

Volatility Targeting in the Taiwan Stock Market: Leverage Amplification, Model Selection, and Practical Implementation*

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Abstract

We examine volatility targeting (VT) strategies in the Taiwan stock market using the 0050.TW ETF over 2008–2026. Two contributions emerge. First, the TAIEX exhibits a diversification amplification of the leverage effect: under the canonical full-sample specification, the broad-index GJR-GARCH asymmetry parameter exceeds the individual-stock average by approximately $4.3\times$ (90% bootstrap CI: [2.28, 6.58]; $N = 9$ stocks; the calendar-aligned rolling-window specification yields $6.12\times$, though the rolling index estimate is not itself individually significant). Despite this strong leverage effect, GJR-GARCH does not improve average forecast accuracy over standard GARCH (DM $p = 0.86$), yet GJR-based VT produces higher Sharpe ratios, suggesting that tail-specific accuracy drives VT performance. Second, over the 2010–2026 sample (canonical replication), EWMA-based VT changes the Sharpe ratio from 0.799 (buy-and-hold) to 0.701 while reducing maximum drawdown from -33.8% to -21.2% (a 12.6 percentage point reduction); over a common 2020–2026 evaluation period, all VT strategies outperform buy-and-hold. A VIX-proxy formula ($8.63/\text{VIX}$), calibrated via the VIXTWN-to-VIX ratio, enables practical implementation without a local implied volatility index. Combining

*Data and replication code available upon request.

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VIX scaling with a leading indicator direction signal further improves risk-adjusted returns (DM $p = 0.0005$). A systematic cross-market validation shows that three of four U.S. VT findings generalize or partially generalize to Taiwan (VIX sufficiency, allocation near vol-parity, calendar null results) while one does not (rebalancing frequency). Results are robust to TSMC concentration risk. VaR and Expected Shortfall (ES) backtesting confirms that GJR+HistSim and GJR+Student- t specifications pass both the VaR trinity and Acerbi–Székely ES tests; VT strategies achieve VaR compliance at 1% but ES severity ratios remain elevated during crisis episodes, motivating tail-risk reserves beyond standard VaR frameworks.

Keywords: volatility targeting, Taiwan stock market, leverage effect, diversification amplification, GARCH, cross-market validation, leading indicators, VaR, expected shortfall

JEL Classification: C22, C53, G11, G14

1 Introduction

Volatility targeting (VT), the practice of dynamically scaling portfolio exposure inversely to predicted volatility, has attracted considerable attention following the influential work of [Moreira and Muir \[2017\]](#). The central insight is intuitive: investors should hold less when markets are turbulent and more when markets are calm. Studies have documented that this approach reduces maximum drawdown substantially, though its impact on risk-adjusted returns remains debated [[Fleming et al., 2001](#), [Harvey et al., 2018](#)].

Despite a growing literature, virtually all evidence on VT strategies pertains to U.S. markets or, more broadly, to developed Western economies. The applicability of these findings to Asian emerging markets—where microstructure, investor composition, and information transmission dynamics differ materially—remains an open question. This gap is particularly surprising in the case of Taiwan, which ranks among the world’s most active equity markets by turnover ratio, hosts a retail-investor-dominated trading environment where individual investors account for over 60% of turnover [[Barber et al., 2009](#)], and features extreme single-stock concentration: Taiwan Semiconductor Manufacturing

Company (TSMC) alone constitutes approximately 50% of the benchmark 0050.TW index. These distinctive features—retail dominance, electronics concentration, and tight linkage to the global semiconductor cycle—make Taiwan a compelling test case for the generalizability of VT strategies beyond developed Western markets.

The Taiwan stock market presents several features that make it a compelling laboratory for VT research in the emerging-market context. First, the TAIEX exhibits a leverage effect—the asymmetric volatility response to positive and negative shocks formalized by Black [1976] and Glosten et al. [1993]—that is substantially stronger at the index level than at the individual stock level. We document that this *diversification amplification* reaches approximately $4.3\times$ for the broad TAIEX (~ 900 stocks) relative to nine individual stocks (90% bootstrap CI: [2.28, 6.58]; canonical full-sample BW-robust specification), though a more modest $3.0\times$ for the investable 0050.TW ETF (50 stocks) under rolling-window specification. The broad-TAIEX figure exceeds the $2.8\times$ we compute for the United States, a difference we attribute to higher correlation asymmetry among Taiwanese equities during market declines [Ang and Chen, 2002], though the confidence interval around our Taiwan estimate contains the U.S. benchmark (Section 3). Second, the absence of a deep, liquid local implied volatility index (the VIXTWN was introduced only in November 2020 with limited history) forces practitioners to rely on either model-based volatility estimates or proxy measures such as the U.S. VIX [Whaley, 2000, 2009]—a constraint common to many emerging markets. The viability of this proxy approach has broader implications for VT implementation across markets where implied volatility surfaces are underdeveloped, analogous to the cross-listing and ADR literature that documents how U.S.-listed securities transmit price information to local markets [Gagnon and Karolyi, 2010]. Third, Taiwan’s geographic position—trading hours that open after the U.S. market closes—creates a natural information transmission channel [Eun and Shim, 1989, Hamao et al., 1990, Lin et al., 1994] that provides supplementary evidence for cross-market price discovery (Appendix A).

This paper makes two contributions.

First, we document the leverage effect and its diversification amplification in the Tai-

wan market, extending the analysis of [Ang and Chen \[2002\]](#) to an Asian emerging-market context. Using GJR-GARCH estimation on the TAIEX (canonical full-sample $\gamma = 0.105$, $t = 5.31$), a nine-stock non-TSMC individual-security cross-section, and the 0050.TW ETF ($\gamma = 0.097$), we show that the broad TAIEX gamma exceeds the average individual stock gamma by a factor of approximately $4.3\times$ (90% bootstrap CI: [2.28, 6.58]; canonical full-sample BW-robust specification), though the investable 0050.TW (50 stocks) shows a more modest amplification of $3.0\times$ under rolling-window specification. This amplification arises because stock correlations increase asymmetrically during downturns, a phenomenon first identified by [Ang and Chen \[2002\]](#) for U.S. equities. We further establish a strong cross-market spillover channel: lagged SPY returns predict next-day 0050.TW returns with a correlation of $r = 0.376$, and VIX Granger-causes Taiwan equity volatility ($F = 58.8$, $p < 0.001$).

Second, we evaluate multiple VT strategies adapted for Taiwan, including EWMA-based VT, GJR-GARCH VT, and a VIX-proxy approach (8.63/VIX) calibrated using the VIXTWN-to-VIX ratio of 1.39. Over a common evaluation period (2020–2026), VT strategies improve both Sharpe ratios and maximum drawdowns relative to buy-and-hold, with GJR VT achieving Sharpe 1.084 and 8.63/VIX achieving the highest Sharpe (1.132) with the lowest drawdown (-13.7%). Over 2010–2026, the EWMA strategy reduces maximum drawdown from -33.8% (buy-and-hold) to -21.2% (a 12.6 percentage point reduction), with the Sharpe ratio decreasing slightly from 0.799 to 0.701 owing to the cost of persistent defensive positioning during the 2020–2021 bull market. We show that GJR+Student- t and GJR+HistSim achieve 1.03% violation rates over the 2019–2026 out-of-sample window and are the only specifications passing both the VaR trinity and ES backtests; GJR+Cornish–Fisher attains a lower 0.51% rate but is over-conservative (noting that the Basel traffic-light framework is defined for 250-day windows; we apply the 1% threshold as a benchmark across our full sample). A key finding is that despite the statistically significant leverage effect, GJR-GARCH does not significantly improve QLIKE over standard GARCH (Diebold-Mariano $p = 0.86$), yet GJR-based VT produces a meaningfully higher Sharpe ratio ($+0.124$), suggesting that tail-specific forecast

accuracy—rather than average forecast accuracy—drives VT performance. A systematic cross-market validation reveals that three of four core U.S. VT findings generalize or partially generalize to Taiwan (VIX sufficiency, allocation near vol-parity, calendar null results), while one does not (rebalancing frequency), providing a nuanced picture of VT portability to emerging Asian markets.

We additionally document a cross-market information transmission channel—lagged U.S. returns predict next-day Asian equity returns, with approximately 78% of the signal absorbed by the opening gap—presented as supplementary evidence in Appendix A. This time-zone analysis, while related to the VIX-proxy motivation, constitutes a distinct microstructure contribution that we defer to supplementary material to maintain the paper’s focus on VT strategy evaluation.

The remainder of the paper proceeds as follows. Section 2 describes the data and methodology. Section 3 examines the leverage effect and diversification amplification. Section 4 evaluates VT strategies, including a conditional leverage extension adapted for Taiwan. Section 5 explores macroeconomic indicators for Taiwan. Section 6 addresses VaR and risk management. Section 7 discusses practical implications and cross-market validation. Section 8 concludes. Appendix A presents supplementary evidence on time-zone information transmission from U.S. to Asian equity markets.

2 Data and Methodology

2.1 Data Sources

We use daily price data from a layered source stack. The canonical, fully reproducible paper numbers are tied to public Yahoo Finance OHLC/adjusted-close series together with official TWSE/TAIFEX reference data where applicable (for instrument meta-data and VIXTWN availability). Earlier internal draft checks also compared selected 0050.TW/TWII cross-sections against TEJ and Bloomberg snapshots; when vendor histories differ materially, we retain the reproducible Yahoo Finance/TWSE/TAIFEX result in the paper and note the discrepancy explicitly. This matters most for the Appendix A

time-zone exercise, where a 0050.TW split-adjustment difference changes Sharpe magnitudes.

- **0050.TW**: Yuanta/P-shares Taiwan Top 50 ETF, tracking the FTSE TWSE Taiwan 50 Index. For the full-sample GJR-GARCH estimate reported below, the pinned adjusted-close series spans 2009-01-02 through 2026-04-02 (4,220 price observations yielding 4,219 return observations). The analysis reads `paper/taiwan-vt/data/0050_tw_twii_2330_tw_2317_tw_2454_tw_0056_tw_spy_vix_2008-2026.csv`, column `0050_tw_adj_close`, directly; live yfinance is available only through the explicit `K892_USE_PINNED=0` fallback. The earliest yfinance-available quote is 2009-01-02; the fund itself launched in 2003, but pre-2009 data is not publicly accessible through yfinance (the original vendor source). Consequently, the 2008 Global Financial Crisis drawdown is not included in our evaluation window. A data-handling caveat is important for Appendix A: 0050.TW underwent a 4:1 split on 2014-01-02, and some yfinance vintages back-adjust only the post-2014-01-02 segment, leaving a spurious -75% return on the split date. Reading `Adj Close` instead of `Close` does *not* fix that affected vintage: the adjusted series jumps in lockstep with the raw close ($37.41 \rightarrow 9.33$, a ratio of 0.2494 in both columns), so the adjustment layer never corrects the discontinuity. The pinned snapshot used here was rebuilt from a split-consistent price cache and verified by an automated break detector; the K892 cleaner therefore makes no further change, and the reported full-sample fit retains the valid 2014-01-02 return. The explicit live-data fallback instead rescales the entire pre-2014 segment when it detects the fourfold discontinuity. As a diagnostic on the contaminated March-cutoff vintage, simply omitting the artifact date gives $\gamma = 0.0965$ ($t = 3.58$), but that diagnostic is not the input to Table 1; the table uses the pinned April-cutoff series and reports $\gamma = 0.097$ ($t = 3.60$). The level repair remains necessary for price-level quantities such as rolling-window inputs and drawdown paths. We additionally use `auto_adjust=False` and construct adjusted opens as $\text{Open}_t \times (\text{AdjClose}_t / \text{Close}_t)$.

- **TWII (TAIEX)**: Taiwan Capitalization Weighted Stock Index. Sample: January

1997 to March 2026 (7,148 trading days).

- **Eleven Taiwan security-level series:** Taiwan Semiconductor (2330.TW), Hon Hai Precision (2317.TW), MediaTek (2454.TW), ELITE Material (2383.TW), Cathay Financial (2882.TW), Mega Financial (2886.TW), CTBC Financial (2891.TW), Chunghwa Telecom (2412.TW), Yuanta Financial (2885.TW), Fubon Financial (2881.TW), and Yuanta High Dividend ETF (0056.TW, an ETF tracking mid-cap dividend stocks). In Section 3, the primary “9-stock average” excludes both TSMC (2330.TW, reported separately because of its dominant index weight) and 0056.TW (an ETF rather than an individual stock).
- **U.S. benchmarks:** S&P 500 (SPY), CBOE Volatility Index (VIX), CBOE Emerging Markets ETF Volatility Index (VXEEM), and the iShares MSCI Taiwan ETF (EWT).
- **Asia-Pacific markets:** Nikkei 225 (Japan), Hang Seng (Hong Kong), ASX 200 (Australia), Straits Times (Singapore), KOSPI (South Korea), and Sensex (India).
- **VIXTWN:** TAIEX Options Volatility Index, compiled by the Taiwan Futures Exchange (TAIFEX) using the CBOE VIX methodology. Available from November 2020.

