Factor Analysis in Finance

Identifying Hidden Risk Factors in Markets

MSc Banking & Finance

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October 22, 2025

Outline

The Fundamental Question

Observation

DeFi token returns are highly correlated:

- UNI and SUSHI: $r = 0.82$
- AAVE and COMP: $r = 0.78$
- Most tokens with ETH: $r = 0.6 - 0.9$

The Question

WHY are these returns correlated?

What are the **hidden common factors** driving these co-movements?

PCA vs Factor Analysis

PCA Says

"I'll find directions that explain maximum **total variance**"

$$X_j = \sum_{k=1}^{p} v_{jk} \cdot PC_k$$

Includes signal + noise

Factor Analysis Says

"I'll find hidden causes that explain the **correlations**"

$$X_j = \sum_{k=1}^{m} \lambda_{jk} F_k + \epsilon_j$$

Separates systematic from idiosyncratic

Key Difference: FA isolates **shared variance only**

Economic Hypothesis

We Hypothesize DeFi Returns are Driven By:

1. **Factor 1 - Market Factor**
   - Overall crypto market sentiment
   - ETH/BTC movements
   - Macro conditions
2. **Factor 2 - Sector Factor**
   - DeFi-specific trends
   - TVL growth
   - Protocol adoption
   - Sector rotation (DEX vs Lending)
3. **Unique Factors**
   - Token-specific events
   - Hacks, governance, upgrades

The Dataset

8 DeFi Tokens Over 5 Weeks

- **UNI** - Uniswap (DEX)
- **SUSHI** - SushiSwap (DEX)
- **AAVE** - Aave (Lending)
- **COMP** - Compound (Lending)
- **MKR** - MakerDAO (Stablecoin)
- **CRV** - Curve (Stableswap)
- **SNX** - Synthetix (Derivatives)
- **LDO** - Lido (Staking)

Raw Weekly Returns (%)

Week	UNI	SUSHI	AAVE	COMP	MKR	CRV	SNX	LDO
1	8.2	9.5	6.3	5.8	7.1	4.2	12.3	10.5
2	-3.5	-4.2	-2.8	-3.1	-1.9	-2.5	-5.8	-4.1
3	5.8	6.3	4.2	3.9	5.5	3.1	8.5	7.2
4	11.2	12.8	8.5	7.9	9.3	6.2	15.7	13.8
5	-2.1	-2.8	-1.5	-1.8	-0.9	-1.2	-3.9	-2.5

Key Observations

- All tokens move **together**
- Positive weeks: 1, 3, 4 | Negative weeks: 2, 5
- SNX and LDO show highest volatility
- Strong suggestion of **common factors**

Correlation Matrix

	UNI	SUSHI	AAVE	COMP	MKR	CRV	SNX	LDO
UNI	1.00							
SUSHI	0.99	1.00						
AAVE	0.98	0.98	1.00					
COMP	0.97	0.97	0.99	1.00				
MKR	0.99	0.99	0.99	0.98	1.00			
CRV	0.96	0.96	0.97	0.97	0.97	1.00		
SNX	0.99	0.99	0.98	0.97	0.99	0.96	1.00	
LDO	0.99	0.99	0.98	0.97	0.99	0.96	0.99	1.00

Interpretation

- **Extremely high correlations:** All > 0.96
- DEX tokens nearly identical: UNI-SUSHI $= 0.99$
- Lending tokens nearly identical: AAVE-COMP $= 0.99$
- **Must be driven by few common factors!**

Factor Model Specification

The Model

For each token j:

$$X_j = \lambda_{j1}F_1 + \lambda_{j2}F_2 + \epsilon_j$$

Where:

- λ_{jk} = loading of token j on factor k (sensitivity)
- F_k = common factor k (affects multiple tokens)
- ϵ_j = unique factor (idiosyncratic to token j)

Variance Decomposition

$$\mathrm{Var}(X_j) = \underbrace{\lambda_{j1}^2 + \lambda_{j2}^2}_{h_j^2 \text{ (communality)}} + \underbrace{\psi_j}_{\text{uniqueness}}$$

$$\text{Systematic Risk} + \text{Idiosyncratic Risk} = \text{Total Risk}$$

Eigenvalues: How Many Factors?

