

Market Risk Connectedness and Tail Risk in the Global High-Bandwidth Memory Oligopoly

Chuantong Yang^{1,*}

¹The Information School, University of Washington, Seattle, WA, United States

*Corresponding author: yct2004@uw.edu

Abstract:

High-Bandwidth Memory (HBM) is a critical AI-semiconductor bottleneck concentrated among Micron, Samsung Electronics, and SK Hynix. Using 1,895 aligned daily USD log returns (2018–2025), this study combines asymmetric GARCH, rolling Diebold-Yilmaz connectedness, and 99% Value-at-Risk (VaR) and Expected Shortfall (ES). The five-variable network has a total connectedness index (TCI) of 38.1%, versus 20.0% for the memory-only triad. Contrary to the initial hypothesis, post-AI connectedness falls from about 43% to 39%. HBM suppliers are net receivers—especially SK Hynix—while SOX and NVIDIA transmit risk. The equal-weighted HBM portfolio's tail risk rises in the AI regime but remains below SOX. HBM firms are therefore best interpreted as downstream risk-absorbing nodes with a supplier-specific connectedness component.

Keywords: Artificial intelligence (AI) semiconductors; High-Bandwidth Memory (HBM); Micron; Samsung Electronics; SK Hynix.

1. Introduction

1.1 Research Background

Generative AI has intensified investment in computing infrastructure, where data movement as well as logic-chip supply constrains performance. HBM addresses this bottleneck by vertically stacking DRAM dies and providing bandwidth above 1.2 TB/s in products such as Micron HBM3E [1]. Commercial advanced HBM is dominated by SK Hynix, Samsung Electronics, and Micron, while industry forecasts show rapid wafer-input and revenue growth [2–4].

Because yield, qualification, export-control, and AI-demand shocks can alter memory pricing, accelerator output, and earnings expectations, this concentrated supply chain is analyzed as a financial-risk network.

1.2 Research Purpose

This paper quantifies financial risk arising from HBM supply concentration through four questions: the strength and direction of volatility connectedness among the three suppliers, the downside risk of an HBM equity portfolio, and the influence of SOX, NVIDIA, and major AI/HBM events.

1.3 Research Questions

RQ1: Does supplier connectedness rise in the AI-HBM expansion period?

RQ2: Which HBM firms transmit or receive volatility risk?

RQ3: Does the HBM portfolio's downside risk rise after the AI break and exceed SOX?

RQ4: Do AI/HBM event windows coincide with higher connectedness and tail risk?

1.4 Research Significance

The study narrows connectedness research to a supply-chain micro-network and tests whether holding several memory suppliers provides diversification or common AI-factor exposure. The results also inform investors, regulators, and downstream chip firms about how concentrated production can transmit or absorb financial stress.

2. Literature Review, Theoretical Framework, and Hypotheses

2.1 Literature Review

The analysis integrates four literatures. ARCH/GARCH, EGARCH, and GJR-GARCH model clustered and asymmetric volatility [5–8]; Diebold-Yilmaz generalized forecast-error variance decompositions measure total and directional spillovers [9,10]; VaR and ES capture downside thresholds and losses beyond them [11–14]; and recent work documents geopolitical, semiconductor, technology-equity, and AI-related risk transmission [15–19]. Existing studies mostly examine broad sectors rather than the HBM supplier triad.

2.2 Theoretical Mechanism

The transmission mechanism is: common AI-demand and supply shocks → cross-firm repricing → volatility connectedness → tail-risk amplification within the HBM oligopoly.

Five channels support this mechanism: shared semiconductor sentiment and AI capital expenditure; supply externalities from capacity, yield, or qualification shocks; concentration in cloud and accelerator customers; information spillovers during HBM3E-to-HBM4 transitions; and stronger volatility responses to negative news.

These channels imply both supplier-specific and common-factor dependence; the empirical issue is whether HBM firms transmit risk outward or absorb shocks from the wider AI-semiconductor complex.

2.3 Research Hypotheses

H1: HBM-supplier connectedness rises after the AI-driven

demand shock.

H2: SK Hynix is a net volatility transmitter during the AI-HBM expansion.

H3: AI/HBM event windows are associated with higher connectedness and tail risk.

H4: The HBM portfolio has higher 99% VaR and ES in the AI regime and potentially exceeds SOX.

2.4 Contribution

The paper contributes by treating HBM suppliers as a micro-network, combining connectedness with tail-risk measurement, controlling explicitly for SOX and NVIDIA, and testing whether market data support the view that HBM vendors lead rather than absorb AI-sector risk.

