Is Volatility Targeting Just Trend Following? Alpha Absorption and the Leverage Effect Across 22 Assets*

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Abstract

Volatility targeting (VT) is often described as repackaged trend following. We examine this claim across 22 assets by regressing the excess returns of a VIX-based VT strategy on a market factor and an orthogonalized time-series momentum (TSMOM) factor, under two pairings of the factors that were fixed before the final estimation: the SPY market and SPY trend factors for every asset (specification A), and each asset's own market and trend factors (specification B). The TSMOM loading is significant at a 5% false-discovery rate for 18 of the 22 assets in A and 20 in B, including all 15 equity assets in both, and no asset has a CAPM alpha that is positive and significant after Holm adjustment. For SPY the loading remains significant at every VIX threshold from 8 to 20 and under Fama–French five-factor, momentum and betting-against-beta controls. Whether the cross-section of loadings is related to the GJR-GARCH asymmetry parameter γ depends on the specification. In A the correlation is $r = 0.49$ (Holm-adjusted $p = 0.062$) and the γ coefficient is indistinguishable from zero once an equity versus

*All errors are my own. The replication package contains the stored input files, the script that produces every estimate in the main tables, and its stored output; the script runs without network access and reproduces the stored output exactly.

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non-equity dummy is added (HC3 $p = 0.686$). In B it is $r = 0.77$ (Holm-adjusted $p < 0.001$) and the coefficient stays positive with the dummy (HC3 $p = 0.013$). We report both results and do not interpret γ as a determinant of the loading. In both specifications the mean loading is larger for equity assets than for non-equity assets.

Keywords: volatility targeting, time-series momentum, leverage effect, VIX, cross-asset

JEL Classification: C22, G11, G12, G15

1 Introduction

Volatility targeting (VT) and time-series momentum (TSMOM) are two of the most extensively documented phenomena in empirical asset pricing. VT strategies, which scale portfolio exposure inversely with forecasted volatility, have been shown to improve risk-adjusted returns across equity factors (Moreira and Muir, 2017) and multiple asset classes (Harvey et al., 2018). TSMOM strategies, which take long (short) positions in assets with positive (negative) past returns, generate significant abnormal returns across 58 futures markets (Moskowitz et al., 2012), with evidence extending to century-long samples across diverse asset classes (Hurst et al., 2017). Despite their apparent differences in construction, a growing literature suggests these two strategies may share a common source of returns. Cederburg et al. (2020) challenge VT on out-of-sample performance grounds: they compare the Sharpe ratios and mean–variance certainty-equivalent returns of real-time implementable volatility-managed strategies with those of unmanaged portfolios, find no systematic improvement, and attribute much of the weak performance to instability in the spanning regressions behind in-sample alphas—a critique we return to in Section 4.

A possible connection between VT and trend following runs through the leverage effect (Black, 1976; Christie, 1982). When equity prices decline, volatility typically rises; a VT rule lowers exposure when volatility rises, so it may deleverage after losses, much like a trend-following strategy. Related evidence comes from Barroso and Santa-Clara (2015), who show that scaling momentum portfolios by their realized volatility substantially reduces momentum crashes. Hood and Raughtigan (2025) report that a TSMOM factor accounts for a large share of the alpha of volatility-managed strategies in a sample of 50 futures contracts. This raises a fundamental question: *Is VIX-based de-risking simply trend following by another name?*

We argue that the answer is partly yes and partly no. VT does carry trend-following exposure: the loading on an orthogonalized TSMOM factor is significant for most of the 22 assets, it is larger for equity assets than for non-equity assets, and it is negative for long-term Treasuries and, when each asset's own factors are used, for gold. A natural

conjecture is that VIX-based de-risking inherits trend-like exposure from the leverage effect, but the evidence on that link is not uniform: it depends on how the market and trend factors are specified, and we do not interpret the leverage-effect parameter as a determinant of the loading. We read the fall in VT alpha when a TSMOM factor is added as evidence of overlap between the two return streams, not as evidence that VT and trend following are the same strategy.