Factor	Eigenvalue	% Variance	Cumulative %
1	**7.825**	**97.81%**	97.81%
2	**0.142**	**1.78%**	99.59%
3	0.018	0.23%	99.82%
4	0.008	0.10%	99.92%
5-8	< 0.005	$< 0.08\%$	100.00%

Critical Finding

- **Factor 1 explains 97.81%** of common variance
- **Factor 2 explains 1.78%** (minor but tradeable)
- Remaining factors negligible
- **One dominant factor** drives nearly everything!

Unrotated Factor Loadings

Token	F1	F2
UNI	0.990	0.118
SUSHI	0.993	0.112
AAVE	0.987	-0.145
COMP	0.982	-0.161
MKR	0.993	0.092
CRV	0.973	-0.189
SNX	0.990	0.135
LDO	0.990	0.119

Interpretation

- **Factor 1:** All loadings ≈ 0.99
- General market factor
- **Factor 2:** Positive for DEX, negative for Lending
- Sector differentiation

Problem: Factor 1 dominates everything

Varimax Rotation

Why Rotate?

Rotation creates **"simple structure"** for better interpretation:

- Each token loads highly on **one** factor
- Each token loads lowly on **other** factors
- Clearer economic meaning

Varimax Criterion

Maximize variance of squared loadings to spread them out:

Makes some loadings large, others small $\rightarrow$ clearer patterns

Key Point

Rotation does NOT change model fit, only interpretability!

Rotated Factor Loadings (Varimax)

Token	Factor 1	Factor 2	Interpretation
UNI	**0.995**	0.069	Market-driven DEX
SUSHI	**0.998**	0.064	Market-driven DEX
AAVE	0.980	-**0.193**	Lending contrarian
COMP	0.974	-**0.220**	Lending contrarian
MKR	**0.997**	0.044	Market-driven
CRV	0.964	-**0.236**	Stableswap contrarian
SNX	**0.999**	0.087	Market-driven deriv
LDO	**0.997**	0.071	Market-driven staking

Key Insight

Factor 1: Market Beta (all > 0.96)

Factor 2: Sector rotation between DEX/Derivatives (+) and Lending (-)

Factor Interpretation

Factor 1: Market Beta

- All tokens > 0.96
- Overall crypto market
- "Rising tide lifts all boats"
- Systematic risk
- **Cannot diversify away**

When Factor 1 $\uparrow$ 1 unit:

- SNX $\uparrow$ 0.999
- CRV $\uparrow$ 0.964

Factor 2: Sector Rotation

- Positive: DEX, Derivatives
- Negative: Lending protocols
- Sector-specific movements
- **Can create diversification**

When Factor 2 $\uparrow$:

- DEX outperforms
- Lending underperforms

Communalities and Uniquenesses

Token	Communality (h^2)	Uniqueness (ψ)	% Common
UNI	0.995	0.005	99.5%
SUSHI	1.000	0.000	100.0%
AAVE	0.997	0.003	99.7%
COMP	0.997	0.003	99.7%
MKR	0.996	0.004	99.6%
CRV	0.985	0.015	98.5%
SNX	1.000	0.000	100.0%
LDO	0.999	0.001	99.9%
Average	**0.996**	**0.004**	**99.6%**

Critical Risk Management Finding

99.6% of variance is systematic! Only 0.4% is idiosyncratic (token-specific)

What This Means for Portfolios

Diversification Reality Check

- **Traditional diversification FAILS**
- Holding 8 DeFi tokens $\neq$ diversification
- 99.6% of risk is **shared across all tokens**
- Only 0.4% can be diversified away

Portfolio Construction Implications

1. **Cannot reduce risk** by adding more DeFi tokens
2. **Must diversify** across asset classes (BTC, stablecoins, real assets)
3. **Or hedge** systematic factors with derivatives
4. **Focus on factor exposures**, not individual tokens

Factor Scores Over Time

Week	Factor 1	Factor 2	Market Story
1	+0.73	-0.97	Bull market, Lending outperforms
2	-1.24	+0.02	Bear market, Neutral rotation
3	+0.31	+0.11	Mild bull, DEX outperforms
4	+1.20	-0.09	Strong bull, Balanced
5	-0.99	+0.94	Bear market, DEX resilient