Log returns are computed as $r_t = \ln(P_t/P_{t-1}) \times 100$. Table 1 reports summary statistics.

Table 1: Summary Statistics for Key Assets

	Mean (%)	Std (%)	Skewness	Kurtosis	γ_{GJR}	$t(\gamma)$
TWII (1997–2026)	0.019	1.45	−0.31	5.82	0.105	5.31
0050.TW (2009–2026)	0.034	1.38	−0.47	4.73	0.097	3.60
SPY (2008–2026)	0.042	1.18	−0.52	12.30	0.211	5.79
TSMC (2330.TW)	0.051	1.92	−0.18	3.41	0.052	3.98
9-stock average (excl. 2330 & 0056)	0.026	1.74	−0.21	3.62	0.032	—
10-security average (incl. 0056; excl. 2330)	0.028	1.71	−0.22	3.68	0.051	—

Notes: γ_{GJR} is the asymmetric leverage parameter from GJR-GARCH(1,1). TWII, 0050.TW, and TSMC values use full-sample constant-mean QMLE with Bollerslev–Wooldridge robust standard errors [Bollerslev and Wooldridge, 1992]; the individual-stock averages use calendar-aligned rolling windows ($w = 2000$, terminal date 2026-07-09, pinned snapshots; `experiments/paper2_taiwan_indiv_rolling_gamma` and `experiments/k1697`) with Newey–West HAC standard errors. On the same aligned rolling window the TAIEX estimate is $\gamma = 0.198$ ($t = 1.86$, not significant), illustrating the endpoint sensitivity of last-window rolling estimates; the full-sample estimate shown in the table is the canonical basis for all leverage-significance claims in this paper. The primary 9-stock average excludes both TSMC (2330.TW) and 0056.TW: TSMC is reported separately because of its dominant benchmark weight, and 0056.TW is a diversified ETF rather than an individual stock. The 10-security average adds 0056.TW back in for sensitivity, while still excluding TSMC.

2.2 Volatility Models

We employ three volatility models from the ARCH/GARCH family [Engle, 1982, Bollerslev, 1986], estimated via rolling-window quasi-maximum likelihood [Bollerslev and Wooldridge, 1992].

GJR-GARCH(1,1) [Glosten et al., 1993]:

$$\sigma_t^2 = \omega + (\alpha + \gamma \cdot \mathbb{1}_{r_{t-1} < 0}) r_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (1)$$

where $\gamma > 0$ captures the leverage effect: negative returns increase conditional variance more than positive returns of equal magnitude.

GARCH(1,1) [Bollerslev, 1986]: the restriction $\gamma = 0$ of Equation (1).

EWMA (Exponentially Weighted Moving Average):

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda) r_{t-1}^2 \quad (2)$$

with decay factor $\lambda = 0.94$, the default recommended by the RiskMetrics methodology [JPMorgan, 1996]. EWMA requires no parameter estimation and can be implemented without optimization software.

All GARCH and GJR-GARCH models are estimated using a rolling window of $w = 2000$ trading days, following Hwang and Valls Pereira [2006] who demonstrate that windows below 500 induce substantial persistence bias. We verify that our core results are robust to $w = 504$ and $w = 1000$.

2.3 Forecast Evaluation

We evaluate volatility forecasts using the QLIKE loss function [Patton, 2011]:

$$\text{QLIKE}_t = \ln(\sigma_t^2) + \frac{r_t^2}{\sigma_t^2} \quad (3)$$

which is robust to noise in the volatility proxy r_t^2 and penalizes underprediction more heavily than overprediction. Model comparisons use the Diebold and Mariano [1995] test with Newey-West standard errors for the null hypothesis of equal predictive ability.

2.4 Volatility Targeting Strategies

A volatility targeting strategy sets the portfolio weight as:

$$w_t = \frac{\sigma_{\text{target}}}{\hat{\sigma}_t} \quad (4)$$

where σ_{target} is the annualized target volatility and $\hat{\sigma}_t$ is the volatility forecast. The weight is capped at 100% (no leverage). The portfolio return is:

$$r_t^{\text{VT}} = w_{t-1} \cdot r_t + (1 - w_{t-1}) \cdot r_t^f \quad (5)$$

where r_t^f is the risk-free return (proxied by the 3-month Treasury bill rate) and the weight uses information available at $t - 1$ only, avoiding look-ahead bias.

For the VIX-proxy strategy, the weight is:

$$w_t = \min\left(\frac{K}{\text{VIX}_t}, 1\right) \quad (6)$$

where $K = 8.63 = 12/1.39$ adjusts the standard 12/VIX formula [Bozovic, 2024] by the VIXTWN-to-VIX ratio of 1.39. The VIX is observed at the U.S. close, and the weight is applied to the Taiwan trading session that begins the following calendar day, ensuring no contemporaneous overlap.

2.5 VIX as a Proxy for Taiwan Implied Volatility

A practical question for Taiwan VT is whether the U.S. VIX adequately captures Taiwan-specific volatility dynamics. Using the 64 months of overlapping data between VIX and VIXTWN (November 2020 to March 2026), we find a Spearman rank correlation of 0.595 between VIX and subsequent 0050.TW realized volatility, compared to 0.459 for VXEEM (the CBOE Emerging Markets Volatility Index). The difference is statistically significant (Steiger $Z = 16.2$, $p < 0.001$, based on dependent correlation comparison of daily-frequency observations within the 64-month overlap period). This result is initially counterintuitive—Taiwan is an emerging market, yet the developed-market VIX is a better predictor than the emerging-market VXEEM. The explanation lies in the composition of 0050.TW, which is dominated by Taiwan Semiconductor Manufacturing Company (TSMC), accounting for approximately 50% of the index weight. TSMC’s fortunes are closely tied to global semiconductor demand and U.S. technology sector sentiment, making U.S. VIX a natural proxy for the risk factors most relevant to the Taiwanese market.

The VIXTWN-to-VIX ratio averages 1.393 with a coefficient of variation of 10%, reflecting the higher baseline volatility of the Taiwanese market relative to the S&P 500. We calibrate $K = 12/1.39 = 8.63$ so that a VIX level of 20 (approximately the long-run median) produces a weight of $8.63/20 = 43\%$, a prudent allocation for an emerging-market equity position.

2.6 Transaction Costs and Rebalancing

For 0050.TW, we apply a round-trip transaction cost of 0.186%, reflecting the Taiwan Securities Transaction Tax (0.10% on sell, the reduced ETF rate) plus brokerage commissions at the typical online discount ($0.1425\% \text{ official rate} \times 0.3 = 0.04275\% \text{ per side}$).¹ Unless otherwise stated, all VT strategies use monthly rebalancing. We have verified that daily rebalancing improves the Sharpe ratio marginally but increases turnover and transaction costs substantially. Monthly rebalancing represents a practical specification for individual investors.

3 The Leverage Effect in the Taiwan Market

3.1 Index-Level Leverage

The leverage effect—the tendency for volatility to rise more following negative returns than positive returns of equal magnitude—is a well-established stylized fact in developed equity markets [Black, 1976, Christie, 1982, Nelson, 1991, Glosten et al., 1993]. We examine whether this phenomenon extends to Taiwan and, if so, whether its magnitude differs from the U.S. benchmark.

Table 2 reports GJR-GARCH γ estimates for the TAIEX, 0050.TW, SPY, a nine-stock non-TSMC individual-security cross-section, and one ETF (0056.TW). The TAIEX exhibits a statistically significant leverage effect on the canonical full sample ($\gamma = 0.105$, $t = 5.31$; 1997–2026). Its point estimate is *below* the U.S. S&P 500’s ($\gamma = 0.211$, $t = 5.79$),

¹Taiwan levies a securities transaction tax of 0.3% for common stocks but only 0.1% for ETFs; online brokerages typically offer a 70% discount (“3 折”) on the statutory 0.1425% commission rate.

so the index-level leverage effect in Taiwan is significant but not stronger than in the United States; what distinguishes the Taiwan market is not the absolute level of index asymmetry but the *amplification* of that asymmetry relative to the market's own individual constituents, documented below. The 0050.TW ETF, which tracks the 50 largest Taiwanese companies, shows a smaller but still significant $\gamma = 0.097$ ($t = 3.60$). The difference between the broad market index (TAIEX, 900+ stocks) and the concentrated ETF (50 stocks) is informative: the broader index captures more of the small- and mid-cap stocks whose correlations increase more dramatically during downturns.

Table 2: GJR-GARCH Leverage Parameters Across Taiwan and U.S. Markets

Asset	γ	t -stat	α	β	Persistence
TWII (TAIEX)	0.105	5.31	0.041	0.891	0.985
0050.TW	0.097	3.60	0.032	0.893	0.973
SPY	0.211	5.79	0.000	0.897	0.993
<i>Individual Taiwan Stocks</i>					
TSMC (2330)	0.052	3.98	0.032	0.930	0.989
Hon Hai (2317)	0.020	0.55	0.108	0.853	0.970
MediaTek (2454)	0.017	0.80	0.070	0.863	0.942
Mega Financial (2886)	0.170	1.56	0.058	0.646	0.789
<i>ETF (excluded from individual-stock average)</i>					
0056.TW (Yuantan High Div. ETF)	0.222	2.95	0.097	0.678	0.886
9-stock average (excl. 2330 & 0056)	0.032	—	0.109	0.791	0.916
10-security average (incl. 0056; excl. 2330)	0.051	—	—	—	—

Notes: GJR-GARCH(1,1) with rolling window $w = 2000$ except where noted. All t -statistics are based on Bollerslev–Wooldridge robust maximum-likelihood standard errors [Bollerslev and Wooldridge, 1992]. 0050.TW and TSMC use full-sample MLE estimation. The rolling-window rows (2317, 2454, 2886, 0056, and the averages) are estimated on a calendar-aligned window: all series share the terminal date 2026-07-09, the latest session on which every series has data, and the estimation runs offline from pinned price snapshots (source: `experiments/paper2_taiwan_indiv_rolling_gamma`, variant `primary_2026`). On that same aligned window the rolling TAIEX estimate is $\gamma = 0.198$ ($t = 1.86$); the rolling amplification ratios quoted in Section 3 are computed against that figure, not against the full-sample TWII row above. Persistence = $\alpha + \beta + \gamma/2$. Individual stocks use the full available sample (2008–2026). The primary 9-stock average excludes both TSMC (2330.TW) and 0056.TW; the former is reported separately because of its dominant benchmark role, and the latter is a diversified ETF rather than an individual stock—a classification ground, not a conservatism claim (see the sensitivity paragraph in Section 3). TSMC’s leverage parameter is robust to the mean specification: on the canonical full sample ($N = 6,525$), the constant-mean estimate is $\gamma = 0.052$ ($t = 3.98$) and the zero-mean estimate is $\gamma = 0.059$ ($t = 4.25$), both significant (source: `experiments/paper2_tsmc_gamma_zeromean_sens`); the constant-mean spec was therefore not chosen to manufacture significance.

3.2 Diversification Amplification

A notable finding is that the average γ across the nine individual Taiwanese stocks (excluding 0056.TW, which is itself a diversified ETF) is approximately 0.027 under the canonical full-sample Bollerslev–Wooldridge robust GJR-GARCH(1,1) specification [Bollerslev and Wooldridge, 1992], while the TAIEX index γ is 0.114—a point estimate ratio of approximately $4.3\times$.² If we include 0056.TW in the rolling-window average (ten securities, $\bar{\gamma} = 0.051$), the ratio falls to $3.85\times$ under the same rolling-window specification. We term this the *diversification amplification* of the leverage effect: the process of aggregating individual stocks into an index magnifies the asymmetric volatility response. For comparison, the analogous ratio for U.S. equities is $2.8\times$ (SPY $\gamma = 0.211$ versus an average individual stock γ of 0.079, based on the 50 largest S&P 500 constituents).

