To Estimate SVAR

**🧠 The Problem With Regular SVAR**

* Banks have **tens of thousands of risk drivers** (interest rates, stock prices, credit spreads, etc.)
* To calculate SVAR, they apply past "shocks" to all of those drivers.
* It’s like trying to explain your whole school’s behavior by tracking **every student’s mood** — too much data!

➡️ So it’s **hard to understand**, **hard to explain**, and **hard to fix** if SVAR is too high.

**🎯 Enter: SVAR Factor Model**

The **SVAR Factor Model** says:

"Instead of tracking 50,000 individual things, let’s summarize them using just **20 to 30 important 'factors'** that really move the market."

**🔑 A "Factor" is:**

* Something simple and economic that we can understand
  + Like **S&P 500 (stocks)**
  + Or **10-Year interest rate (bonds)**
  + Or **USD/JPY exchange rate (currencies)**

**🧰 How It Works (Simple Steps)**

1. **Pick your factors**  
   Choose 20–30 things that really matter to your portfolio.
2. **Link everything to those factors**  
   Use math (regression) to find out how each risk driver (like a bond or stock) moves when the factor moves.
3. **Use factor shocks instead of 50,000 shocks**  
   Apply stress-period shocks (like from 2008) to just the factors, not everything.
4. **Estimate SVAR again**  
   Now the loss is modeled using a simpler formula:

**🛡️ Why Is This Useful?**

| **Benefit** | **Why It Matters** |
| --- | --- |
| ✅ **Simpler** | Easier to understand and explain to regulators |
| ✅ **Actionable** | You can hedge (protect) the portfolio by using instruments tied to the same factors (like futures, swaps) |
| ✅ **Saves Capital** | Lower SVAR = Less capital banks must hold = More money available to invest or lend |
| ✅ **Smarter Decisions** | You can say: “60% of our SVAR comes from interest rates — let’s hedge that!” |

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| --- | --- | --- |
| **Aspect** | **Traditional SVaR (All Risk Drivers)** | **Factor-Based SVaR** |
| Shocks | All 50K+ risk drivers individually | Only 20–30 key factors |
| PnL Formula |  | Same formula, but ΔX\Delta XΔX = shocked factor returns |
| Example Shift | 100 forward rate points | 100bps move in 10Y SOFR |
| Explainability | Hard to trace | Easy to attribute ("40% of SVaR is from credit") |
| Hedging | Difficult | You can hedge SPX, SOFR, CDS easily |

**How the Modeling Works in Practice**

**Example:**

Let’s say you have a **portfolio of corporate bonds** and **convertibles**, and you’ve chosen:

|  |  |  |
| --- | --- | --- |
| **Factor** | **Shocked Move (during stress)** | **Instrument Sensitivity** |
| SPX | -35% | Convertibles, hybrid bonds |
| 10Y SOFR | +100bps | Bonds, swaps |
| 5Y A CDS | +75bps | Corp bonds, CLO tranches |

You:

1. Run regressions or mapping to estimate sensitivities to each factor.
2. Compute Δ and Γ for those factors (instead of 50,000 risk drivers).
3. Apply shocks from historical stress window (e.g., 2008 or 2020).
4. Get a **factor-based PnL estimate** — and decompose SVaR easily.

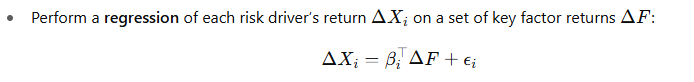
**Problem Being Solved**

* **Too many risk drivers (50,000+)** make it hard to understand and explain SVaR.
* You want to **model SVaR using a smaller set of economic factors** that make it easier to interpret and hedge.
* Current SVaR is computed using the **delta-gamma approximation** on full risk driver shocks:



**✅ Proposed Factor Model Solution (Step 2)**

1. **Model Each Risk Driver Using Factors**



* Perform a **regression** of each risk driver’s return ΔXi\Delta X\_iΔXi​ on a set of key factor returns ΔF\Delta FΔF:
* 

So instead of shocking every risk driver, you estimate how each driver responds to 30 common factors.

* **Cholesky decomposition** is used to make sure the factors are independent and reduce overlap.