Our paper makes two contributions. First, we document the TSMOM exposure of a VIX-based VT strategy in a 22-asset cross-section under two pairings of market and trend factors fixed in advance (Tables 1 and 2). The orthogonalized loading is significant for 18 assets in specification A and 20 in B, including all fifteen equity assets, and for SPY it remains positive and significant under Fama–French five-factor, momentum and betting-against-beta controls (Table 4). Second, we show that the cross-sectional relation between the loading and the leverage-effect parameter γ depends on the specification (Table 3). With SPY factors the correlation is $r = 0.49$ with a Holm-adjusted p-value of 0.062, the decision of the pre-specified rule changes under two of six sensitivity variants, and the relation disappears once an equity versus non-equity dummy is added. With each asset's own factors the correlation is $r = 0.77$ (Holm-adjusted $p < 0.001$) and the relation survives the dummy. We report both results and draw no single conclusion about γ. We emphasize that this cross-sectional association ($N = 22$, mixed asset classes) links two quantities estimated on the same return series and is not a causal estimate.

We limit the claims in three further ways. We do not study maximum drawdown or the split of VT's benefit between a Sharpe-ratio channel and a drawdown channel: those questions need resampled return paths and a different design, and we leave them to future work. We do not model transaction costs, so the VT returns measure exposure, not executable performance. And we do not assess investor welfare, so the paper is silent on the out-of-sample performance critique of Cederburg et al. (2020) beyond the alpha evidence reported here.

Our paper contributes to several literatures. We extend Hood and Raughtigan (2025), who study 50 futures contracts, to a VIX-based VT strategy applied to 22 exchange-

traded assets across equities, commodities, bonds and real estate, and we show that the TSMOM loading varies across assets and between equity and non-equity assets. We clarify that VT loads on an asset-specific TSMOM factor, which is distinct from diversified managed-futures strategies that trade across dozens of uncorrelated markets (Moskowitz et al., 2012; Baltas and Kosowski, 2013). Our finding is related to Daniel and Moskowitz (2016), who show that momentum crashes occur in panic states, following market declines and when market volatility is high, and it builds on the evidence of Fleming et al. (2001) on the economic value of volatility timing.

The remainder of the paper is organized as follows. Section 2 describes our data and methodology. Section 3 presents the empirical results. Section 4 discusses implications and limitations. Section 5 concludes.

2 Data and Methodology

2.1 Data

The sample comprises 22 assets across equities (SPY, QQQ, IWM, XLF, XLE, DIA, EEM, EFA, FXI, EWZ, EWJ, EWG, EWU, EWA, INDA), commodities (GLD, SLV, USO), bonds (TLT, LQD, HYG), and real estate (VNQ). Daily adjusted closes (the "Adj Close" field, which adjusts for splits and dividends), the VIX and the 13-week Treasury bill yield (IRX) are daily series from Yahoo Finance, downloaded on 3 October 2026 and stored as fixed files whose SHA-256 hashes are recorded in the replication package. The 22-asset window runs from 2007-01-01 to 2026-03-19. The TSMOM signal needs 252 prior trading days and the first calendar month is excluded, so the regressions begin in January 2008 and contain 4,580 daily observations for 21 assets in A (INDA, listed in 2012, has 3,533) and for 20 assets in B (HYG has 4,513 and INDA 3,298, because own-factor momentum starts at listing). Two trading days in the window have no IRX quote (2010-10-11 and 2016-11-11); the previous quote is carried forward.

The factor-control regressions for SPY (Section 3.3) use the window 2005-01-01 to 2026-03-20 and, after the same exclusions, begin on 2006-01-04 with $T = 5{,}084$ obser-

vations, which is longer than the SPY sample of the 22-asset regressions ($T = 4{,}580$). Fama–French five-factor data (MKT, SMB, HML, RMW, CMA) and the momentum factor (MOM) are obtained from Kenneth French's data library. The betting-against-beta factor (BAB) is an ETF-based proxy: the return spread between the SPLV and SPHB ETFs after May 2011, and between IWD and QQQ before that date. Because the proxy is spliced, M5 is also estimated on the post-2011 sample, where the proxy is the SPLV–SPHB spread throughout ($T = 3{,}740$).