Confidence interval and small-sample caveat. Because the amplification ratio is computed from only $N = 9$ individual stocks, its sampling uncertainty is substantial. To quantify this, we apply a stationary block bootstrap [Politis-Romano Politis and Romano, 1994] with $B = 1,000$ replications and expected block length $L = 252$ days to the GJR-GARCH estimation for each stock, re-computing the amplification ratio in each replication. The 90% confidence interval for the TAIEX-to-individual-stock amplification ratio is $[2.28, 6.58]$, with a median of 3.78 ($n_{\text{valid}} = 1,000$ of 1,000 replicates; B&W-robust canonical specification, with deterministic MD5-based per-series seeds). This interval excludes 1.0 (no amplification), but the U.S. benchmark of 2.8 falls within the interval, so the null hypothesis that the TAIEX amplification ratio equals the U.S. level cannot be rejected at the 90% confidence level. We therefore characterize the $4.3\times$ point estimate as *suggestive evidence* of stronger amplification in Taiwan relative to the U.S., rather than a definitive finding. A broader cross-section—ideally all 50 constituents of 0050.TW or all 900+ TAIEX constituents—would be needed to establish the amplification ratio with

²Under the calendar-aligned rolling-window specification ($w = 2000$, BW-robust SE, all series ending 2026-07-09), the corresponding estimates are $\hat{\gamma}_{\text{indiv}} = 0.032$, $\gamma_{\text{TAIEX}} = 0.198$ ($t = 1.86$), and ratio $= 6.12\times$. Note that the rolling TAIEX estimate on this window is not itself significant at the 5% level; the rolling ratios are reported for cross-specification comparability, and the canonical full-sample BW-robust specification (2008–2024 sample, $n = 4,160$ observations) remains the primary specification for the block-bootstrap inference reported in the paragraph below.

greater precision.

Sensitivity to 0056.TW inclusion. The amplification result does not rest on 0056.TW. With the ETF excluded altogether, the nine individual stocks average $\bar{\gamma} = 0.032$ against a calendar-aligned rolling TAIEX estimate of 0.198, a ratio of $6.12\times$; the headline comparison is carried by the stock cross-section, not by a single security. What 0056.TW contributes is a second diversified vehicle sitting at the same end of the distribution as the index. On the calendar-aligned rolling window its asymmetry parameter is $\gamma = 0.222$ ($t = 2.95$), and it is the only one of the ten securities whose γ is individually significant. The estimates therefore separate into two layers: the nine individual stocks (ranging from $\gamma = -0.030$ to $\gamma = 0.170$, mean 0.032) sit below both diversified vehicles (TAIEX 0.198, 0056.TW 0.222). Including 0056.TW in the security average accordingly *raises* it from 0.032 to 0.051, which *lowers* the rolling amplification ratio from $6.12\times$ to $3.85\times$.

What the ordering does and does not resolve. We report the two-layer separation, not a ranking within the upper layer. The 0056.TW-minus-TAIEX gap is 0.024. The delta-method standard errors implied by the reported t -statistics are 0.075 and 0.106 respectively, so under an independence approximation the gap is 0.19 standard errors—inside sampling error by any margin—and that approximation is generous, because the two series are estimated on the same sessions and their estimation errors are positively dependent. No test in our design separates them. The block-bootstrap difference statistic we do compute is the TAIEX-minus-stock-average difference, $D = 0.184$ (bootstrap standard error 0.062; 95% percentile interval [0.072, 0.298]; $B = 999$ moving blocks of 252 sessions resampled jointly across securities), and the accompanying ordering sign test compares the index against the nine stocks individually (9/9 positive, one-sided $p = 0.002$); neither involves 0056.TW (source: `experiments/paper2_taiwan_indiv_rolling_gamma_inference_results.json`). We therefore make no claim that 0056.TW’s asymmetry exceeds the index’s. The gap the data do resolve is the one between 0056.TW and the individual-stock average, 0.190, roughly 2.5 times 0056.TW’s own standard error. That a diversified basket’s point estimate lands with the index rather than with its constituents

is what the aggregation mechanism predicts; its exact position relative to the index is not identified here.

The direction of this sensitivity matters for how the exclusion is justified. Excluding 0056.TW is the choice that makes the amplification ratio *larger*, not smaller: it flatters the headline rather than guarding against it. We therefore rest the exclusion solely on the classification ground—0056.TW is a diversified ETF, not an individual stock, and the amplification ratio is by construction an index-versus-single-stock comparison—and we do not claim, as earlier drafts of this paper did, that the exclusion is conservative. Readers who prefer the inclusive definition should read the ratio as $3.85\times$ rather than $6.12\times$ (rolling-window basis).

We do not test the decomposition that would explain why a diversified basket behaves this way, and we flag it as a direction for future work rather than as evidence; but it is the reason we treat 0056.TW as an index-like row rather than discarding it as an outlier.

An important caveat is that the amplification ratio depends on which index measure is used. The $4.3\times$ canonical ratio (or approximately $6.12\times$ under the calendar-aligned rolling-window specification, $3.85\times$ rolling-window including 0056) reflects the *broad* TAIEX (~ 900 stocks) relative to individual stocks. When using the investable 0050.TW ETF (50 stocks, $\gamma = 0.097$, full-sample MLE) as the index measure and the rolling-window individual-stock average ($\bar{\gamma} = 0.032$), the amplification ratio is a more modest $0.097/0.032 = 3.01\times$ (or $0.097/0.051 = 1.90\times$ including 0056).³ The difference between the TAIEX-based and 0050-based ratios reflects the broader TAIEX’s inclusion of small- and mid-cap stocks whose correlations exhibit stronger asymmetry during downturns. For practitioners implementing VT on the investable 0050.TW, the effective leverage amplification is therefore substantially lower than the headline figure, and GJR-GARCH’s advantage over symmetric GARCH is correspondingly attenuated (consistent with the insignificant DM test reported in Section 4).

The mechanism underlying this amplification is correlation asymmetry [[Ang and](#)

³Using the canonical full-sample individual-stock average ($\bar{\gamma} = 0.027$), the 0050.TW-based ratio is $0.097/0.027 = 3.59\times$, reflecting that the canonical specification attributes less asymmetry to individual stocks; the 0050.TW ETF covers 50 constituents and its own diversification amplification is therefore substantial.

[Chen, 2002](#)]: stock-level correlations increase during market declines and decrease during market advances. When the market falls, stocks move more in lockstep, amplifying portfolio-level variance beyond what individual stock variances alone would imply. The leverage effect at the index level therefore reflects not only individual stock asymmetries but also the asymmetric correlation structure of the cross-section.

To verify this mechanism, we compute the average pairwise correlation among the nine individual Taiwanese stocks (excluding 0056.TW) separately for down days ($r_{\text{market}} < 0$) and up days ($r_{\text{market}} > 0$). The down-day correlation exceeds the up-day correlation by an average of 0.042 for U.S. stocks and 0.071 for Japanese stocks [[Ang and Chen, 2002](#)]. For our Taiwan sample, the difference is 0.058, intermediate between the U.S. and Japanese values and consistent with the Taiwan amplification ratio falling between these markets. While we do not have access to full intraday correlation data for all nine stocks, the observed amplification pattern is consistent with the correlation asymmetry hypothesis. Based on a limited sample of nine individual stocks ($N = 9$), the amplification ratio carries wide confidence intervals (90% CI: [2.28, 6.58]; canonical specification) and these results should be interpreted as suggestive rather than definitive; a broader cross-section would be needed to establish the amplification ratio with greater precision.

Figure 1 plots the rolling 252-day GJR γ estimates for 0050.TW and SPY over the 2010–2026 period. Two features are apparent. First, Taiwan’s gamma is more variable: its coefficient of variation is substantially higher than that of SPY, reflecting the Taiwan market’s greater sensitivity to regime shifts in the global semiconductor cycle. Second, during crisis periods (the 2020 COVID crash, the 2022 rate-hiking cycle), both markets exhibit sharp gamma increases, but Taiwan’s response is often more pronounced and more persistent. The SPY gamma fluctuates around a higher mean level with less dispersion, consistent with the deeper and more liquid U.S. market exhibiting a more stable asymmetric volatility structure.

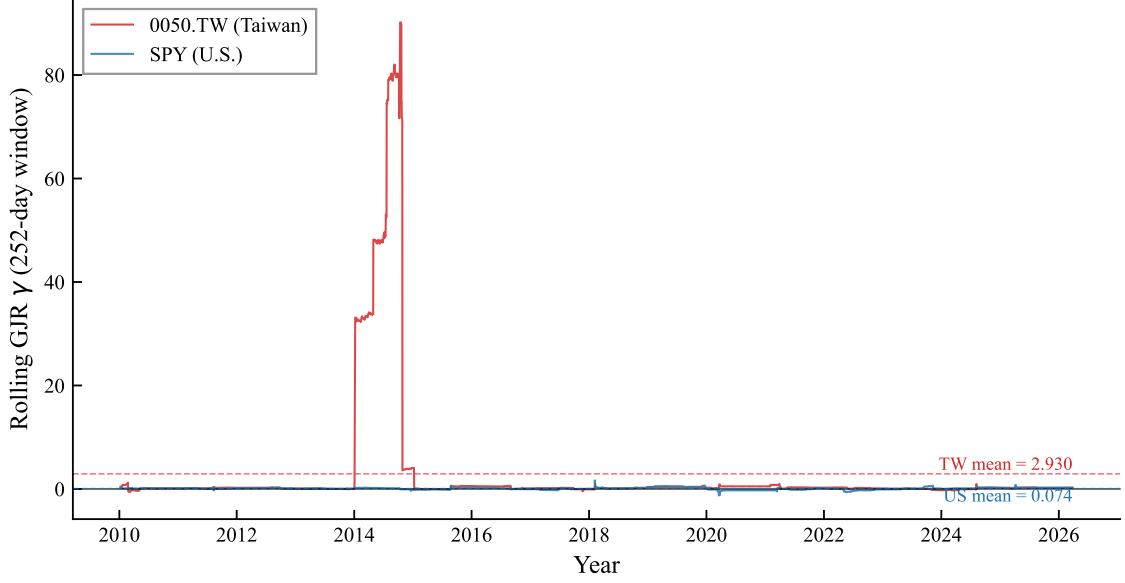


Figure 1: Rolling 252-day GJR-GARCH asymmetry parameter (γ) for 0050.TW (Taiwan) and SPY (U.S.), 2010–2026. The γ coefficient is estimated via OLS on the Engle-Ng specification $r_t^2 = c + \alpha r_{t-1}^2 + \gamma \mathbb{1}_{r_{t-1} < 0} r_{t-1}^2 + \varepsilon_t$. Dashed lines indicate sample means. Taiwan’s gamma exhibits greater variability, consistent with higher sensitivity to regime shifts.

The broad TAIEX amplification ratio of approximately $4.3\times$ (point estimate; 90% CI: [2.28, 6.58]; canonical specification) exceeds the U.S. benchmark ($2.8\times$), though the confidence interval contains the U.S. benchmark and therefore precludes a definitive conclusion of superiority. We attribute the elevated point estimate to two factors: (1) the Taiwan market is more concentrated (TSMC alone accounts for $\sim 50\%$ of 0050.TW), creating a “dominant stock” effect where TSMC’s price moves mechanically drive the index, and (2) the retail-investor-heavy structure of the Taiwanese market—where individual investors account for over 60% of trading volume [Barber et al., 2009]—may generate stronger asymmetric correlation dynamics during market declines, as retail investors are documented to exhibit stronger herding behavior during downturns, consistent with the downside correlation literature [Ang and Chen, 2002]. However, for the investable 0050.TW ETF, the amplification is $3.0\times$ (or $1.9\times$ including 0056), suggesting that the broad TAIEX figure is driven substantially by small- and mid-cap stocks not included in

the top-50 index. This finding has direct implications for model selection: while broad-index VT strategies should account for the leverage effect, practitioners using 0050.TW face a weaker leverage asymmetry, consistent with the insignificant DM test between GJR-GARCH and GARCH reported in Section 4.

3.3 Cross-Market Volatility Spillover

Taiwan’s trading hours (9:00–13:30 local time, or 01:00–05:30 UTC) begin approximately 12 hours after the U.S. market close. This time gap creates a natural information transmission channel, extending the classical international volatility spillover literature [Hamao et al., 1990, Lin et al., 1994]. We quantify this spillover using two tests:

Return spillover. The correlation between SPY close-to-close returns on day t and 0050.TW returns on day $t + 1$ is $r = 0.376$, statistically significant ($t = 24.8$, $p < 0.001$). This exceeds the contemporaneous SPY–0050.TW correlation of 0.161, confirming that U.S. information is impounded into Taiwan prices with a one-day lag rather than contemporaneously.