3. Industry and Risk Context

3.1 HBM Supply Chain and Supplier Concentration

SK Hynix, Samsung, and Micron produce nearly all advanced commercial HBM, giving a CR3 near 100% and an estimated 2025 HHI of roughly 4,000–4,600—well above the usual 2,500 high-concentration threshold [2]. The transition from HBM3E to HBM4, standardized as JEDEC JESD270-4 in 2025, adds qualification and yield uncertainty [20].

3.2 Heterogeneous Business Exposure

Exposure differs materially: Samsung is diversified across electronics, foundry, and memory; Micron is a U.S. memory-focused supplier; and SK Hynix is closest to an HBM pure play. Equity returns are therefore proxies rather than pure HBM fundamentals. SOX and NVIDIA controls, plus residual-network estimation after orthogonalizing memory returns against both benchmarks, separate supplier-specific risk from broad sector beta.

3.3 Main Risk Channels

The main channels are supply and customer concentration, HBM3E-to-HBM4 technology-transition risk, AI-valuation risk, KRW/USD exposure for Korean firms, and geopolitical or export-control shocks.

4. Data and Methodology

4.1 Data and Sample Construction

Daily adjusted-close data from Yahoo Finance cover MU, Samsung (005930.KS), SK Hynix (000660.KS), NVDA, SOX, and KRW/USD from January 2018 to December 2025. After converting Korean prices to USD and aligning common trading days, the sample contains 1,895 obser-

vations. Raw log returns are the baseline to preserve fat tails; 1%/99% winsorization is used only for robustness.

4.2 Return Construction and Currency Adjustment

Returns are percentage log differences:

$$r_t = 100 \times \ln(P_t / P_{t-1}) \quad (1)$$

For Samsung and SK Hynix, KRW prices are converted by $P_{USD,t}^{USD} = P_{KRW,t}^{KRW} / E_t$, where E_t is won per dollar, placing all firms on a common international-investor basis.

4.3 Conditional Volatility Model

GJR-GARCH(1,1) and EGARCH(1,1) with skewed Student-t innovations are estimated. GJR-GARCH captures leverage effects directly; EGARCH models log variance without positivity constraints. The lower-BIC model for each series supplies conditional volatility and tail-risk forecasts.

4.4 Connectedness Model

Connectedness is estimated from GARCH-based log conditional variances using a rolling Diebold-Yilmaz generalized FEVD. Each 200-day window fits a parsimonious VAR(1) and a 10-step, order-invariant decomposition to obtain TCI, TO, FROM, and NET = TO – FROM; positive NET denotes a transmitter. Higher lags and TVP-

VAR/DCC-GARCH are robustness extensions.

4.5 Tail-Risk Measurement

Tail risk is measured by 99% VaR and ES. VaR is the 1% loss threshold and ES the average loss beyond it. Kupiec unconditional-coverage and Christoffersen conditional-coverage tests evaluate VaR adequacy.

4.6 Robustness and Identification Strategy

Robustness checks compare local-currency and USD returns, two-day and lag-adjusted returns for non-synchronous trading, alternative GARCH models, winsorization, and VAR lags. Identification is strengthened by including SOX/NVIDIA and re-estimating the residual memory network after orthogonalization.

5. Empirical Results and Discussion

5.1 Descriptive Statistics

Table 1 shows stationary returns (ADF $p < 0.01$), significant ARCH effects, and fat tails: kurtosis ranges from 4.43–4.48 for the Korean firms to 8.15 for SOX, with normality strongly rejected. Samsung is least volatile, while MU and NVDA are most volatile, supporting asymmetric GARCH and ES.

Table 1. Descriptive statistics of daily USD log returns, 2018–2025 (1,895 observations)

Series	Mean	Std. dev.	Skew.	Kurt.	Jarque-Bera	ARCH-LM p
MU	0.102	3.173	-0.288	6.76	1143.98	0.000
Samsung	0.041	1.938	0.098	4.48	175.40	0.000
SK Hynix	0.102	2.746	0.111	4.43	165.65	0.000
NVDA	0.192	3.273	-0.151	7.48	1593.74	0.000
SOX	0.091	2.287	-0.212	8.15	2107.85	0.000

5.2 Conditional Volatility Results

BIC selects EGARCH for MU, Samsung, NVDA, and SOX and GJR-GARCH for SK Hynix (Table 2). Volatility

is persistent ($\alpha + \beta \approx 0.96$), leverage effects are positive for all memory firms and strongest for MU, and degrees of freedom near 6–8 confirm fat tails. Fig. 1 shows spikes during COVID and the 2024–2025 AI-cycle turbulence.