1. **Model SVaR Using Factor Attribution**

* Replace the full risk driver shocks with shocks to just the factors.
* Use transformed delta and gamma terms via betas from the regressions:



* Now, SVaR is expressed as a function of **just the factors**, not every single risk driver.

 **Factor Model can sometimes produce higher or lower SVaR**, depending on how well the factor structure captures tail risk.

 But it offers **explainability** and **hedge-ability**, which the traditional method lacks.

**Scenario Simulated**

* Most risk driver movements are explained by **5 macro factors** (like SPX, SOFR, CDS).
* But on a few rare days (tail events), **idiosyncratic shocks** (unexplained by factors) occur — just like a firm-specific downgrade or a commodity shock.

**Key Takeaways**

1. **Factor models may understate tail risk** if the largest losses come from unique, name-specific events.
2. **SVaR may be underestimated**, leading to **under-capitalization**.
3. **Best practice**: factor models should include a **residual volatility buffer**, or hybrid models that mix factor and full risk exposure for high-risk names.

################## Credit specific

**Major Contributors to Loss**

The **A, BBB, and BB buckets account for $254M of the $266.7M loss** — these three ratings are where most of the **concentrated negative Spread01 exposures** exist.

* These are **investment-grade and crossover** buckets — commonly large and liquid, hence explaining their impact in SVaR.
* The **shocks (200–400 bps)** are large but historically valid.

|  |  |  |  |
| --- | --- | --- | --- |
| **Rating** | **Spread01** | **Shock (bps)** | **Estimated PnL** |
| **A** | -450,000 | 200 | **($90M)** 🔴 |
| **BBB** | -440,000 | 200 | **($88M)** 🔴 |
| **BB** | -190,000 | 400 | **($76M)** 🔴 |
| **CCC** | -40,000 | 400 | ($16M) |
| **NR** | -20,000 | 400 | ($8M) |
| **AAA** | -13,000 | 200 | ($2.6M) |
| **AA** | 20,000 | 200 | +$4M ✅ |
| **B** | -3,000 | 400 | ($1.2M) |
| **IG CDS** | 210,000 | 10 | +$2.1M ✅ |
| **HY CDS** | 30,000 | 300 | +$9M ✅ |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Rating** | **Spread01** | **Shock\_bps** | **Shock** | **Traditional\_PnL** | **Factor** | **Factor\_Shock** | **FactorModel\_PnL** |
| **A** | **-450000** | **200** | **0.02** | **-9000** | **IG** | **0.02** | **-9000** |
| **BBB** | **-440000** | **200** | **0.02** | **-8800** | **IG** | **0.02** | **-8800** |
| **BB** | **-190000** | **400** | **0.04** | **-7600** | **HY** | **0.04** | **-7600** |
| **CCC** | **-40000** | **400** | **0.04** | **-1600** | **HY** | **0.04** | **-1600** |
| **NR** | **-20000** | **400** | **0.04** | **-800** | **HY** | **0.04** | **-800** |
| **AAA** | **-13000** | **200** | **0.02** | **-260** | **IG** | **0.02** | **-260** |
| **AA** | **20000** | **200** | **0.02** | **400** | **IG** | **0.02** | **400** |
| **B** | **-3000** | **400** | **0.04** | **-120** | **HY** | **0.04** | **-120** |
| **IG CDS** | **210000** | **10** | **0.001** | **210** | **IG** | **0.02** | **4200** |
| **HY CDS** | **30000** | **300** | **0.03** | **900** | **HY** | **0.04** | **1200** |

**Traditional SVaR**

* Uses **actual historical shocks** by rating:
  + A, BBB: 200 bps
  + BB, B, CCC, NR: 400 bps
  + IG CDS: 10 bps
  + HY CDS: 300 bps
* Each rating has its own shock, producing a more **granular loss profile**.

**🧠 Factor Model SVaR**

* Groups exposures into **macro factors**:
  + IG-rated and IG CDS → **IG factor** → shocked by 200 bps
  + HY-rated and HY CDS → **HY factor** → shocked by 400 bps
* All names in a group receive the **same shock**, resulting in a **smoothed exposure**.
* Can **under- or over-estimate** risk if actual rating-level shocks deviate from group averages.