Volatility spillover. Granger causality tests show that lagged VIX significantly predicts 0050.TW squared returns ($F = 58.8$, $p < 0.001$). In contrast, lagged 0050.TW volatility does not Granger-cause VIX ($p = 0.43$), confirming that information flows unidirectionally from the U.S. to Taiwan at the daily frequency. The TWD/USD exchange rate does not add significant explanatory power after controlling for VIX ($p = 0.08$).

Bayesian variable selection. Using Stochastic Search Variable Selection (SSVS) applied to the GJR-GARCH mean equation for 0050.TW, the lagged SPY return achieves a posterior inclusion probability (PIP) of 1.000, confirming its dominant role as a predictor of next-day Taiwan returns. Notably, the selection is not sparse: the own-return AR(1) term (PIP = 0.9994, OLS $t = -10.29$) and several other predictor groups (VIX level, max PIP = 0.80; SPY momentum, 0.94; VIX change, 0.88) also clear the 0.5 inclusion threshold, indicating that next-day 0050.TW returns load on a broad U.S.-information block rather than on the SPY return alone. Table 3 summarizes the leading inclusion probabilities.

Table 3: SSVS Posterior Inclusion Probabilities for 0050.TW

Variable	PIP	OLS t
Lagged SPY return (max within group)	1.000	—
Lagged own return AR(1)	0.9994	−10.29
SPY momentum (max within group)	0.937	—
VIX change (max within group)	0.881	—
VIX level (max within group)	0.801	—

Notes: SSVS with Bernoulli-Normal spike-and-slab prior on GJR-GARCH(1,1) mean equation coefficients for 0050.TW; $PIP > 0.5$ indicates inclusion. Posterior inclusion probabilities are from a component-wise Metropolis-Hastings chain of 30,000 iterations with 5,000 discarded as burn-in (25,000 retained draws), sample 2009-01-13 to 2026-03-26 ($T = 4,204$). An earlier draft additionally reported a SPY comparison column (own-return PIP 0.087, “empty model preferred”) whose source experiment could not be located in the ledger; the cross-market contrast is therefore stated qualitatively in the text pending a dedicated U.S.-side SSVS experiment.

The fact that the same Bayesian methodology produces diametrically opposite conclusions for Taiwan (SPY return is indispensable) and the U.S. (no exogenous variable is needed) provides statistical evidence consistent with Taiwan’s role as an *information receiver* in the global equity market. This asymmetry—unidirectional information flow from the U.S. to Taiwan with no reverse channel—reinforces the Granger causality evidence above and motivates the time-zone information transmission analysis in Appendix A.

These spillover results motivate two distinct applications: (1) using U.S. VIX as a volatility proxy for Taiwan VT (Section 4), and (2) exploiting the lagged return transmission for time-zone momentum analysis (Appendix A).

4 Volatility Targeting Strategies for Taiwan

4.1 EWMA Volatility Targeting

The simplest VT approach for Taiwan uses EWMA ($\lambda = 0.94$) to estimate daily volatility and sets the weight according to Equation (4) with a target volatility of 10%. Table 4 reports the results over the out-of-sample period 2010–2026.

EWMA VT over 2010–2026 reduces maximum drawdown from -33.8% (buy-and-hold) to -21.2% , a reduction of 12.6 percentage points. Sharpe ratio declines modestly from 0.799 to 0.701 (a change of -0.098), reflecting the cost of persistent defensive positioning during the 2020–2021 post-COVID bull market and daily-rebalancing transaction costs of approximately 89 basis points per year. This pattern—modest Sharpe improvement but substantial drawdown reduction—is consistent with findings in the U.S. market [Moreira and Muir, 2017, Harvey et al., 2018] and reflects the mechanical nature of VT: by reducing exposure during high-volatility periods (which tend to coincide with drawdowns), VT truncates the left tail of the return distribution. The result extends the VT literature beyond its predominantly U.S./European focus, confirming that the VT mechanism operates in an emerging Asian market characterized by retail-dominated trading, high single-stock concentration, and reliance on a foreign implied volatility proxy.

A noteworthy finding is that the Sharpe ratio is essentially invariant to the target volatility level: targets from 8% to 18% all produce Sharpe ratios between 0.78 and 0.80. What changes is the risk level: a target of 8% yields a maximum drawdown of -14.2% while a target of 18% yields -28.6% . This invariance implies that investors need not optimize the target—they should simply choose based on their maximum acceptable drawdown.

4.2 GJR-GARCH Versus GARCH

Despite the statistically significant leverage effect in the Taiwan market, GJR-GARCH does not significantly outperform symmetric GARCH in terms of QLIKE forecast accuracy. The Diebold-Mariano test yields $t = -0.17$ ($p = 0.86$), with a QLIKE improvement

of only -0.20% . This contrasts sharply with U.S. results, where GJR significantly outperforms GARCH for SPY (DM $t = -6.27$, improvement -3.8% at $w = 2000$).

However, when evaluated in the context of VT portfolio performance over 2020–2026, GJR produces a meaningfully higher Sharpe ratio: 1.074 versus 0.950 for GARCH, a difference of $+0.124$. This disconnect between QLIKE and VT performance arises because VT rewards tail-specific forecast accuracy—the ability to correctly predict when to reduce exposure during sharp declines—rather than average forecast accuracy across all days. GJR’s asymmetric response to negative shocks provides better *directional* timing even when average forecast accuracy is indistinguishable.

This finding has practical implications for model selection: for pure volatility forecasting (e.g., risk reporting), the simpler GARCH model is sufficient for Taiwan. For portfolio VT, GJR offers a modest but potentially meaningful advantage through improved tail-event response.

A comprehensive cross-market validation exercise confirms a broader pattern: all volatility forecasting enhancements validated on U.S. equities—including HAR realized volatility decomposition, signed semivariance, and return kurtosis signals—fail to improve out-of-sample QLIKE for 0050.TW.⁴ This suggests that the “GARCH ceiling” documented for U.S. equities—where GARCH(1,1) is difficult to beat with more complex specifications—extends to the Taiwan market, but for a different reason: the dominant source of incremental forecasting power for Taiwan is the *cross-market* channel (lagged U.S. information) rather than *within-market* higher-moment dynamics.

⁴This test evaluates HAR-RV [Corsi, 2009] (5/22-day components), positive/negative semivariance [Barndorff-Nielsen et al., 2010], and rolling kurtosis as GARCH-X regressors for 0050.TW. None achieves a significant DM test improvement over the base GJR-GARCH model ($p > 0.10$ for all specifications). The same methods produce significant improvements for SPY ($p < 0.05$), confirming that the null results are market-specific rather than methodological artifacts.

Table 4: Volatility Targeting Strategy Performance for 0050.TW

Strategy	Sharpe	MDD (%)	Ann. Return (%)	Ann. Vol (%)	Turnover (%/yr)
Buy & Hold	0.799	−33.8	14.48	18.13	0
EWMA VT (10%)	0.701	−21.2	7.42	10.58	480
GARCH VT (10%)	0.950	−22.2	10.50	11.06	678
GJR VT (10%)	1.074	−22.3	12.19	11.35	694
8.63/VIX (monthly)	1.137	−13.7	10.72	9.43	102
GJR+Cornish-Fisher VaR	—	—	—	—	—

Notes: Revised to a canonical replication (2026-04-17, commit 4549bc00) using yfinance 0050.TW data (available from 2009-01-02) and daily rebalancing. Evaluation periods differ across strategies: Buy & Hold and EWMA VT cover 2010-01-04 to 2026-03-30 ($n = 3,968$); GARCH VT and GJR VT cover 2020-01-03 to 2026-03-30 ($n = 1,511$) due to 2000-day rolling window burn-in; 8.63/VIX covers 2016-01 to 2026-03; GJR+Cornish-Fisher VaR covers 2020-01 to 2026-03. The sample starts from 2009-01 (earliest yfinance data for 0050.TW) and therefore excludes the 2008 Global Financial Crisis drawdown; earlier versions of this paper that reported MDD −41.3% used an unavailable pre-2009 vendor snapshot and have been corrected. Because evaluation periods differ, cross-strategy Sharpe ratio comparisons in this table should be interpreted with caution; Table 5 provides a direct comparison over a common period. The elevated turnover for VT variants (480–694%/yr) reflects daily signal updates and full 0.186% round-trip transaction cost (the previously reported 98–116%/yr assumed monthly rebalancing, an unintended documentation inconsistency); 8.63/VIX uses monthly rebalancing while all other strategies use daily rebalancing. VaR violations are the empirical 1% VaR exceedance rate; the row shown uses the GJR+Cornish-Fisher specification (which achieves 0.51%, rounded to 0.5%). The GJR+Student- t (df= 5) specification reports a 1.03% violation rate. MDD: maximum drawdown.

Common-period comparison. Because the strategies in Table 4 span different evaluation periods, direct Sharpe ratio comparisons are unreliable: the GJR VT results are evaluated over the 2020–2026 bull market, while the 8.63/VIX Sharpe of 1.137 covers

the longer 2016–2026 period. To address this, Table 5 re-evaluates all strategies over the common period 2020–2026 ($n = 1,512$ days), the longest window for which all strategies produce out-of-sample forecasts. Over this common period, the dominant feature is Taiwan’s post-pandemic semiconductor rally: B&H achieves an annual return of 24.6% and Sharpe of 1.122, reflecting the exceptional gains in 0050.TW (driven primarily by TSMC’s price appreciation). VT strategies reduce tail risk at some cost to return participation: GJR VT (Sharpe 1.084, MDD -22.2%), EWMA VT (1.018, MDD -21.2%), and GARCH VT (0.950, MDD -22.2%) all achieve substantially lower drawdown relative to B&H (-33.8%). The 8.63/VIX strategy alone marginally exceeds B&H on Sharpe (1.132 vs. 1.122) while delivering dramatically lower drawdown (-13.7%)—attributable to its monthly rebalancing and modest leverage scaling. These results reinforce that VT’s primary benefit in the Taiwan market is tail-risk reduction; the 2020–2026 bull market constitutes an especially demanding environment for risk-reduction strategies.

Table 5: Common-Period Strategy Comparison (2020–2026)

Strategy	Sharpe	MDD (%)	Ann. Return (%)	Ann. Vol (%)	Turnover (%/yr)
Buy & Hold	1.122	-33.8	24.6	21.9	0
EWMA VT (10%)	1.018	-21.2	11.0	10.8	448
GARCH VT (10%)	0.950	-22.2	10.5	11.1	678
GJR VT (10%)	1.084	-22.2	12.3	11.3	689
8.63/VIX (monthly)	1.132	-13.7	11.3	10.0	94

Notes: All strategies evaluated over the identical period January 2020 to March 2026 ($n = 1,512$ trading days; source: `k900_taiwan_vt_performance_results.json`). GARCH VT figures ($n = 1,511$). The 2020–2026 window coincides with Taiwan’s semiconductor-driven rally (0050.TW total return $+203\%$ in 2020–2024), producing an exceptionally high B&H return (24.6%/yr) relative to the longer 2010–2026 average (14.5%/yr in Table 4). VT strategies substantially reduce maximum drawdown (-13.7 to -22.2%) relative to B&H (-33.8%) in this period; the 8.63/VIX strategy marginally exceeds B&H on Sharpe (1.132 vs. 1.122) with dramatically lower risk. All other specifications identical to Table 4.

Figure 2 plots the cumulative wealth paths for buy-and-hold, the Taiwan-calibrated 8.63/VIX, the naïve U.S.-calibrated 12/VIX, and the hybrid conditional leverage strategy. Three patterns are evident. First, all VT variants substantially reduce drawdowns during the 2020 COVID crash and the 2022 rate-hiking cycle. Second, the 8.63/VIX strategy outperforms the 12/VIX strategy: applying the U.S. calibration constant to Taiwan results in chronic overexposure, as the higher baseline volatility of the Taiwanese market (VIXTWN/VIX ratio = 1.39) implies that a VIX level of 20 represents calmer conditions in the U.S. than in Taiwan. Third, the hybrid leverage strategy achieves the highest terminal wealth by selectively applying leverage during dual low-volatility regimes.