2.2 Volatility Targeting Construction

We implement a VIX-based VT rule in the spirit of Božović (2024):

$$w_m = \min\left(\frac{12}{\mathrm{VIX}_{m-1}}, 1\right), \tag{1}$$

where w_m is the fraction of the portfolio allocated to the risky asset in month m and VIX_{m-1} is the closing VIX on the last trading day of the previous calendar month. The weight is held for every trading day of month m, so the allocation uses only information available at the end of the previous month. The remainder earns the risk-free rate, so the VT excess return is $r_{\mathrm{VT},t} - r_{f,t} = w_m\,(r_t - r_{f,t})$, where $r_{f,t}$ is the daily IRX yield divided by 252. The threshold of 12 is a calibration choice; Section 3 reports the SPY loading for thresholds from 8 to 20. We do not model transaction costs.

2.3 TSMOM Factor Construction

Following Moskowitz et al. (2012), we construct a time-series momentum factor using the sign of the past 252-day (12-month) cumulative return of a factor source s, measured through day $t-1$:

$$\mathrm{TSMOM}_t = \mathrm{sign}\left(\sum_{j=1}^{252} r^s_{t-j}\right) \times r^s_t, \tag{2}$$

where r^s is the daily return of the source. This notation matches the implementation's explicit lagging of the signal before applying period-t returns. We use two pairings of the market factor MKT and the factor source, both fixed in advance. In specification A

the market factor is the SPY excess return and the source is SPY, for every asset. In specification B the market factor is the asset's own excess return and the source is the asset itself. The two coincide for SPY. Mixed pairings (SPY market with own TSMOM, and own market with SPY TSMOM) are computed and stored but receive no verdict under the rules below.

To address correlated-regressor bias, we construct an *orthogonalized* TSMOM factor as the residual of a full-sample regression of TSMOM on a constant and the market factor of the specification, $\mathrm{TSMOM}_t = \hat{a} + \hat{b}\,\mathrm{MKT}_t + \mathrm{TSMOM}_t^{\perp}$, that is

$$\mathrm{TSMOM}_t^{\perp} = \mathrm{TSMOM}_t - \hat{a} - \hat{b} \cdot \mathrm{MKT}_t, \tag{3}$$

where $\hat{a}$ and $\hat{b}$ are the full-sample OLS estimates. $\mathrm{TSMOM}^{\perp}$ has zero sample mean and zero sample covariance with MKT.

2.4 Alpha Decomposition

For each of the 22 assets, in each specification, we estimate two models of the VT excess return:

$$\text{M1:} \quad r_{\mathrm{VT},t} - r_{f,t} = \alpha_1 + \beta_1\,\mathrm{MKT}_t + \varepsilon_t, \tag{4}$$

$$\text{M2:} \quad r_{\mathrm{VT},t} - r_{f,t} = \alpha_2 + \beta_1'\,\mathrm{MKT}_t + \beta_2\,\mathrm{TSMOM}_t + \varepsilon_t, \tag{5}$$

where TSMOM is the raw factor of Eq. (2). Because $\mathrm{TSMOM}_t = \hat{a} + \hat{b}\,\mathrm{MKT}_t + \mathrm{TSMOM}_t^{\perp}$ by construction, M2 can equally be written with $\mathrm{TSMOM}^{\perp}$ in place of TSMOM (we call that form M3). By the Frisch–Waugh–Lovell theorem the coefficient on the TSMOM term, its standard error and the R^2 are the same in the two forms, while the intercept and the market loading of the orthogonalized form are those of M1; the intercept of the raw form satisfies

$$\hat{\alpha}_2 = \hat{\alpha}_1 - \hat{\beta}_2\,\hat{a}. \tag{6}$$

The alpha reduction (the "absorption" of the title) is therefore defined on the raw specification:

$$\Delta\alpha_{\text{raw}} = \frac{\hat{\alpha}_1 - \hat{\alpha}_2}{\hat{\alpha}_1} \times 100\%. \tag{7}$$

For the factor-control regressions of SPY (Table 4) the TSMOM factor enters in its orthogonalized form, and five nested models are estimated: M1 as above; M2 adds TSMOM$^{\perp}$ to MKT; M3 adds the four Fama–French factors SMB, HML, RMW and CMA to M2; M4 adds MOM; M5 adds the BAB proxy. All standard errors are Newey–West HAC (Newey and West, 1987) with lag $\ell = \lfloor 4(T/100)^{2/9} \rfloor$ (Newey and West, 1994), which gives $\ell = 8$ to 9 for the 22 assets, $\ell = 9$ at $T = 5{,}084$ and $\ell = 8$ at $T = 3{,}740$ for the SPY factor-control regressions. The threshold sweep of Section 3 fixes $\ell = 10$ (see the footnote there).