Table 2. Model selection by BIC (skewed-t innovations)

Series	GJR-GARCH BIC	EGARCH BIC	Preferred
MU	9518.52	9506.24	EGARCH
Samsung	7779.20	7774.12	EGARCH
SK Hynix	9108.69	9110.06	GJR-GARCH
NVDA	9513.31	9501.77	EGARCH
SOX	8100.81	8095.42	EGARCH

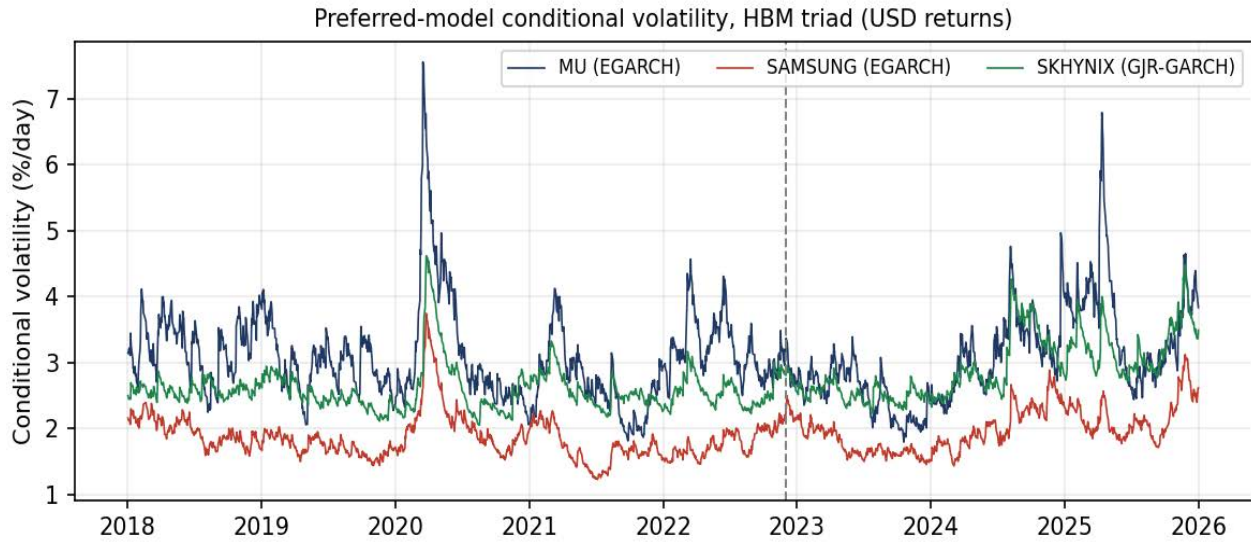


Fig. 1 Preferred-model conditional volatility of HBM-exposed suppliers (USD returns), 2018–2025

5.3 Dynamic Connectedness and H1

The full network TCI is 38.1%, but the memory-only triad is 20.0%, so most connectedness links suppliers to the broader AI-semiconductor complex. H1 is rejected: static TCI falls from 40.2% before 30 November 2022 to 36.8%

afterward, while the rolling mean declines from 42.9% to 38.8%; alternative 2023 breaks also produce lower post-break values. Fig. 2 shows a U-shaped path—near 23% in early 2024 amid firm-specific qualification divergence, then toward 45% in 2025 as broad AI drivers reassert themselves.