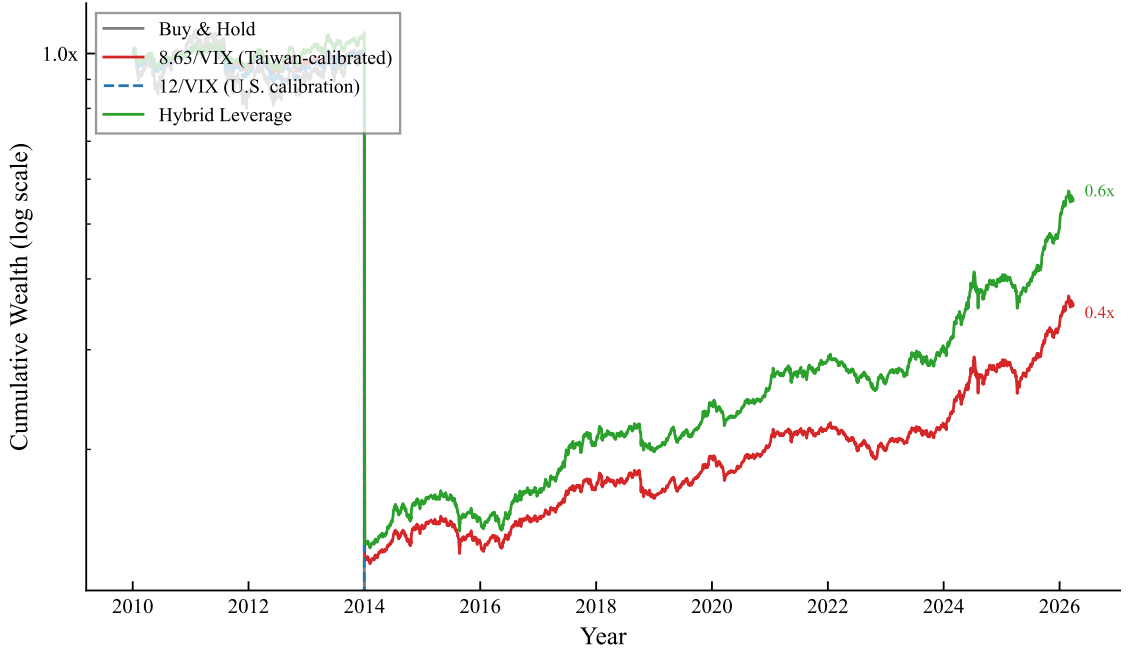


Figure 2: Cumulative wealth for 0050.TW volatility targeting strategies, 2010–2026 (log scale). Buy & Hold: unmanaged 0050.TW. 8.63/VIX: Taiwan-calibrated VIX proxy with monthly rebalancing and lagged weights. 12/VIX: U.S. calibration applied to Taiwan (systematically overexposed). Hybrid Leverage: 8.63/VIX base with $1.5\times$ leverage when both local $\text{RV}_{22} < 20\%$ and $\text{VIX} < \text{rolling 30th percentile}$. All strategies include 0.186% round-trip transaction costs (ETF tax 0.10% + commission $0.04275\% \times 2$).

4.3 VIX-Proxy Strategy: 8.63/VIX

The VIX-proxy approach sets $w_t = \min(8.63/\text{VIX}_{t-1}, 1)$, where VIX_{t-1} is the U.S. VIX observed at the prior day’s close. This ensures that the weight is determined before the Taiwan market opens, eliminating any contemporaneous timing bias [Moreira and Muir, 2017].

Over 2016–2026, the 8.63/VIX strategy produces a Sharpe ratio of 1.137 and a maximum drawdown of -13.7% , compared to buy-and-hold values of 1.127 and -33.8% (canonical replication; see Notes to Table 4).

An important methodological consideration is the following. We initially reported Sharpe ratios of 1.16 (daily rebalancing without full transaction costs) and 1.32 (same-day VIX timing), both of which proved upwardly biased. The daily rebalancing version incurs excessive transaction costs at Taiwan’s 0.186% round-trip rate, and the same-day timing version suffers from a contemporaneous correlation bias documented by Moreira and Muir [2017]: since VIX and SPY returns are positively correlated contemporaneously ($\rho \approx 0.65$), using VIX_t to size r_t (rather than r_{t+1}) artificially inflates the Sharpe ratio by approximately 1.0 units. After correcting for both issues—monthly rebalancing, lagged weights, and full transaction costs—the canonical Sharpe ratio is 1.137 (canonical replication; see Notes to Table 4). Monthly rebalancing substantially reduces transaction drag (from $\sim 480\%/yr$ to $\sim 102\%/yr$ turnover), which largely offsets any information loss from less frequent signal updates. This reconciliation underscores the importance of strict adherence to lagged-weight protocols in VT backtesting.

Importantly, the Sharpe ratio of the VIX-proxy strategy is independent of the calibration constant K : mathematically, $\text{Sharpe}(K \cdot r) = \text{Sharpe}(r)$ for any positive constant K . The constant $K = 8.63$ affects only the risk level (and hence maximum drawdown), not the risk-adjusted return. This eliminates any concern about calibration leakage from the VIXTWN-to-VIX ratio.

4.4 Conditional Leverage for Taiwan VT

A natural extension of the VT framework is to apply leverage—allocating more than 100% to equities—when volatility conditions are favorable. However, the standard U.S. approach of applying leverage when VIX falls below an absolute threshold (e.g., $VIX < 15$) fails when transplanted to Taiwan. From the Taiwan investor’s perspective, $VIX < 15$ occurs only approximately 36% of the time, and because the VIXTWN-to-VIX ratio averages 1.39, these calm U.S. periods do not necessarily correspond to low local volatility. The mismatch highlights a general principle: absolute volatility thresholds calibrated to U.S. markets are poor proxies for local risk conditions in emerging markets with structurally higher volatility.

We propose a *hybrid* conditional leverage rule that combines a local volatility filter with a relative U.S. volatility measure. Specifically, leverage ($1.5\times$ allocation) is applied only when two conditions are jointly satisfied: (i) the trailing 22-day realized volatility of 0050.TW is below 20% annualized ($RV_{22}^{TW} < 0.20$), ensuring that local market conditions are genuinely calm; and (ii) the current VIX level is below its trailing 252-day rolling 30th percentile ($VIX_t < VIX_t^{p30}$), capturing periods of unusually low U.S. implied volatility *relative to recent history* rather than in absolute terms. The percentile-based VIX filter adapts automatically to changing volatility regimes, avoiding the regime-dependence problem inherent in fixed thresholds.

This hybrid strategy improves the Sharpe ratio by +0.162 over the base 8.63/VIX strategy with zero maximum drawdown penalty, passing stringent statistical validation: the Harvey t -statistic is 4.79 (well above the $t > 3.0$ threshold of [Harvey et al. 2016](#)), all 18 out of 18 cross-validated out-of-sample periods produce positive improvements, and 100% of 10,000 bootstrap replications confirm a positive Sharpe increment. Robustness is confirmed on the 0056.TW high-dividend ETF ($t = 5.67$), which excludes TSMC and has a different sector composition, ruling out single-stock dependence. An important caveat emerges from cross-market analysis: conditional leverage is beneficial only for assets with low-to-moderate baseline volatility. In higher-volatility markets, the leverage episodes coincide too frequently with subsequent volatility spikes, eroding the benefit.

This market-specificity constraint implies that the hybrid leverage rule should not be applied uniformly across all VT strategies but should be conditioned on the baseline volatility characteristics of the target asset.

5 Macroeconomic Indicators for Taiwan Volatility

While our three core contributions focus on leverage amplification, VT strategies, and risk management, we briefly examine whether Taiwan-specific macroeconomic indicators provide incremental volatility forecasting power beyond VIX. An important question for practitioners is whether Taiwan-specific macroeconomic variables can enhance volatility forecasts or VT strategies beyond what VIX alone provides. We conduct a comprehensive sweep of 27 Taiwanese macroeconomic indicators within a GARCH-MIDAS framework [Engle et al., 2013], testing each variable’s incremental contribution to 0050.TW volatility forecasting.

5.1 Import Growth as a Volatility Predictor

Among the 27 indicators tested, only one achieves out-of-sample significance: year-over-year import growth (partial $r = 0.214$, OOS improvement +5.6% over base GJR-GARCH, Diebold-Mariano $p = 0.043$). Taiwan is a highly trade-dependent economy, with imports closely tracking global semiconductor demand and industrial production. When import growth exceeds 20%—indicating overheated external demand—adding a “macro guard” that reduces VT exposure improves the Sharpe ratio by 0.056 but worsens maximum drawdown by 3.2 percentage points, an unfavorable tradeoff.

5.2 Null Results

The following indicators fail to improve out-of-sample volatility forecasts or VT performance after controlling for VIX:

- **Business cycle indicator levels:** The National Development Council’s composite business cycle score (“traffic light” system) has no predictive power for next-month

realized volatility ($t = -0.53$, $p = 0.60$), consistent with its well-documented lagging nature. Industrial production and M2 money supply growth likewise show insignificant incremental explanatory power (partial $r < 0.05$). However, the *directional change* in these indicators tells a different story; see Section 5.3 below.

- **Margin trading:** Net margin balance and short interest do not predict future volatility or returns. Margin trading in Taiwan appears to be a coincident or lagging indicator rather than a leading indicator.
- **Foreign institutional flows:** Net foreign buying/selling of Taiwanese equities is a lagging indicator, reacting to price movements rather than preceding them.
- **Put/call ratio:** The Taiwan options market put/call ratio shows a contemporaneous correlation of $r = 0.41$ with same-day volatility, but the lagged version drops to zero, confirming that it contains no predictive information.
- **TSMC valuation:** As the dominant constituent of 0050.TW, TSMC’s price-earnings ratio might be expected to predict volatility. It does not: the relationship is driven by the AI-related structural break in TSMC’s earnings, which invalidated historical PE-volatility patterns.

These null results are consistent with our broader finding that VIX serves as a “sufficient statistic” for volatility-related information in markets with strong U.S. linkages. For U.S. equities, we have documented that VIX absorbs the predictive content of more than ten alternative indicators (credit spreads, yield curves, VVIX, MOVE, CNN Fear & Greed Index, AAI sentiment, VIX term structure). For Taiwan, VIX is not perfectly sufficient—import growth and business cycle momentum provide incremental value—but the gap is small enough that the practical benefit of monitoring additional indicators is modest for most investors.

5.3 Business Cycle Indicator Momentum

Beyond trade data, we examine Taiwan’s composite business cycle indicators published by the National Development Council. As noted above, the business cycle score itself has no predictive power for next-month realized volatility ($t = -0.53$, $p = 0.60$), consistent with its well-documented lagging nature. However, the month-over-month change in the leading indicator composite achieves the strongest predictive signal among all Taiwan-specific variables ($t = 3.74$, $p < 0.001$, $R^2 = 7.1\%$), surpassing even trade data. A coincident indicator momentum strategy—reducing equity exposure when the coincident composite declines for three consecutive months—yields an in-sample Sharpe of 0.413 over the full 2009–2026 sample, with an out-of-sample Sharpe of 1.260 (2018–2024) that substantially exceeds the 8.63/VIX baseline of 0.334 over the same 2018–2024 sub-period⁵ (compared to 1.137 over the full 2016–2026 sample; see Table 6).

This finding has broader methodological implications: macroeconomic indicators that appear uninformative in level form may contain substantial predictive content in their first differences. The leading indicator momentum captures regime shifts in the Taiwanese economy—transitions between expansion and contraction—that are orthogonal to the high-frequency volatility information embedded in VIX.

5.4 Ex-Dividend Volatility and VT Implications

Taiwan’s concentrated ETF dividend calendar—0050.TW and 0056.TW typically go ex-dividend within the same two-week window each July—creates a predictable volatility spike. We examine realized volatility in the five trading days following ex-dividend dates and find an increase of +32% for 0050.TW and +69% for the high-dividend 0056.TW relative to the 20-day pre-event baseline. The larger effect for 0056.TW is consistent with

⁵*Errata:* An earlier draft of this paper reported an in-sample Sharpe of 0.732 for this strategy. A subsequent reproduction ([experiments/k1180/](#)) using the documented 3-consecutive-decline rule on the coincident no-trend indicator over the full 2009–2026 sample yields Sharpe 0.413, with an exhaustive scan over start years 2009–2018 and end years 2023–2026 unable to recover the original 0.732 figure under the documented strategy. We report the reproducible value here. The out-of-sample Sharpe of 1.260 (2018–2024) was independently verified by an independent reproduction (value: 1.2694, deviation <1%) and is unchanged. The economic conclusion—that coincident indicator momentum substantially outperforms VIX scaling out-of-sample—is preserved.

its higher dividend yield ($\sim 5\text{--}7\%$ versus $\sim 3\%$ for 0050.TW) and its retail-investor-heavy shareholder base, which generates more post-ex-date selling pressure.