2.5 Cross-Sectional Tests

We test whether the leverage effect predicts VT's TSMOM exposure. For each asset i, we estimate the GJR-GARCH(1,1) model (Glosten et al., 1993) with normal errors and a constant mean on daily percent returns over the asset's whole window:

$$\sigma^2_{i,t} = \omega_i + (\alpha_i + \gamma_i \cdot \mathbb{1}_{r_{i,t-1}<0})\, r^2_{i,t-1} + \beta_i\, \sigma^2_{i,t-1}, \tag{8}$$

where γ_i captures the asymmetric volatility response; it does not depend on the specification. We then compute Pearson and Spearman correlations between γ_i and the TSMOM loading $\hat{\beta}^{\perp}_{\text{TSMOM},i}$ across assets, with a percentile bootstrap 95% interval for the Pearson correlation (10,000 resamples of the asset pairs, seed 42). To check whether the relation reflects a discrete equity versus non-equity grouping rather than a continuous gradient in the leverage-effect parameter, we regress the loading on γ_i and a dummy that equals one for the seven non-equity assets, with HC3 standard errors, and we compare the mean loadings of the two groups with a Welch test.

2.6 Decision Rules, Multiple Testing and Robustness

Four claims are evaluated with rules fixed before the final estimation, separately for each specification. (L) The loading claim is supported if at least 15 of the 22 TSMOM$^{\perp}$ loadings are significant at 5% after Benjamini–Hochberg adjustment over the 22 assets. (A) The no-alpha claim holds if no asset has a positive M1 alpha with a Holm-adjusted p-value below 0.05. (G) The association claim is supported if the Pearson correlation between γ and the loading is positive, its Holm-adjusted p-value is below 0.05, and the bootstrap interval excludes zero. (C) The claim that the association survives the class control is supported if the γ coefficient of the regression with the non-equity dummy is positive with an HC3 p-value below 0.10 (unadjusted). The cross-sectional p-values (Pearson, Spearman, the HC3 p-value of the γ coefficient and the Welch test) are adjusted jointly by the Holm method within each specification. A verdict is called robust if it is unchanged in each of six one-at-a-time variants of the baseline: daily weights from the previous day's VIX; the weight alignment of our earlier panel (month-end labels, forward-filled over the following month and lagged one day); GARCH estimation from 2010; Student-t GARCH errors; a 126-day TSMOM lookback; and the mean of the 21-, 63- and 252-day signals. Otherwise the verdict is grid-dependent, and we say so. When the two specifications disagree we report both and select neither.

2.7 Data Vintage, Replication Scope and What Was Known Before Estimation

Every estimate in Tables 1–4 is produced by one script from three stored input files (the Yahoo Finance price and rate series, the Fama–French five-factor file and the momentum file), run with network access disabled. Yahoo Finance revises adjusted prices retroactively, so a fresh download gives slightly different estimates; the stored files fix the vintage. A re-run of the script on a clean copy of the replication package, with network access disabled, reproduces all stored numerical results exactly. The threshold sweep of Section 3 is computed from its own stored price file. The bootstrap uses a fixed seed.

Specification A repeats a probe that we had run and read before the rules were written; its results are therefore not independent evidence, and the outcome for specification A was not blind. Specification B, the mixed pairings, the six sensitivity variants and every adjusted p-value had not been run when the rules were written. The rules above were fixed in a dated document before the estimation reported here was completed, together with four amendments that dealt with data-alignment and data-diagnostic details; they were therefore not chosen after seeing the present results of B or of any sensitivity variant.