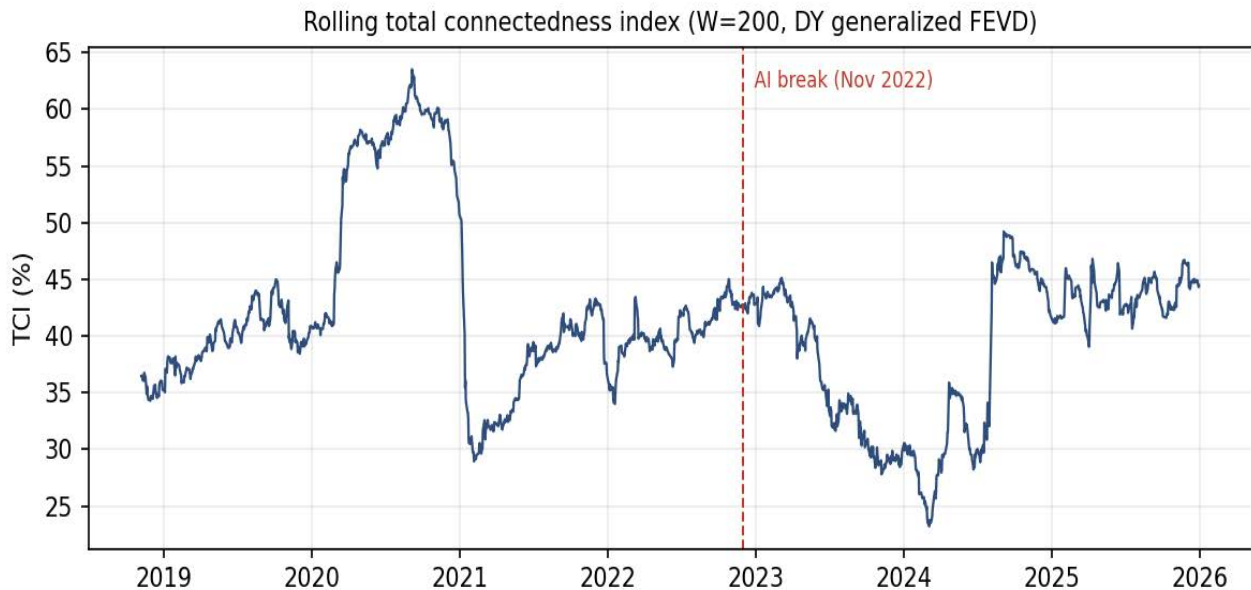


Fig. 2 Rolling total connectedness index, 200-day window (DY generalised FEVD)

5.4 Net Risk Transmission and H2

Table 3 rejects H2. SOX (NET +14.62) and NVDA (+4.30) are transmitters; MU (−2.52), Samsung (−5.56), and SK

Hynix (−10.84) are receivers. Risk therefore flows mainly from the broad AI-semiconductor complex into memory suppliers.

Table 3. Directional connectedness in the full network (%)

Variable	TO	FROM	NET	Role
SOX	62.49	47.87	+14.62	Transmitter
NVDA	45.32	41.02	+4.30	Transmitter
MU	37.20	39.72	-2.52	Receiver
Samsung	23.13	28.69	-5.56	Receiver
SK Hynix	22.23	33.08	-10.84	Largest receiver

Within the memory-only triad (Table 4), MU transmits risk (+5.27), while Samsung (−0.75) and SK Hynix (−4.52) receive it. MU bridges U.S. sector and memory exposure, whereas the Korean firms absorb more shocks.

Table 4. Directional connectedness in the memory-only triad (%)

Variable	TO	FROM	NET
MU	12.36	7.09	+5.27
Samsung	23.87	24.62	-0.75
SK Hynix	23.90	28.42	-4.52

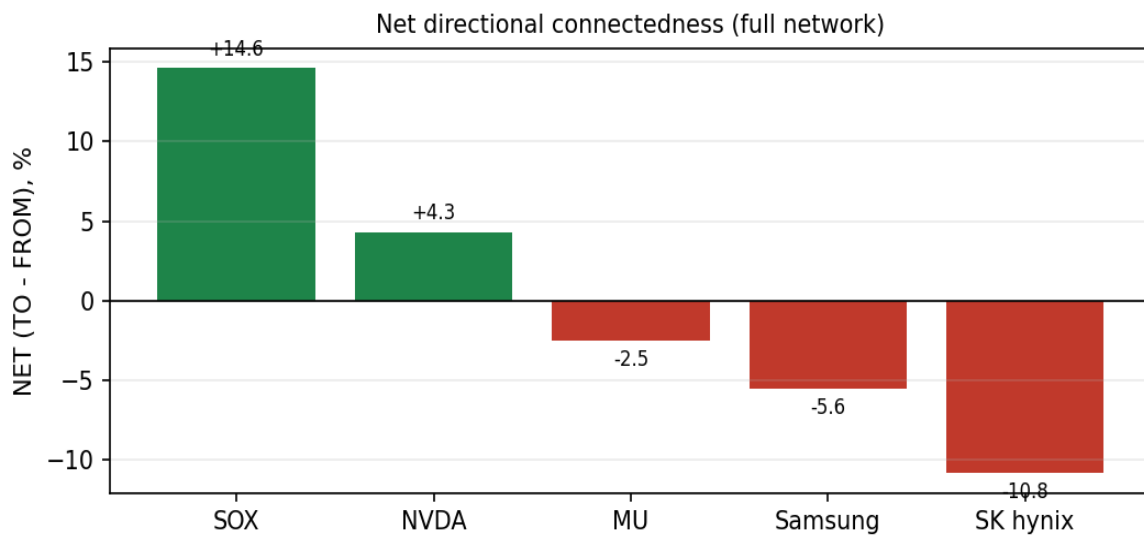


Fig. 3 Net directional connectedness, full network

SK Hynix's exposure purity thus makes it the most vulnerable receiver, not the source of risk. Direction is interpreted as network structure rather than strict causality because SOX contains MU and NVDA, creating some mechanical index-constituent overlap.