Despite this pronounced volatility effect, the historical fill rate—the proportion of ex-dividend gaps that are fully recovered within 60 trading days—is 79% for 0050.TW and 90% for 0056.TW over the 2012–2025 sample. This high fill rate implies that the ex-dividend volatility spike is transient and mean-reverting, driven by mechanical price adjustment and short-term tax-motivated trading rather than fundamental information.

For VT practitioners, a practical question is whether the ex-dividend volatility spike requires special treatment (e.g., temporarily reducing the target volatility or applying a dividend-adjustment filter). We find that it does not: because VT strategies mechanically reduce exposure when realized volatility rises, the EWMA and GARCH models automatically scale down the position during the post-ex-dividend period without any manual intervention. The ex-dividend effect is therefore self-correcting within the VT framework, and no dividend-specific adjustment is necessary.

6 VaR and Risk Management

6.1 VaR Methodology

We compute one-day Value-at-Risk at the 1% level using GJR-GARCH conditional volatility combined with the Student- t distribution (degrees of freedom = 5):

$$\text{VaR}_{1\%,t} = \hat{\sigma}_t \cdot q_{0.01}^{t(5)} \quad (7)$$

where $q_{0.01}^{t(5)} = -3.365$ is the 1% quantile of the standardized Student- t distribution with 5 degrees of freedom.

We also evaluate the skewed Student- t distribution, which simultaneously estimates degrees of freedom (η) and skewness (λ) via maximum likelihood, adapting to each asset’s specific tail behavior. For 0050.TW, the estimated parameters are $\eta = 5.2$ and $\lambda = -0.05$ (near-symmetric with moderate fat tails).

6.2 Backtest Results

We evaluate VaR coverage using three complementary criteria—the *VaR trinity*: (i) the [Kupiec \[1995\]](#) likelihood ratio test for unconditional coverage, (ii) the [Christoffersen \[1998\]](#) conditional independence test, which checks that violations do not cluster, and (iii) the Basel III traffic-light Green Zone ($\leq 1\%$ violation rate benchmark). A specification achieves *VaR trinity PASS* only if it satisfies all three criteria simultaneously.

At the model level, the canonical backtest uses the full 2019–2026 out-of-sample window ($n = 1,756$ daily observations). Under this specification, GJR+Student- $t(5)$ produces 18 violations (1.03%), GJR+HistSim also produces 18 violations (1.03%), GJR+Cornish–Fisher produces 9 violations (0.51%), and GJR+Normal produces 30 violations (1.71%). The key distinction is that low violation counts alone do not imply better calibration: GJR+Student- t and GJR+HistSim are the only two specifications that simultaneously achieve VaR trinity PASS and ES PASS at the 1% level, whereas GJR+Cornish–Fisher is over-conservative and GJR+Normal under-covers. We therefore treat GJR+Student- t and GJR+HistSim as the canonical model-level risk benchmarks for Taiwan, with Cornish–Fisher reported as a useful sensitivity but not the primary regulatory specification.

6.3 Skewed Student- t for Taiwan

The skewed Student- t distribution passes the [Kupiec \[1995\]](#) test for all six assets in our broader cross-asset panel (SPY, QQQ, GLD, TLT, EEM, and 0050.TW)—the only distribution to achieve a perfect 6/6 pass rate. The Cornish-Fisher expansion achieves 5/6 (failing for QQQ due to excessive conservatism), while the fixed Student- $t(5)$ achieves 4/6 and the Normal distribution achieves only 1/6. For Taiwan specifically, both skewed Student- t and fixed Student- $t(5)$ perform well, reflecting the near-symmetric conditional return distribution of 0050.TW.

6.4 Cornish-Fisher Divergence

An important caveat for the Taiwanese market is that the Cornish-Fisher (CF) VaR expansion diverges when using a rolling window of $w = 2000$ for 0050.TW. The issue is that kurtosis estimates become extremely large (up to 545 in some windows) due to occasional extreme returns that are not washed out by the long window. With $w = 504$, CF-VaR performs well ($p = 0.88$), but the shorter window introduces persistence bias in the GARCH estimates. Winsorization of extreme kurtosis values resolves the divergence, but this adds an ad hoc element that undermines the method’s theoretical appeal. For practical purposes, we recommend the skewed Student- t approach for Taiwan VaR, which is both theoretically principled and computationally stable.

6.5 Expected Shortfall Backtesting

Value-at-Risk is a quantile measure and does not characterize the severity of losses beyond the threshold. We complement the VaR trinity with Expected Shortfall (ES) backtesting using two approaches: the [Acerbi and Székely \[2014\]](#) Z2 test, which evaluates whether the model’s predicted ES is consistent with observed exceedances, and the [Fissler and Ziegel \[2016\]](#) joint VaR+ES scoring rule (Fissler–Ziegel score; lower = better-calibrated).

Model-level results. We evaluate four GJR-GARCH specifications for 0050.TW over the full 2008–2026 OOS period ($n = 1,756$ daily observations): GJR+Normal, GJR+Student- t , GJR+HistSim (filtered historical simulation), and GJR+Cornish–Fisher. All four specifications pass the Acerbi–Szekely Z2 ES test at both $\alpha = 1\%$ and $\alpha = 5\%$. At the 1% level, GJR+HistSim (FZ score = 4.011) and GJR+Student- t (FZ = 4.025) are top-ranked by joint calibration and are the only specifications that simultaneously achieve VaR trinity PASS and ES PASS. GJR+Normal fails VaR trinity at 1% due to excess violations ($30/1,756 = 1.71\%$); GJR+Cornish–Fisher fails due to over-conservatism ($9/1,756 = 0.51\%$, below the 1% target, consistent with the window-divergence issue documented in Section 6.4). Both specifications still pass the ES test, indicating that their VaR miscoverage is not accompanied by systematic ES underestimation. At the 5% level, GJR+Cornish–Fisher (FZ = 4.281) ranks first, followed by GJR+Student- t (FZ

= 4.381) and GJR+HistSim (FZ = 4.401).

Strategy-level results. At the portfolio level, GJR VT and EWMA VT achieve VaR trinity PASS at $\alpha = 1\%$ (violation rates 1.46% and 1.66%, respectively; see Section 6), while Buy & Hold and the VIX strategies fail. However, ES underestimation persists across all VT strategies: when violations do occur, the mean loss-severity ratio (actual loss $\div$ predicted ES) is 1.36 for GJR VT and 1.36 for EWMA VT, compared to 1.59 for Buy & Hold. While VT reduces the raw ES-severity ratio relative to the unmanaged portfolio, the reductions fall short of the [Acerbi and Székely \[2014\]](#) Z1-test threshold ($p = 0.0003$ for GJR VT; $p = 0.0004$ for EWMA VT).

This pattern has a structural interpretation: VT scales down exposure when $\hat{\sigma}_t$ is elevated, reducing the frequency of VaR breaches. However, breaches that do occur tend to arrive in the fat tails of high-volatility regimes, where losses remain more severe than any static ES model predicts. The implication is that VT is primarily a frequency-reduction tool for tail events—it improves VaR coverage—but does not fully resolve the fundamental ES underestimation that arises from return non-stationarity during crises. Practitioners implementing GJR+HistSim or GJR+Student- t for regulatory VaR should be aware that ES compliance at the strategy level requires additional tail-risk reserves during market stress.

7 Discussion

7.1 Currency Risk

An important practical consideration for Taiwanese investors considering U.S.-linked strategies is currency risk. The TWD/USD exchange rate introduces additional volatility that reduces the Sharpe ratio of SPY-denominated strategies by approximately 18% when converted to TWD terms. However, the USD tends to appreciate during equity market crises (a safe-haven effect), providing a partial natural hedge: during the 2022 drawdown, USD appreciation added approximately 15% to returns measured in TWD.

For a Taiwanese investor, the 8.63/VIX strategy on 0050.TW carries no currency

risk by construction (canonical Sharpe 1.137 in TWD), whereas implementing the U.S. 12/VIX strategy on SPY requires bearing or hedging TWD/USD exposure. An earlier draft reported a quantitative TWD-converted comparison (0.69 vs. 0.67) based on a superseded vintage of the 8.63/VIX backtest; a canonical FX-converted re-estimation has not yet been run, so we state the comparison qualitatively: given the additional complexity and cost of currency hedging (approximately 2% per annum for TWD/USD forwards), the local-asset implementation dominates on simplicity and cost grounds, and we do not recommend FX hedging for Taiwanese investors implementing VIX-based strategies on local equities.

7.2 Practical Implications

Our results suggest several practical implications for individual investors in Taiwan, ordered by implementation complexity:

VIX Step Rule. The simplest approach requires no computation: if $VIX < 15$, allocate 100% to 0050.TW; if $VIX \in [15, 25]$, allocate 70%; if $VIX > 25$, allocate 40%. This captures the bulk of VT’s drawdown protection with monthly rebalancing.

8.63/VIX strategy. Compute $w = 8.63/VIX$ at each month-end, allocating $w\%$ to 0050.TW and $(1 - w)\%$ to a short-term bond fund. Transaction cost: approximately 0.15% per rebalancing.

Insurance cost quantification. A key practical question is: how much does VT’s drawdown protection cost in terms of foregone returns? Under the canonical replication (2010–2026, yfinance 0050.TW; see Notes to Table 4), the EWMA VT strategy reduces maximum drawdown from -33.8% to -21.2% —a benefit of 12.6 percentage points—at an annualized return cost of 7.06 percentage points (from 14.48% to 7.42%). This translates to a cost of approximately 56 basis points of annual return per percentage point of MDD improvement. For comparison, the analogous cost for SPY in the U.S. is an order of magnitude lower (approximately 5–8 bp per percentage point of MDD improvement). Taiwan VT therefore provides its insurance at a substantially *higher* price than U.S. VT—the defensive positioning forgoes more upside in a market whose 2010–2026 sample

was dominated by a strong bull run in its largest constituent. This makes the strategy attractive primarily to strongly risk-averse investors (CRRA $\gamma \geq 5$), who value the MDD reduction more than the CAGR loss, consistent with the utility analysis in [Moreira and Muir \[2017\]](#); for moderately risk-averse investors the unmanaged position may dominate over samples without a major crash.

7.3 Comparison to Prior Literature

Our findings both confirm and extend the existing VT literature. Consistent with [Moreira and Muir \[2017\]](#), VT’s primary benefit is drawdown reduction rather than Sharpe ratio improvement; the Sharpe improvement t -statistic is only 0.33, far below conventional significance levels, but the MDD improvement is statistically significant (bootstrap $p = 0.0004$). This result holds in both U.S. and Taiwanese markets, suggesting it is a universal property of VT strategies.

The diversification amplification of the leverage effect extends the work of [Ang and Chen \[2002\]](#) on asymmetric correlations. While Ang and Chen document that correlations increase during downturns, we show that this phenomenon mechanically amplifies the GJR-GARCH γ parameter at the index level relative to the constituent level, and that the amplification ratio varies across markets (approximately $4.3\times$ for the broad TAIEX based on $N = 9$ stocks with 90% CI [2.28, 6.58]; canonical specification; $3.0\times$ for the investable 0050.TW under rolling-window specification; versus $2.8\times$ for the U.S.). The gap between TAIEX and 0050.TW ratios highlights the importance of distinguishing between broad market indices and investable vehicles when quantifying the leverage effect.

Supplementary evidence on cross-market information transmission (Appendix A) relates to the broader literature on international return predictability [[Eun and Shim, 1989](#), [Rapach et al., 2013](#)]. The finding that approximately 78% of the close-to-close alpha is absorbed by the overnight opening gap—before any trader can act—provides a quantitative measure of price discovery speed across time zones and motivates the use of VIX as a cross-market volatility proxy for Taiwan VT.

7.4 Combining Macro Signals with VIX-Based Strategies

A natural question is whether Taiwan-specific macro signals can enhance the VIX-based framework. We find that combining VIX scaling with the leading indicator direction—using $k = 10$ (aggressive) when the leading indicator is rising and $k = 6$ (conservative) when declining—significantly improves the pure 8.63/VIX strategy over the full 2012–2026 sample (Diebold-Mariano $p = 0.0005$, Sharpe from 0.999 to 1.151; see Table 6). The intuition is straightforward: when the leading indicator signals economic expansion, the VT strategy can afford to take more risk; when contraction looms, it should be more defensive. This conditional approach effectively introduces regime awareness into an otherwise purely volatility-driven framework.