3 Empirical Results

3.1 VT Has Significant TSMOM Exposure

Tables 1 and 2 report the alpha decomposition for all 22 assets under specifications A and B. Adding the TSMOM factor reveals substantial trend-following exposure. The loading, its t-statistic and the R^2 are the same for the raw factor and for the orthogonalized factor TSMOM$^{\perp}$ (Section 2.4), so we write $\hat{\beta}^{\perp}_{\text{TSMOM}}$ for the loading. After Benjamini–Hochberg adjustment at 5%, 18 of the 22 loadings are significant (of either sign) in specification A and 20 in B, so the pre-specified threshold of 15 is met in both. Across the baseline and the six variants of Section 2.6 the count lies between 18 and 21 in A and between 20 and 21 in B, so the claim does not depend on one calibration.

All 15 equity assets have a significant positive loading in both specifications; the mean loading is 0.098 in A and 0.113 in B. For SPY, $\hat{\beta}^{\perp}_{\text{TSMOM}} = 0.107$ ($t = 6.56$) in both specifications, so a daily TSMOM$^{\perp}$ return that is one percentage point higher is associated with a same-day VT return that is about 10.7 basis points higher.

Non-equity assets are mixed. In specification A, long-term Treasuries (TLT) have a significantly negative loading (-0.049, $t = -5.14$), gold (GLD), HYG, LQD and real estate (VNQ) are not significant after adjustment, and USO and SLV load positively. In specification B, gold and Treasuries both have significantly negative loadings (-0.059 and -0.070), USO, HYG and VNQ load positively, and LQD and SLV are not significant. The negative loadings for Treasuries, and in B for gold, accompany their negative leverage-

effect parameters ($\gamma = -0.033$ for gold and -0.016 for Treasuries); VNQ has a positive γ (0.090) and a loading that is not distinguishable from zero in A but positive in B, and we do not explain it.

Under M1, VT earns a positive alpha for 8 of the 22 assets in specification A and for 9 in B, but no alpha is significantly positive after Holm adjustment: the smallest Holm-adjusted p-value is 0.366 in A and 1.000 in B. The closest case is QQQ in specification A, whose alpha of 3.89% a year has a Newey–West t-statistic of 2.40 (unadjusted $p = 0.017$, Holm-adjusted $p = 0.366$); it is significant only before adjustment for 22 tests. In specification B the largest alpha t-statistic is 1.39 (SPY).

The $\Delta\alpha_{\text{raw}}$ column reports by how much the M1 alpha falls when the raw TSMOM factor is added to the CAPM. The orthogonalized specification does not change the alpha, because TSMOM$^{\perp}$ has zero sample mean and is uncorrelated with MKT by construction. The fall in the raw-factor specification equals $\hat{\beta}_{\text{TSMOM}}\,\hat{a}$ (Eq. 6), where $\hat{a}$ is the intercept of TSMOM on a constant and MKT, that is, the CAPM alpha of the raw factor itself. For SPY, whose alpha is the same in both specifications, adding the raw factor lowers the alpha by 30.3%. Where the alpha is close to zero the ratio is unstable, as for IWM (-78.7% in A and 151.9% in B), and we do not interpret it. The R^2 improvement from adding TSMOM is substantial for SPY ($0.839 \to 0.881$) but modest for gold in specification B ($0.888 \to 0.894$).

The sign and significance of the TSMOM loading of SPY do not depend on the VIX threshold in the VT formula. Re-estimating M2 for SPY at the thresholds 8, 10, 12, 15, 18 and 20, the orthogonalized TSMOM coefficient is positive and significant at every threshold (t-statistics from 7.98 to 10.91, all $p < 0.001$); its size does vary with the threshold, from 0.117 to 0.197 across these thresholds.[1] The sign and significance of the SPY loading are therefore not artifacts of a particular calibration choice.

[1]The sweep uses its own sample of 4,834 daily observations beginning in 2007, so its coefficients are not directly comparable with those in Table 1; we use it only for the sign and significance at each threshold and for how the coefficient moves across thresholds. Its Newey–West lag is fixed at 10, whereas the formula of Section 2.4 gives 9 at this sample size.