**Takeaway**

* **Traditional SVaR** captures rating-specific shocks but is complex and harder to hedge.
* **Factor Model SVaR** simplifies exposure to tradable factors like **CDX IG and CDX HY**, making hedging and capital planning easier — but at the cost of **precision**.

|  |  |  |
| --- | --- | --- |
| Rating | Beta\_IG | Beta\_HY |
| AAA | 0.205752 | 0.00668 |
| AA | 0.307101 | -0.02313 |
| A | 0.583271 | -0.015 |
| BBB | 0.688881 | 0.094716 |
| IG CDS | 1.026564 | 0.006927 |
| BB | 0.09147 | 0.700125 |
| B | 0.005678 | 0.802477 |
| CCC | 0.026662 | 0.994624 |
| NR | -0.00747 | 0.8984 |
| HY CDS | 0.210853 | 1.013348 |

Here are the **estimated beta coefficients** showing how each credit rating's spread return moves with the **IG** and **HY** market factors:

* **Beta\_IG** tells you how much a rating’s spread responds to IG market moves.
* **Beta\_HY** tells you the sensitivity to HY market moves.

For example:

* IG CDS has a strong **Beta\_IG ≈ 1.03**, showing it closely follows IG factor.
* BBB is partially sensitive to both IG and HY (crossover risk).
* A, AA, and AAA mainly follow IG.

These betas are key inputs in the **factor-based SVaR** — they are your β\betaβ matrix that maps risk drivers to macro factors.

# Steps to Compute Factor-Based SVaR Using Delta-Gamma Approximation

## 1. Define Objective

To estimate stressed Value-at-Risk (SVaR) using a factor-based delta-gamma approach, which simplifies 50,000+ risk drivers into a manageable set of economic factors like IG and HY credit indices.

## 2. Select Economic Factors

Identify key macroeconomic or tradable factors (e.g., IG, HY) that influence the credit spread behavior across ratings.

## 3. Collect Historical Time Series

Gather daily return data for selected factors over a stress window (e.g., 250 days). This forms the matrix ΔF\_t ∈ ℝ^{T × K}, where T is the number of days and K is the number of factors.

## 4. Gather Rating Return Data

Simulate or collect historical spread changes for each rating bucket (e.g., A, BBB, BB). This gives you ΔX ∈ ℝ^{T × N}, where N is the number of ratings or instruments.

## 5. Estimate Factor Loadings (β)

Regress each rating’s spread return on the factor returns:

ΔX\_i = β\_iᵀ ΔF + ε\_i

This yields the β ∈ ℝ^{N × K} matrix.

## 6. Project Sensitivities into Factor Space

Obtain Δ ∈ ℝ^N: vector of first-order sensitivities (Spread01).

Obtain Γ ∈ ℝ^{N × N}: diagonal matrix of second-order sensitivities.

Project:

- Δ^F = βᵀ Δ ∈ ℝ^K

- Γ^F = βᵀ Γ β ∈ ℝ^{K × K}

## 7. Compute Daily PnL for Stress Period

For each day t in the stress window:

PnL\_t = Δ^F · ΔF\_t + 0.5 · ΔF\_tᵀ Γ^F ΔF\_t

## 8. Calculate SVaR

Sort the 250 daily PnLs.

SVaR = Second-worst PnL (or another percentile as required by regulation).

## 9. Validate and Compare

Compare factor-based SVaR to traditional full risk driver SVaR.

Analyze contributions per factor for explainability.

## 10. Optional: Adjust for Residual Risk

Add back idiosyncratic volatility not explained by factors.

Apply residual volatility buffers to account for misfit.

This approach provides a tractable and business-intuitive way to explain, decompose, and optimize regulatory capital driven by SVaR.

Questions

You're building a **mapping between each risk driver** (like a rating bucket or issuer spread) and **a set of macro factors** (like IG or HY). The goal is to estimate how much each risk driver **moves when the factor moves** — that’s a **return-to-return** relationship.