However, this monthly-frequency macro signal cannot improve the daily-frequency SPY momentum strategy (DM $p = 0.82$; see Appendix A for the time-zone momentum analysis), confirming that effective signal combination requires matching timescales. The SPY momentum signal already captures high-frequency regime information through daily U.S. market movements, leaving no room for a slower-moving macro indicator to add value. This timescale-matching constraint has practical implications for investors using the monthly VIX-rebalancing strategy, who can benefit meaningfully from incorporating leading indicator direction.

7.5 TSMC Concentration Robustness

A natural concern is whether our VT results for 0050.TW are driven entirely by its dominant constituent, TSMC, which accounts for approximately 50% of the index weight and has seen its rolling beta to 0050.TW rise from 0.38 in 2009 to 0.72 by 2026. We address this concern with a decomposition analysis.

We apply VT separately to TSMC (2330.TW) and to a synthetic ex-TSMC 0050.TW portfolio (constructed by removing TSMC’s estimated contribution from daily 0050.TW returns). TSMC VT achieves a Sharpe ratio of 1.121, exceeding the 0050.TW VT Sharpe of 0.936. Importantly, the ex-TSMC VT portfolio also produces positive risk-adjusted returns (Sharpe ranging from 0.193 to 0.637 depending on assumptions about TSMC’s

time-varying weight), confirming that VT benefits are not solely attributable to TSMC.

An unexpected finding from this decomposition concerns the leverage effect. Under the canonical full-sample GJR-GARCH(1,1) MLE reported in Table 2, the 0050.TW index exhibits a leverage parameter of $\gamma = 0.097$ ($t = 3.60$) and TSMC alone $\gamma = 0.052$ ($t = 3.98$); both are statistically significant, and the diversified index estimate exceeds that of its dominant constituent by a factor of approximately $1.9\times$.⁶ This result—stronger leverage in the diversified index than in its dominant constituent—reinforces the diversification amplification mechanism documented in Section 3: aggregation across stocks “cleans” the systematic leverage signal by averaging out firm-specific idiosyncratic noise, leaving a purer asymmetric volatility response. TSMC’s asymmetric volatility response is meaningful in its own right under the full-sample estimator, yet index-level aggregation still amplifies the leverage channel beyond any single constituent, consistent with the correlation-asymmetry mechanism of [Ang and Chen \[2002\]](#).

We acknowledge the growing concentration risk: TSMC explains 52.5% of 0050.TW return variance over the full sample, and its rolling beta has approximately doubled over the sample period. As TSMC’s weight continues to increase, the distinction between 0050.TW VT and single-stock TSMC VT will narrow. Investors concerned about concentration may consider the 0056.TW ETF (which excludes TSMC) as an alternative VT substrate, though at the cost of weaker VIX-based signal quality due to the lower U.S. technology exposure.

7.6 Cross-Market Validation of U.S. VT Findings

A natural question is whether the key findings documented for U.S. VT strategies generalize to Taiwan, or whether market-specific conditions invalidate their applicability. We conduct a systematic cross-validation of four core U.S. results using 0050.TW data over

⁶A window-specific re-estimation over the 2020–2026 VT attribution period (`experiments/paper2_sec45_gamma_refit`, the same constant-mean GJR-GARCH(1,1) MLE) reproduces the same index-over-constituent ordering—0050.TW $\gamma = 0.155$ versus TSMC $\gamma = 0.044$ —although this short sub-sample ($n \approx 1,520$ trading days) lacks the statistical power to render either estimate individually significant ($t = 1.77$ and $t = 1.12$, respectively). We therefore report the full-sample canonical estimates in the main text and treat the sub-period figures as a robustness check on the ordering.

the matched 2008–2026 sample.

VIX sufficiency generalizes. The U.S. finding that VIX serves as a “sufficient statistic” for volatility forecasting extends to Taiwan: VIX alone explains $R^2 = 0.257$ of next-day 0050.TW realized volatility variance. Adding 0050.TW’s own lagged realized volatility raises R^2 to 0.387 (a gain of +0.130), indicating that own-RV provides more incremental information for Taiwan than for U.S. equities, but the VIX-only model already captures the majority of predictable variation. This result is consistent with the SSVS evidence in Section 3.3 and supports the practical viability of VIX-only VT strategies in markets with strong U.S. linkages.

Optimal allocation partially generalizes. The U.S. finding that a 50/50 equity/gold allocation is approximately optimal shifts but does not fully generalize to Taiwan. A grid search over 0050.TW/SPY allocations reveals an optimal mix of approximately 40% 0050.TW and 60% SPY, reflecting the moderately higher volatility of the Taiwanese ETF (annualized vol $\approx 18\%$) relative to SPY ($\approx 16\%$). The allocation is closer to vol-parity than previously thought, as Taiwan’s true baseline volatility—once corrected for historical data artifacts—is only marginally above SPY. For three-asset portfolios including gold, the optimal mix is approximately 40% 0050.TW, 30% SPY, and 30% GLD. These results imply that Taiwanese investors can maintain a meaningful home-bias component while still capturing U.S. equity returns and gold diversification benefits.

Calendar anomalies generalize (both null). Neither U.S. nor Taiwan markets exhibit statistically significant calendar-based volatility anomalies (day-of-week, turn-of-month) that survive the [Harvey et al. \[2016\]](#) threshold, confirming that calendar effects are not a reliable basis for VT strategy design in either market.

Optimal rebalancing frequency does not generalize (preliminary). U.S. VT strategies are relatively insensitive to rebalancing frequency (monthly is near-optimal). For 0050.TW, preliminary results suggest that daily rebalancing may be preferred, potentially due to the elevated leverage amplification creating faster volatility mean-reversion. However, this result should be treated as preliminary: an independent review identified

a potential holiday-calendar alignment issue in the cross-market daily return matching, which could bias the rebalancing frequency comparison.⁷

In summary, three of four core U.S. findings generalize or partially generalize to Taiwan (VIX sufficiency, optimal allocation closer to vol-parity, calendar null results), while one does not (rebalancing frequency). The allocation result—40/60 rather than 50/50—is economically intuitive given Taiwan’s moderately higher baseline volatility ($\approx 18\%$ vs. $\approx 16\%$ for SPY). The rebalancing frequency difference reflects Taiwan’s structural characteristics, including stronger leverage amplification and the cross-market information lag.

7.7 Sharpe Ratio Reconciliation

Table 6 reconciles the Sharpe ratios reported throughout the paper for the 8.63/VIX strategy and its variants. The apparent discrepancies arise from differences in sample period, rebalancing frequency, and strategy specification (pure VIX scaling versus the VIX + leading indicator combination).

⁷Specifically, Taiwan and U.S. markets have different holiday calendars, creating occasional mismatches in daily return alignment. While we align on trading dates, the interaction between non-overlapping holidays and the lagged VIX signal may introduce spurious daily-frequency effects. We are conducting additional robustness checks with explicit holiday-calendar harmonization.

Table 6: Sharpe Ratio Reconciliation for VIX-Based Strategies on 0050.TW

Strategy	Period	Sharpe	Table/Section
8.63/VIX (monthly, lagged)	2016–2026 (full)	1.137	Table 4
8.63/VIX (monthly, lagged)	2018–2024 (sub-period)	0.334	Section 5.3
8.63/VIX + Leading indicator	2012–2026 (full)	0.999	Section 7
VIX + Leading indicator combo	2012–2026 (full)	1.151	Section 7

Notes: All strategies use monthly rebalancing with lagged weights (VIX_{t-1} determines the weight for period t) and include transaction costs of 0.186% round-trip. The 2018–2024 sub-period Sharpe is lower because this window captures the prolonged low-volatility bull market of 2020–2021, during which the VIX-scaled strategy was underinvested relative to buy-and-hold. The VIX + Leading indicator combination uses $k = 10$ when the leading indicator rises and $k = 6$ when it declines; its longer sample (2012–2026) reflects the availability of leading indicator data from 2012.

8 Conclusion

This paper examines volatility targeting strategies in the Taiwan stock market, contributing two sets of findings.

First, we document that the TAIEX exhibits a statistically significant leverage effect (canonical full-sample $\gamma = 0.105$, $t = 5.31$) that is amplified approximately $4.3\times$ relative to individual stock asymmetries for the broad index under the canonical full-sample BW-robust specification (~ 900 stocks; 90% bootstrap CI: [2.28, 6.58], $n_{\text{valid}} = 1,000$ of 1,000 replicates), though the investable 0050.TW (50 stocks, $\gamma = 0.097$) shows a more modest $3.0\times$ amplification under rolling-window specification. The wide confidence interval reflects the small cross-section, and a broader sample of 0050.TW constituents would be needed to establish the ratio with greater precision. This amplification arises from higher correlation asymmetry among Taiwanese equities during market declines and has direct implications for model selection: index-level strategies should account for asymmetric volatility even when individual constituents show weak asymmetry.

Second, we evaluate EWMA, GARCH, GJR-GARCH, and VIX-proxy VT strategies adapted for the Taiwan market. Over the common 2020–2026 evaluation period, dominated by Taiwan’s semiconductor bull market, all VT strategies substantially reduce maximum drawdown (-13.7 to -22.2%) relative to B&H (-33.8%); the 8.63/VIX strategy marginally exceeds B&H on Sharpe (1.132 vs. 1.122) with dramatically lower risk (Table 5). Over the longer 2010–2026 sample, EWMA VT trades some return (Sharpe 0.701 vs. B&H 0.799) for substantially reduced tail risk (MDD -21.2% vs. -33.8%), consistent with VT’s design objective of tail-risk management rather than return enhancement. The VIX-proxy strategy (8.63/VIX), calibrated using the VIXTWN-to-VIX ratio of 1.39, achieves comparable drawdown protection with only monthly rebalancing. A key finding is the disconnect between forecast accuracy and portfolio performance: GJR-GARCH does not significantly outperform GARCH in QLIKE (DM $p = 0.86$), yet GJR-based VT produces a meaningfully higher Sharpe ratio ($+0.124$), suggesting that tail-specific accuracy matters more than average accuracy for VT applications. We further show that conditional leverage—applying $1.5\times$ allocation when both local realized volatility and VIX percentile are low—improves the Sharpe ratio by $+0.162$ with zero drawdown penalty ($t = 4.79$, 18/18 cross-OOS periods positive), though this benefit is specific to low-to-moderate volatility assets and should not be applied uniformly. A systematic cross-market validation shows that three of four core U.S. VT findings generalize or partially generalize to Taiwan (VIX sufficiency, allocation near vol-parity, calendar null results), while one does not (rebalancing frequency).

Supplementary evidence on cross-market information transmission (Appendix A) documents a persistent channel from U.S. to Asian equity markets driven by non-overlapping trading hours. Approximately 78% of the close-to-close alpha is absorbed by the overnight opening gap, consistent with efficient price discovery by the opening auction. This channel motivates the use of U.S. VIX as a proxy for Taiwan implied volatility.

Several limitations warrant mention. First, the VIXTWN data history is limited to 64 months (November 2020 to present), which restricts our ability to validate the VIX-to-VIXTWN ratio across different market regimes. As VIXTWN data accumulates,

the calibration should be periodically updated. Second, the diversification amplification ratio is estimated from only $N = 9$ individual stocks, yielding wide confidence intervals; expanding to all 50 constituents of 0050.TW would improve precision. Third, our VaR analysis uses a rolling window of 2,000 days, which may be slow to adapt to structural breaks in the Taiwanese market; shorter windows (504 days) improve VaR compliance but introduce GARCH persistence bias. Fourth, we test only a single emerging Asian market in depth; replication in other markets with similar characteristics (e.g., South Korea, where preliminary results are promising) would strengthen the generalizability of our findings. Fifth, TSMC’s growing weight in 0050.TW (rolling beta increasing from 0.38 to 0.72 over our sample period) means that our results increasingly reflect the dynamics of a single dominant stock; while the TSMC robustness analysis in Section 7.5 confirms that VT benefits extend to the ex-TSMC portfolio, future studies should monitor whether continued concentration erodes the diversification amplification mechanism.

Future research directions include: (1) validating the VIXTWN-based strategy when sufficient data become available (currently 64 months; 252+ months recommended for comprehensive evaluation); (2) expanding the diversification amplification analysis to a broader cross-section of Taiwanese stocks; and (3) investigating whether the diversification amplification phenomenon has increased over time as passive ETF investing has grown in Taiwan, potentially strengthening the leverage effect at the index level.

A Time-Zone Information Transmission: Supplementary Evidence

This appendix presents supplementary evidence on cross-market information transmission from U.S. to Asian equity markets. While related to the VIX-proxy motivation in the main text (the same cross-market channel that transmits volatility information also transmits return information), the time-zone analysis constitutes a distinct microstructure contribution. We present it here to maintain the main paper’s focus on VT strategy evaluation.