Table 1: VT Alpha Decomposition, Specification A: SPY Market and SPY TSMOM Factors ($N = 22$)

		M1: market only			M2/M3: market + TSMOM			
Asset	γ	α (%)	t_{NW}	R^2	$\hat{\beta}^{\perp}_{\text{TSMOM}}$	t_{NW}	R^2	$\Delta\alpha_{\text{raw}}$ (%)
Equity assets								
SPY	0.216	1.28	1.39	0.839	$0.107^{\dagger}$	6.56^{***}	0.881	30.3
QQQ	0.180	3.89	2.40	0.664	$0.148^{\dagger}$	6.64^{***}	0.718	13.8
IWM	0.135	−0.69	−0.37	0.618	$0.150^{\dagger}$	7.49^{***}	0.666	−78.7
XLF	0.174	−0.44	−0.23	0.628	$0.060^{\dagger}$	2.11^{**}	0.635	−49.5
XLE	0.085	−2.30	−0.75	0.387	$0.095^{\dagger}$	5.92^{***}	0.400	−15.0
DIA	0.216	0.87	0.79	0.769	$0.095^{\dagger}$	6.81^{***}	0.806	39.3
EEM	0.111	−3.71	−1.63	0.525	$0.081^{\dagger}$	3.83^{***}	0.537	−7.9
EFA	0.138	−2.63	−1.68	0.621	$0.100^{\dagger}$	6.19^{***}	0.651	−13.8
FXI	0.068	−4.05	−1.15	0.312	$0.055^{\dagger}$	2.13^{**}	0.315	−4.9
EWZ	0.079	−4.46	−1.06	0.275	$0.096^{\dagger}$	4.10^{***}	0.283	−7.8
EWJ	0.101	−1.08	−0.54	0.412	$0.083^{\dagger}$	5.62^{***}	0.431	−27.9
EWG	0.117	−3.44	−1.60	0.519	$0.128^{\dagger}$	7.45^{***}	0.553	−13.5
EWU	0.135	−2.82	−1.58	0.529	$0.090^{\dagger}$	5.85^{***}	0.551	−11.6
EWA	0.109	−3.78	−1.72	0.520	$0.102^{\dagger}$	5.74^{***}	0.539	−9.8
INDA	0.107	−2.32	−0.72	0.254	$0.088^{\dagger}$	4.12^{***}	0.263	9.9
Non-equity assets								
GLD	−0.033	5.08	1.95	0.000	0.016	1.21	0.001	1.2
TLT	−0.016	2.57	1.24	0.057	$-0.049^{\dagger}$	-5.14^{***}	0.067	−7.0
USO	0.065	−4.08	−0.82	0.083	$0.093^{\dagger}$	4.92^{***}	0.090	−8.3
HYG	0.156	0.15	0.18	0.436	0.017	1.64	0.440	41.3
LQD	0.085	0.98	0.92	0.028	−0.017	−1.48	0.032	−6.2
VNQ	0.090	−0.41	−0.19	0.476	0.004	0.18	0.476	−3.4
SLV	−0.022	3.69	0.75	0.024	$0.086^{\dagger}$	4.51^{***}	0.031	8.5

Notes: The market factor is the SPY excess return and the TSMOM factor is built from SPY for every asset (specification A). Window 2007-01-01 to 2026-03-19; regressions start in January 2008 after the 252-day TSMOM warm-up and the exclusion of the first calendar month, with $N = 4{,}580$ daily observations except where noted in Section 2.1. γ is the GJR-GARCH asymmetry parameter (full window, normal errors). M1 regresses the VT excess return on the market factor; M2 adds the raw TSMOM factor and M3 the orthogonalized factor TSMOM$^{\perp}$. With the market factor in the model, the TSMOM coefficient, its t-statistic and the R^2 are identical in M2 and M3 (Section 2.4), so one set is shown. α is annualized (%), taken from M1 (equal to the M3 intercept). t_{NW} is the Newey–West t-statistic. $\Delta\alpha_{\text{raw}} = (\alpha_{\text{M1}} - \alpha_{\text{M2}})/\alpha_{\text{M1}} \times 100\%$ refers to the raw factor and is unstable when the M1 alpha is near zero; it carries no interpretation there. † marks a loading whose Benjamini–Hochberg-adjusted p-value over the 22 assets is below 0.05. ***, **, * denote unadjusted significance of the loading at the 1%, 5% and 10% levels.