5.5 Tail Risk, Portfolio Risk, and H4

H4 is partially supported (Table 5). In the AI regime, the HBM portfolio's mean VaR deepens from −4.876% to −5.120% and ES from −6.206% to −6.515%. Tail risk rises relative to its own pre-AI baseline but remains below SOX, whose AI-regime VaR and ES are −5.554% and −6.900%.

Table 5. Mean daily 99% VaR and ES by regime (% returns)

Portfolio / Asset	VaR99 pre-AI	VaR99 AI	ES99 pre-AI	ES99 AI
HBM equal-weight portfolio	-4.876	-5.120	-6.206	-6.515
SOX benchmark	-5.683	-5.554	-7.059	-6.900

VaR backtests (Table 6) show conventional coverage for the individual memory firms and SOX. The HBM portfolio has 16 exceptions and passes Kupiec ($p = 0.484$) but

fails Christoffersen independence ($p = 0.006$), indicating clustered tail losses and reinforcing ES as the key downside metric.

Table 6. 99% VaR backtests (expected exceptions ≈ 18.9)

Series	Exceptions	Kupiec p	Christoffersen p	
HBM portfolio	16	0.484	0.006	Clustered
SOX	19	0.991	0.535	Pass
MU	18	0.825	0.162	Pass
Samsung	18	0.825	0.557	Pass
SK Hynix	19	0.991	0.184	Pass

5.6 Event-Based Interpretation and H3

H3 receives descriptive, not formal, support. COVID produces the largest common-stress increase; early 2024 shows a trough associated with divergent HBM qualifications; and connectedness rebounds through 2025. A formal event-window regression—particularly around the January 2025 DeepSeek demand-expectation shock—is left for future work.

5.7 Heterogeneity Analysis

Heterogeneity is cross-firm, cross-regime, and business-model based: MU transmits within the triad while all memory firms receive from SOX/NVDA; the AI period combines higher portfolio tail risk with lower average connectedness; and SK Hynix is most sector-sensitive while diversified Samsung is least volatile.

5.8 Mechanism and Identification

After regressing memory returns on SOX and NVDA, residual triad TCI remains 17.8% versus 20.0% in the raw triad. Thus, a genuine supplier-specific component survives common-factor removal. Generalized FEVD avoids ordering dependence; remaining caveats are index overlap and non-synchronous U.S.–Korean trading.

5.9 Portfolio and Risk-Management Implications

HBM investors should monitor SOX and NVDA as upstream risk transmitters and size positions using regime-dependent ES rather than unconditional volatility. Downstream AI firms should diversify suppliers and use long-term procurement contracts for both operational and financial resilience.

5.10 Summary of Hypothesis Tests

Overall, H1 and H2 are rejected, H3 is descriptively supported, and H4 is partially supported. Connectedness falls after the AI break; SK Hynix is the largest receiver; the

HBM portfolio's VaR/ES increase but remain below SOX; and residual TCI of 17.8% confirms a supplier-specific risk component.

6. Conclusion

Using 2018–2025 daily data, this study finds moderate HBM-related connectedness that decreases rather than rises mechanically after the AI break. HBM suppliers are downstream risk absorbers: SK Hynix is the most exposed receiver, while SOX and NVIDIA are upstream transmitters. The HBM portfolio becomes riskier in the AI regime but still has lower absolute VaR and ES than SOX; a distinct HBM-supplier component nonetheless persists after sector controls.

Practically, multiple HBM holdings should not be treated as independent AI winners. Risk managers should use SOX/NVIDIA volatility as early warnings, and downstream firms should recognize that supplier concentration has both operational and financial consequences.

Limitations include equity returns as imperfect HBM proxies, Samsung's diversified news exposure, SOX constituent overlap, non-synchronous trading, rolling VAR(1) specification, and descriptive event analysis. Future work can use supplier revenue or shipment data, option-implied or realized volatility, formal event studies, TVP/quantile/frequency connectedness, and Chinese memory entrants.

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