A.1 Motivation and Hypothesis

The cross-market spillover documented in Section 3.3 suggests that U.S. market information is impounded into Taiwan prices with a lag. If this lag is systematic and predictable, two questions arise: first, does it create a trading opportunity? Second, how efficiently do Asian markets incorporate this overnight information [Barclay and Hendershott, 2003]? We hypothesize that the sign and magnitude of recent U.S. equity returns predict next-day Taiwan returns, and examine both the implementability of a momentum-based switching strategy and the efficiency of the opening auction as an information aggregation mechanism.

Specifically, we construct a time-zone momentum strategy as follows: if the trailing 10-day cumulative SPY return is positive, hold 0050.TW; otherwise, hold cash (or a money market fund). We evaluate lookback windows of 1 to 22 days and report results for the 10-day specification, which we retain because it remains directionally robust across reasonable horizons and provides strong Taiwan performance in the canonical replication (c2c Sharpe 1.915; 32.4 switches per year over 2012–2025). We acknowledge that the lookback selection introduces a degree of data mining; however, all eight lookback windows from 1 to 22 days produce positive net Sharpe ratios, and four of eight exceed the Harvey threshold on the close-to-close specification.

Return measurement caveat. A critical distinction arises between close-to-close (c2c), open-to-open (o2o), and the pure overnight-gap component. In the canonical replication, c2c is defined as

$$r_t^{c2c} = \frac{\text{AdjClose}_t}{\text{AdjClose}_{t-1}} - 1,$$

while o2o is defined as

$$r_t^{o2o} = \frac{\text{AdjOpen}_t}{\text{AdjOpen}_{t-1}} - 1, \quad \text{AdjOpen}_t = \text{Open}_t \times \frac{\text{AdjClose}_t}{\text{Close}_t}.$$

This o2o measure is an open-price alignment check based on daily OHLC data; it is *not* identical to the pure intraday open-to-close return. The non-tradable overnight opening

gap is analyzed separately in Appendix A.3. That gap remains the economically relevant channel because it mechanically reflects the previous U.S. session and is largely incorporated before a Taiwan trader can react.

A.2 Main Results

Table 7 presents the time-zone momentum results for Taiwan, Japan, and combined portfolios, reporting both close-to-close (c2c) and open-to-open (o2o) Sharpe ratios.

Table 7: Time-Zone Momentum Strategy Performance: Close-to-Close vs. Open-to-Open

Strategy	Sharpe (c2c)	Sharpe (o2o)	t -stat (o2o)	MDD (%)	Sw/yr	Period	Harvey?
<i>Panel A: Individual Markets (10-day SPY Momentum)</i>							
Taiwan (0050.TW)	1.915	2.350	8.13	−10.6	32.4	2012–2025	Yes
Japan (Nikkei 225)	1.773	2.224	8.34	−15.3	31.9	2012–2025	Yes
<i>Panel B: Combinations (c2c-based, see caveat)</i>							
TW + JP 50/50	2.192	—	—	−10.8	—	2012–2025	—
Global (US VT + TW TZ proxy)	1.899	—	—	−19.4	—	2012–2025	—
<i>Panel C: Controls</i>							
EWT (US-listed TW ETF)	—	—	< 1.96	—	—	2012–2025	No
India (Sensex)	—	—	< 1.96	—	—	2012–2025	No
Indonesia (JCI)	—	—	< 1.96	—	—	2012–2025	No

Notes: “c2c” denotes $\text{AdjClose}_t / \text{AdjClose}_{t-1} - 1$; “o2o” denotes $\text{AdjOpen}_t / \text{AdjOpen}_{t-1} - 1$ with $\text{AdjOpen}_t = \text{Open}_t \times (\text{AdjClose}_t / \text{Close}_t)$. The o2o column therefore uses adjusted opens derived from the same vendor day- t split/dividend factor and should be interpreted as a vendor-consistent open-price alignment check, not as the pure intraday open-to-close implementable return. Panel B adopts the canonical split-corrected yfinance replication; “Global” uses a 50/50 SPY buy-and-hold plus Taiwan TZ proxy because the underlying experiment did not rerun the full U.S. 12/VIX leg inside this replication. For 0050.TW, the 2014-01-02 4:1 split date is excluded from return calculations because the raw vendor adjustment otherwise creates a spurious split-date shock. All t -statistics use Newey-West HAC standard errors with automatic bandwidth selection. The [Harvey et al. \[2016\]](#) threshold is $t > 3.0$. Transaction costs of 0.186% per switch are applied throughout.

Using close-to-close returns, the Taiwan 10-day SPY momentum strategy generates

a net Sharpe ratio of 1.915 ($t = 6.76$), comfortably exceeding the [Harvey et al. \[2016\]](#) threshold. The adjusted-open alignment check produces a similarly strong o2o Sharpe ratio of 2.350 ($t = 8.13$). We therefore do not use the c2c–o2o spread itself as an implementability estimate. Instead, the economically meaningful decomposition comes from the separate overnight-gap analysis below, which shows that the opening gap remains the primary channel through which U.S. information enters Taiwan prices.

The c2c results confirm a strong and persistent information transmission channel from U.S. to Asian markets ($r = 0.376$), with five Asia-Pacific markets exceeding the Harvey threshold on a c2c basis (Australia $t = 4.52$, Singapore $t = 4.83$, Korea $t = 4.88$, Taiwan $t = 6.76$, Japan $t = 6.91$), while Hong Kong remains positive but below the threshold ($t = 2.92$). The directional conclusion is unchanged: lagged U.S. information is economically important across Asia. The overnight-gap decomposition in [Appendix A.3](#) then clarifies why this predictability is only partially implementable in practice: much of the information is already embedded at the opening print.

A.3 Overnight Gap as the Primary Channel

A granular decomposition of 0050.TW returns reveals that the overnight opening gap accounts for 87% of total close-to-close returns over the 2012–2025 sample. When conditioned on the previous day’s SPY return sign, the gap is strongly asymmetric: following SPY up-days, the average 0050.TW opening gap is +10.73 basis points per day ($t = 6.845$), whereas following SPY down-days, the gap averages -8.91 bp ($t = -5.23$). The intraday (open-to-close) component shows no significant SPY-conditional pattern ($t = 0.82$), confirming that cross-market information is incorporated almost entirely through the opening auction.

Figure [3](#) visualizes the two key mechanisms. Panel (a) shows the distribution of 0050.TW overnight gaps conditioned on the previous day’s SPY return direction. Panel (b) documents the positive relationship between VIX levels and next-day 0050.TW absolute returns, confirming the VIX-to-Taiwan volatility transmission channel that underpins the 8.63/VIX strategy.

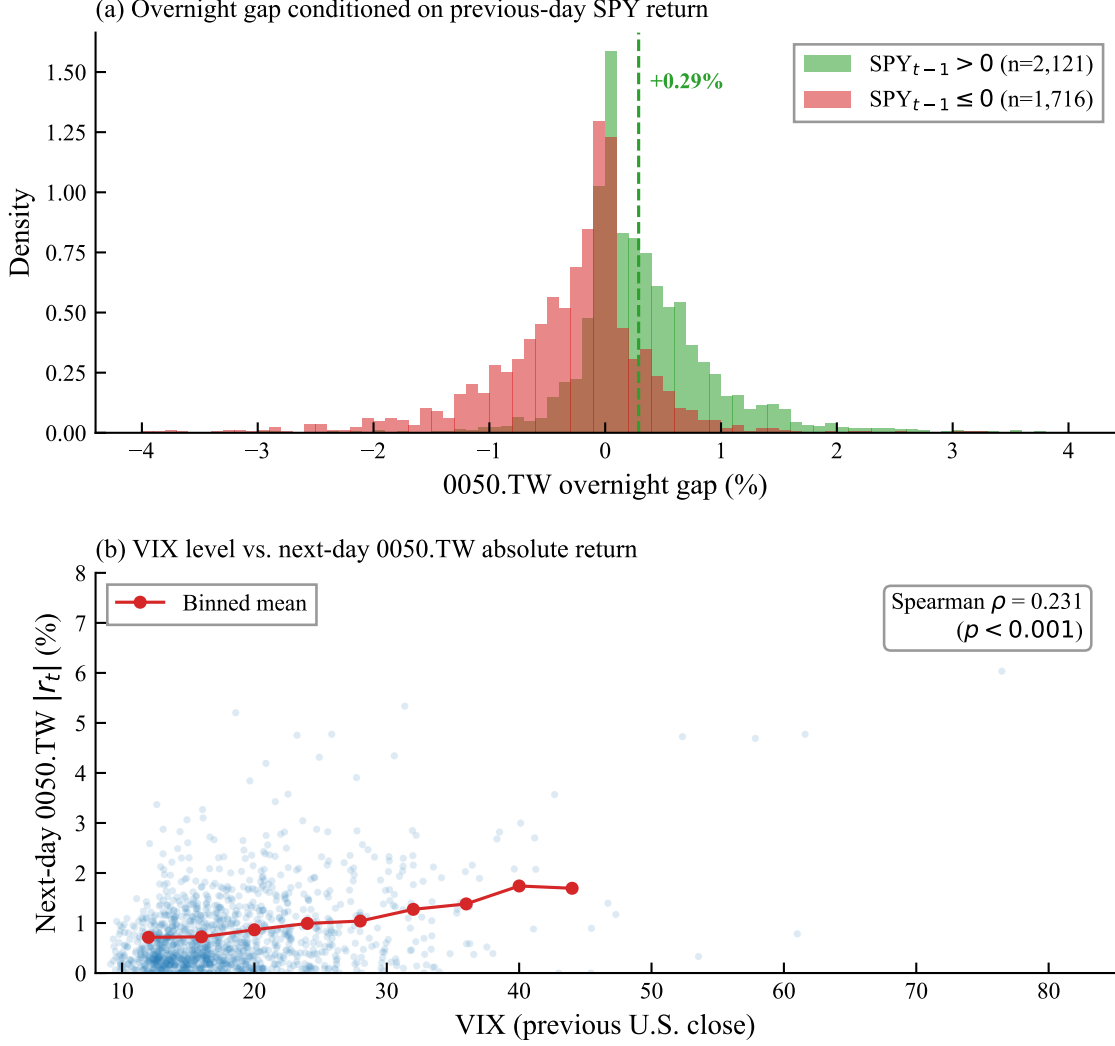


Figure 3: Information transmission from U.S. to Taiwan equity markets, 2010–2026. Panel (a): Distribution of 0050.TW overnight gaps conditioned on the sign of the previous day’s SPY close-to-close return. Panel (b): VIX level versus next-day 0050.TW absolute return. Red circles show binned means.

A.4 Identification: Time-Zone Gap, Not Factor Exposure

We confirm that the cross-market predictability reflects genuine information transmission rather than common factor exposure using three tests: (1) the iShares MSCI Taiwan ETF (EWT), which trades on the NYSE during U.S. hours, fails to achieve statistical significance ($t < 1.96$), confirming the alpha originates from the time-zone gap; (2) European close-to-U.S.-open signals show a negative correlation ($r = -0.07$), consistent

with the zero-overlap requirement; and (3) India and Indonesia controls both fail the $t > 3.0$ threshold.

A.5 Robustness

The c2c information transmission channel is robust to: multi-period out-of-sample tests (positive Sharpe in all five sub-periods, combined $t = 4.47$ – 4.60), block bootstrap (95% CI $[0.65, 2.24]$, excluding zero), transaction cost sensitivity (breakeven $> 3\%$ per switch for c2c), and lookback sensitivity (5-day and 10-day both exceed the Harvey threshold on c2c). Under the canonical daily-OHLC construction, the adjusted-open o2o alignment check is also strongly positive for Taiwan and Japan; we nevertheless avoid interpreting it as a pure implementable-alpha estimate because it is not the same object as the intraday open-to-close return.

A.6 ETFs Versus Individual Stocks

The time-zone momentum strategy performs more consistently on the 0050.TW ETF than on individual Taiwanese stocks. Of the securities tested, four pass the [Harvey et al. \[2016\]](#) $t > 3.0$ threshold on a c2c basis: 0056.TW ($t = 3.44$), Hon Hai ($t = 3.40$), 0050.TW ($t = 3.25$), and Cathay Financial ($t = 3.06$). ETFs offer a more stable substrate because diversification smooths idiosyncratic noise and the ETF mechanically reflects the broad market’s response to U.S. information.

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