Economic Narrative

- **Week 1:** Rally + flight to quality (Lending)
- **Week 2:** Market crash dominates (indiscriminate selling)
- **Week 3:** Recovery + risk appetite returns (DEX gains)
- **Week 4:** Strong rally (broad-based)
- **Week 5:** Correction, but DEX shows relative strength

Application 1: Factor-Neutral Portfolio

Objective

Construct portfolio with **zero exposure to Factor 2** (sector rotation)

Strategy

Equal weights on positive and negative Factor 2 tokens:

- 12.5% each token
- Balance positive F2 exposure
- with negative F2 exposure

Result

Factor exposures:

- Factor 1: 0.988
- Factor 2: ≈ 0.00

Pure market exposure
Neutral to sector rotation

Application 2: Sector Rotation Strategy

Strategy: Long DEX, Short Lending

When forecasting positive Factor 2:

- Long: UNI (50%), SUSHI (50%)
- Short: AAVE (50%), COMP (50%)

Factor Exposures

- **Factor 1:** Near-neutral (long and short similar betas)
- **Factor 2:** +0.273 (strong positive exposure)

Profits when DEX outperforms Lending

Market-neutral, sector-tilted strategy

Application 3: Risk Attribution

Equal-Weighted Portfolio Risk Breakdown

- Factor 1 (Market): **97.6%** of variance
- Factor 2 (Sector): **0.1%** of variance
- Idiosyncratic: **0.0%** of variance

Risk Management Insight

Portfolio risk is **97.6% market risk**

To reduce risk:

- Hedge Factor 1 (market exposure)
- Use ETH/BTC futures
- Increase stablecoin allocation
- Add non-crypto assets

Application 4: Performance Attribution

Week 4 Attribution (Strong Bull Week)

Portfolio return: +118.3%

Decomposition:

- Market factor (Factor 1): **+118.1%** (99.8%)
- Sector factor (Factor 2): **+0.2%** (0.2%)
- Alpha (selection): $\approx$ **0%**

Insight

Performance driven **entirely by market rally**
Sector selection contributed **negligibly**

Market timing $\gg$ Token selection

PCA vs Factor Analysis

Component	PCA % Var	FA % Common Var
1	98.90%	97.81%
2	0.76%	1.78%
3-8	0.34%	0.41%

PCA

- Explains *total* variance
- Includes noise
- PC2 suppressed
- Data compression

Factor Analysis

- Explains *common* variance
- Separates noise
- Factor 2 visible
- Causal interpretation

Use FA to understand WHY correlations exist

DeFi vs Traditional Equity Markets

Characteristic	Equity Markets	DeFi Markets
Number of factors	3-5	1-2
Market factor dominance	30-50%	**97.8%**
Idiosyncratic variance	20-40%	**0.4%**
Factor stability	High	Low (nascent)
Diversification benefit	Moderate	**Minimal**

Key Insight

DeFi is **less mature** with:

- Stronger co-movement
- Higher systematic risk
- Limited diversification benefits
- Greater role for factor timing

Behavioral Economics Insights

Herding Behavior

Extremely high loadings suggest **strong herding**:

- Investors treat DeFi as **single asset class**
- Decision heuristic: "Buy crypto" or "Sell crypto"
- Limited protocol differentiation
- Information cascades

Mental Accounting

Factor 2 represents investors' mental buckets:

- **"Safe" bucket:** Lending protocols
- **"Risky" bucket:** DEX and derivatives
- Flight to quality during uncertainty
- Risk-seeking during euphoria

Key Takeaways

1. **Two factors explain 99.6% of DeFi token variance**
   - Factor 1 (Market): 97.8% - dominant
   - Factor 2 (Sector): 1.8% - minor but tradeable
2. **99.6% systematic, 0.4% idiosyncratic**
   - Traditional diversification ineffective
   - Must diversify across asset classes
   - Or hedge systematic factors
3. **Factor structure reveals trading opportunities**
   - Factor-neutral strategies
   - Sector rotation plays
   - Risk attribution and performance evaluation

