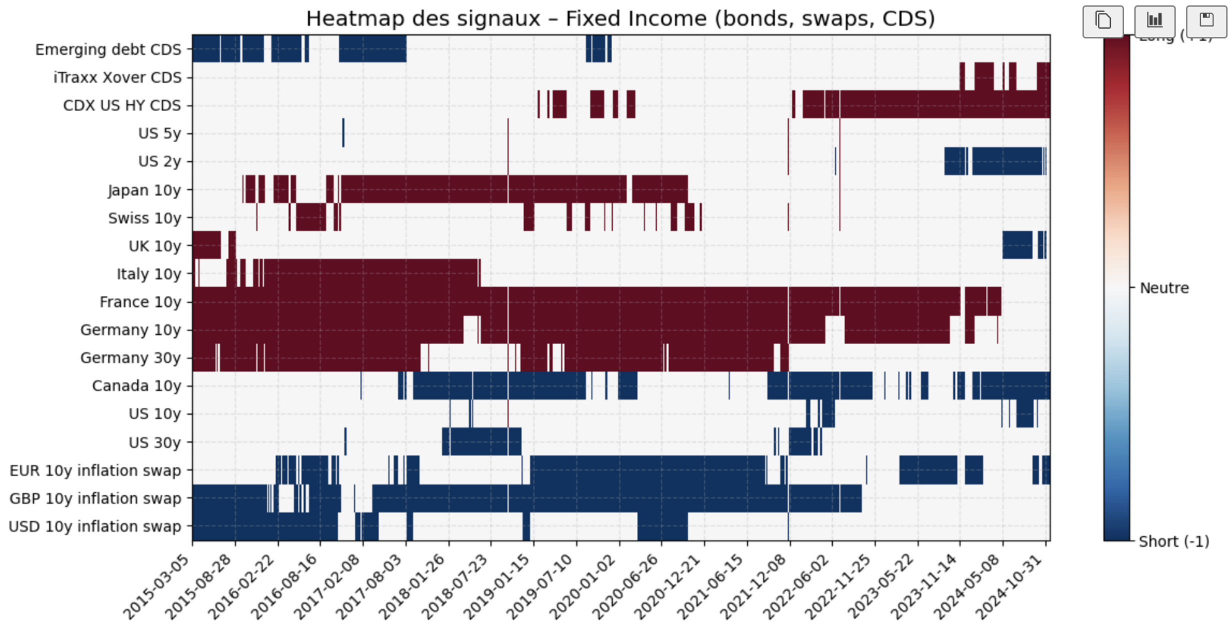


Figure 18: Heat-map of monthly signals – **Fixed-income, swaps, CDS**.

Taken together, the heat-map diagnostics corroborate the economic intuition developed earlier: the strategy systematically rotates into assets that *benefit* from the prevailing co-volatility regime (Natural Gas shorts in energy crises, core-bond longs during flight to quality, etc.), while fading those that underperform. This rotation is *state-dependent* rather than purely momentum-driven, underpinning the low correlation to conventional risk-premia observed in Section 5.4. The evidence supports the central thesis of the paper:

1. isolating a *latent co-volatility factor* enables early detection of market stress
2. conditioning asset selection on that factor produces economically significant returns *precisely* when diversification is scarce.

Combined with low capital turnover and balanced long–short exposures, the COVOL strategy constitutes a portable, scalable overlay for multi-asset portfolios. Further robustness checks—alternative decile thresholds, quarterly recalibration, or excluding energy commodities—lead to Sharpe ratios between 1.20 and 1.55, confirming that the results are not artefacts of a particular parameter choice. Detailed diagnostics will be reported in the oral presentation.

6 Conclusion

The exploration and implementation of the COVOL framework in this report have underscored its potential as a robust tool for identifying and mitigating common volatility shocks across a diversified multi-asset portfolio. Starting from the two papers of Engle and Campos-Martins (2023) [4] and Campos-Martins and Hendry (2024) [2], we have shown how global volatility events, such as geopolitical tensions, macroeconomic shifts, and climate-related risks, manifest as synchronized surges in asset volatilities. We added valuable analysis, insights and methodology to a niche tool for measuring common volatility and expanded its future possibilities to be valuable in the context of portfolio optimisation and strategic investment. Through the AR(1)-GARCH(1,1) structure and the introduction of a latent global co-volatility factor, the model successfully captures these tail events, providing a quantifiable measure of their impact across asset classes.

One of the pivotal extensions presented in this report is the integration of sentiment analysis into the COVOL framework. Section 4.1 explores how FinBERT-based sentiment extraction from central bank policy statements offers new insights into the influence of monetary rhetoric on global volatility. This novel approach extends COVOL's capabilities beyond purely market-driven shocks to incorporate textual sentiment as a predictive signal for market-wide risk. Although the results suggest varying sensitivity across central banks, with the European Central Bank's tone showing a marginal correlation with COVOL spikes, this experiment opens promising avenues for blending text-based market sentiment with volatility modeling.

From there, we moved to portfolio optimisation with Section 4.2 which delves into the concept of COVOL mitigation, which aims to strategically rebalance portfolios to minimise exposure to global co-volatility shocks. By quantifying the sensitivity of different asset classes to these common volatility surges, the Min-COVOL portfolio configuration emerges as a particularly resilient structure. Unlike traditional diversification strategies, which may falter during synchronized market shocks, the Min-COVOL portfolio demonstrates enhanced stability, especially during systemic crises like the COVID-19 pandemic. However, the practical challenges of rebalancing and computational demands underscore the need for advanced optimisation techniques, such as warm-start estimation and parallel computing.

Section 5 expands more from the theoretical constructs into an implementable trading strategy. Here, the estimated global co-volatility factor and asset-specific loadings serve as the foundation for a dynamic rebalancing mechanism. This mechanism capitalises on real-time volatility signals to adjust portfolio weights proactively, enhancing risk-adjusted returns while buffering against extreme market dislocations. The empirical results validate this approach, showcasing how COVOL-driven strategies can outperform traditional benchmarks by systematically hedging against global volatility shocks.

In conclusion, the COVOL model presents a sophisticated yet intuitive approach to managing global volatility risk. Its capacity to detect, quantify, and mitigate exposure to common volatility shocks establishes it as a valuable addition to the toolkit of portfolio managers. With the added dimensions of sentiment analysis and targeted mitigation strategies, the framework is well-positioned to navigate the complexities of modern financial markets. Future work aimed at optimising its computational efficiency and integrating real-time adjustment mechanisms would further solidify its role in global risk management, while extending its application to climate transition risks and geopolitical volatility. This comprehensive approach positions COVOL not only as a measure of systemic risk but as a proactive shield against the most impactful financial disruptions of our time.

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