Where:

* ΔXi\Delta X\_iΔXi​ = return of the i-th risk driver (e.g., spread change of BBB)
* ΔF\Delta FΔF = vector of factor returns (e.g., IG and HY)
* βi\beta\_iβi​ = estimated sensitivity to the factors

You do **not** want to regress historical **PnL**, because:

* PnL is already affected by position size, sensitivities, and scaling.
* It adds noise that masks the pure **statistical behavior** of the underlying risk factor.

“Do we plan to regress based on **log-returns**, **absolute changes**, or **z-scored returns** to control for volatility scaling

How are we deciding which risk drivers to include in the factor modeling universe?  
(e.g., issuer-level curves, rating buckets, sector aggregates?)

* How are we handling **factored risk drivers that show poor fit** (low R²) to the selected factors? Are we planning to overlay residual volatility or treat them separately?
* Have we considered **idiosyncratic risk drivers** that aren’t strongly tied to macro factors but still cause material SVaR spikes (e.g., distressed names, structured tranches)

What window are we using to calibrate factor relationships?  
(Short-term like 3 months may react to market noise; long-term like 2 years may miss current regimes.)

### Tail Risk & Hedging Considerations

* How are we planning to identify and capture **tail behavior** in names or sectors that don't align well with broad IG/HY moves?
  + Will we build a tail overlay for distressed or low-liquidity instruments?
* To help frame the next steps (and support where needed), I wanted to raise a few key questions and considerations — particularly around **tail hedging** and the goal of capturing more **specific risk dynamics** beyond broad market moves:

### Trade-off Questions to Ask

* If our long-term goal is to move from **ratings → sector × region → issuer-level** risk drivers, how do we reconcile that with a **compressed factor model** that aggregates back up to 20–30 macro factors?
* Could this approach risk **over-smoothing or masking** meaningful sector-specific dynamics, especially during market dislocations?
* Are we planning to **scale the factor model alongside our granularity push** — for example, introducing **sector-specific factors** (e.g., U.S. Energy IG, EU Financials HY) instead of relying solely on broad IG/HY aggregates?

particularly around **tail hedging** and the goal of capturing more **specific risk dynamics** beyond broad market moves:

Here’s an updated version of your email that keeps the supportive tone, subtly reinforces your expertise, and raises **thoughtful questions** about potential **SVaR underestimation or overestimation** — without sounding confrontational:

**Subject:** Re: Factor-Based SVaR – Scope, Assumptions & Alignment

Hi Team,

Really glad to see the traction on building a factor-based SVaR framework — this could be a big step forward in enhancing transparency and optimizing capital, especially if it helps link SVaR to meaningful hedging instruments.

Before we proceed with data extraction, I wanted to ask a few framing questions — mostly to understand the scope, assumptions, and intended usage, and to help ensure the model delivers both explainability and robustness.

### 🔍 **Clarifying Scope**

* Is the model intended to **replace** the rating-based SVaR aggregation or to run **alongside it** (e.g., as an attribution layer)?
* Will we eventually expand from IG/HY to a more **granular factor taxonomy** (e.g., sector-region combinations)?

### ⚖️ **Model Risk & Calibration Questions**

* Do we expect this approach to **underestimate SVaR** in cases where residual/idiosyncratic risks are high — for example, in distressed names or niche sectors that don't align well with macro factors?
* Conversely, is there a risk it could **overestimate SVaR** in diversified books where factor shocks get multiplied across loosely correlated exposures?
* Will residuals from the beta regressions be tracked or included in a **volatility buffer** to guard against misfit?

 Is the factor-based approach being developed to **complement** the current full-driver SVaR (e.g., for attribution and capital optimization), or is the intention to evolve it into a **primary methodology**?

 How are we balancing the simplification that factor models offer with the goal of introducing **greater granularity** (e.g., region-sector-level breakdowns), which we know could help achieve the **estimated ~$20M SVaR reduction**?

### **Model Risk & Estimation Questions**

* Could relying on macro factor proxies **underestimate SVaR** if we miss key sector- or issuer-specific risks not captured by IG/HY dynamics?
* Conversely, is there a risk of **overestimating SVaR** if exposures are pushed into broad factor shocks that don’t reflect actual diversification?
* Will we be tracking **regression residuals** or unexplained variance to understand where the model is or isn't fitting well?