Practical Implications

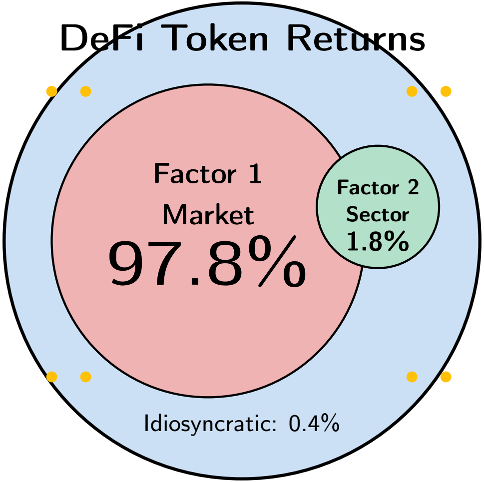
For Portfolio Managers

- **Focus on factor exposures**, not individual tokens
- Design **factor-based strategies**
- Use derivatives for **factor hedging**
- Monitor factor scores in real-time

For Risk Managers

- Measure risk in terms of **factor exposures**
- Set **factor limits** rather than position limits
- Understand that holding 10 DeFi tokens $\neq$ diversification
- Stress test against **factor scenarios**

The Big Picture



One factor dominates everything

Future Research Directions

Extensions to Explore

1. **Dynamic Factor Models**
   - Allow loadings to vary over time
   - Capture regime changes
2. **Augmented Factor Models**
   - Include observable macro factors (ETH, VIX, Fed policy)
   - DeFi-specific factors (TVL, gas prices)
3. **Alternative Risk Premia**
   - Liquidity, yield, governance, smart contract risk
4. **Machine Learning Integration**
   - Nonlinear factors, neural network forecasting

Limitations

Important Caveats

- **Small sample:** 5 weeks - results are illustrative
- **Linear assumption:** May miss nonlinear relationships
- **Static model:** Factors assumed constant over time
- **No exogenous factors:** Doesn't include ETH, macro conditions
- **Nascent market:** Factor structure may evolve

Recommendations for Practice

- Use **rolling windows** (2+ years of data)
- Validate **out-of-sample**
- Monitor **factor stability**
- Combine with **fundamental analysis**

Implementation Roadmap

Step 1: Data Collection (Week 1)

- Gather 2+ years of daily/weekly returns
- Include 20-50 major DeFi tokens

Step 2: Model Estimation (Week 2-3)

- Run factor analysis with various specifications
- Test stability across subperiods

Step 3: Strategy Development (Week 4-6)

- Design factor-based strategies
- Backtest historical performance

Step 4: Live Implementation (Week 7+)

- Real-time factor monitoring

The Factor Model

$X = \text{˜}F + \epsilon$

Where:

- $X \in \mathbb{R}^{n \times p}$: Observed returns
- $\text{˜} \in \mathbb{R}^{p \times m}$: Factor loadings
- $F \in \mathbb{R}^{n \times m}$: Common factors
- $\epsilon \in \mathbb{R}^{n \times p}$: Unique factors

Covariance Structure

$\circ = \text{˜˜}^T + \text{¯}$

- ˜˜^T: Common variance
- ¯: Unique variance (diagonal)

Fama-French vs DeFi Factors

Fama-French (Equity)

$$R_{it} = \alpha_i + \beta_M R_M + \beta_{SMB} SMB + \beta_{HML} HML + \epsilon_i$$

Factors:

- Market (30-50%)
- Size (10-15%)
- Value (10-15%)

Multiple factors

DeFi Model

$$R_{it} = \alpha_i + \beta_1 F_1 + \beta_2 F_2 + \epsilon_i$$

Factors:

- Market (97.8%)
- Sector (1.8%)
- Idio (0.4%)

One dominant factor

DeFi has simpler, less mature factor structure

Factor-Based Trading Strategies

Strategy 1: Market Timing

Objective: Time exposure to Factor 1
Signals: Momentum on Factor 1 scores, ETH/BTC trends, macro sentiment
Action: Increase/decrease overall DeFi exposure

Strategy 2: Sector Rotation

Objective: Profit from Factor 2 movements
Signals: TVL flows, yield spreads, Factor 2 momentum
Action: Overweight DEX or Lending

Risk Management Framework

Factor Risk Limits

Set limits on factor exposures:

Factor	Limit Range	Current
Factor 1 (Market)	0.50 - 1.20	0.988
Factor 2 (Sector)	-0.30 - +0.30	-0.026

Benefits

- Controls actual risk sources
- More flexible than position limits
- Enables factor-based optimization

Performance Measurement

Factor-Adjusted Performance

Traditional: $\text{Sharpe} = \frac{r_p - r_f}{\sigma_p}$

Factor-Adjusted: $\text{Sharpe}_{\text{adj}} = \frac{\alpha}{\sigma_\epsilon}$

Where α = return after removing factor contributions

Why This Matters

Separates **skill** (alpha) from **factor exposure** (beta)

High Sharpe might just mean high market beta, not skill

Case Study: Week 4 Deep Dive

Market Conditions

Factor Scores:

- Factor 1: +1.195 (strong bull)
- Factor 2: -0.089 (slight lending bias)

Returns

Highest:

- SNX: +15.7%
- LDO: +13.8%

Lowest:

- CRV: +6.2%
- COMP: +7.9%

Attribution

Difference explained by Factor 1 loading:

- SNX: 0.999 loading
- CRV: 0.964 loading

Not skill, but systematic exposure!

High returns = High beta $\times$ High market factor

Key Message

In DeFi, you're not picking tokens—

you're picking factor exposures

Factor understanding is essential for risk, portfolios, and strategies

Summary: The Journey

1. **Started:** High correlations (Why?)
2. **Applied:** Factor Analysis (Find hidden factors)
3. **Identified:** 2 factors (Market 97.8%, Sector 1.8%)
4. **Rotated:** For interpretation (Clear meaning)
5. **Decomposed:** Risk (99.6% systematic, 0.4% idio)
6. **Built:** Applications (Portfolios, strategies)
7. **Compared:** With traditional finance (DeFi unique)
8. **Concluded:** Diversification fails, focus on factors

Questions to Consider

For Discussion

1. How would factor structure change during a crypto winter?
2. Could new DeFi primitives create new factors?
3. What role does chain selection play?
4. How to incorporate protocol fundamentals?
5. Should we use time-varying betas for volatility?

Backup: Loading Calculation Example

Computing Factor Loading for UNI

Given:

- Eigenvalue 1: $\lambda_1 = 7.825$
- Eigenvector element: $v_{1,1} = 0.354$

Calculate: $\text{Loading}_{UNI,1} = \sqrt{\lambda_1} \times v_{1,1} = \sqrt{7.825} \times 0.354 = 2.797 \times 0.354 = 0.990$

Interpretation

UNI has 0.990 correlation with Factor 1

When Factor 1 $\uparrow$ 1 std dev, UNI $\uparrow$ 0.990 std devs

Backup: Communality Calculation

Computing Communality for AAVE

Given rotated loadings:

- Factor 1: $\tilde{\lambda}_{AAVE,1} = 0.980$
- Factor 2: $\tilde{\lambda}_{AAVE,2} = -0.193$

Calculate: $h^2_{AAVE} = (0.980)^2 + (-0.193)^2 = 0.960 + 0.037 = 0.997$

Interpretation

99.7% of AAVE's variance explained by two factors

Only 0.3% is unique to AAVE

Backup: Model Fit Statistics

Metric	Value	Threshold
RMSR	0.002	< 0.05
TLI	1.002	> 0.95
RMSEA	0.000	< 0.05
Chi-square p	1.000	> 0.05

Interpretation

All metrics indicate **excellent fit**

2-factor model adequately explains correlations

No evidence of misspecification

Backup: Factor Score Calculation

Computing Factor 1 Score for Week 1

Week 1 standardized: $z_1 = [0.70, 0.76, 0.77, \ldots, 0.73]^T$
Factor 1 loadings: $\boldsymbol{\lambda}_1 = [0.995, 0.998, \ldots, 0.997]^T$

Score: $F_{1,1} = \frac{\boldsymbol{\lambda}_1^T z_1}{\boldsymbol{\lambda}_1^T \boldsymbol{\lambda}_1} = \frac{5.744}{7.907} = 0.726$

Interpretation

Factor 1 was 0.726 std devs above mean in Week 1
Indicates moderately bullish market