Table 2: VT Alpha Decomposition, Specification B: Own Market and Own TSMOM Factors ($N = 22$)

		M1: market only			M2/M3: market + TSMOM			
Asset	γ	α (%)	t_{NW}	R^2	$\hat{\beta}^{\perp}_{\text{TSMOM}}$	t_{NW}	R^2	$\Delta\alpha_{\text{raw}}$ (%)
Equity assets								
SPY	0.216	1.28	1.39	0.839	0.107†	6.56***	0.881	30.3
QQQ	0.180	1.37	1.29	0.858	0.103†	6.15***	0.887	33.6
IWM	0.135	0.24	0.20	0.841	0.124†	9.80***	0.893	151.9
XLF	0.174	1.76	1.38	0.832	0.133†	10.05***	0.892	38.1
XLE	0.085	−0.98	−0.67	0.842	0.096†	6.93***	0.874	−49.3
DIA	0.216	1.01	1.11	0.834	0.128†	10.34***	0.895	64.9
EEM	0.111	−0.57	−0.46	0.826	0.118†	7.63***	0.871	−71.6
EFA	0.138	−0.20	−0.21	0.842	0.105†	7.49***	0.880	149.6
FXI	0.068	−0.49	−0.34	0.846	0.105†	6.75***	0.880	91.1
EWZ	0.079	−1.27	−0.69	0.836	0.107†	6.20***	0.867	87.6
EWJ	0.101	0.38	0.40	0.848	0.129†	9.04***	0.897	−64.1
EWG	0.117	−0.52	−0.44	0.844	0.103†	7.74***	0.879	−1.6
EWU	0.135	−0.35	−0.33	0.838	0.100†	6.38***	0.871	−23.1
EWA	0.109	−1.33	−1.06	0.832	0.106†	7.40***	0.871	3.2
INDA	0.107	−0.34	−0.25	0.858	0.125†	4.07***	0.894	213.0
Non-equity assets								
GLD	−0.033	−0.24	−0.28	0.888	−0.059†	−2.80***	0.894	−7.2
TLT	−0.016	−0.08	−0.12	0.879	−0.070†	−4.93***	0.890	−29.4
USO	0.065	1.20	0.55	0.844	0.065†	3.68***	0.856	6.6
HYG	0.156	0.18	0.36	0.841	0.106†	6.38***	0.883	336.0
LQD	0.085	−0.17	−0.40	0.869	0.038	1.71*	0.873	−26.2
VNQ	0.090	0.77	0.61	0.806	0.132†	10.12***	0.878	36.0
SLV	−0.022	−1.88	−1.16	0.896	0.028	1.43	0.898	−7.1

Notes: The market factor is the asset's own excess return and the TSMOM factor is built from the asset's own return (specification B). Window 2007-01-01 to 2026-03-19; regressions start in January 2008 after the 252-day TSMOM warm-up and the exclusion of the first calendar month, with $N = 4{,}580$ daily observations except where noted in Section 2.1. γ is the GJR-GARCH asymmetry parameter (full window, normal errors). M1 regresses the VT excess return on the market factor; M2 adds the raw TSMOM factor and M3 the orthogonalized factor TSMOM$^{\perp}$. With the market factor in the model, the TSMOM coefficient, its t-statistic and the R^2 are identical in M2 and M3 (Section 2.4), so one set is shown. α is annualized (%), taken from M1 (equal to the M3 intercept). t_{NW} is the Newey–West t-statistic. $\Delta\alpha_{\text{raw}} = (\alpha_{\text{M1}} - \alpha_{\text{M2}})/\alpha_{\text{M1}} \times 100\%$ refers to the raw factor and is unstable when the M1 alpha is near zero; it carries no interpretation there. † marks a loading whose Benjamini–Hochberg-adjusted p-value over the 22 assets is below 0.05. ***, **, * denote unadjusted significance of the loading at the 1%, 5% and 10% levels.

3.2 The Leverage Effect and TSMOM Loading

Table 3 presents the cross-sectional evidence linking the leverage effect to VT's trend-following exposure under both specifications. By the rule of Section 2.6, the association is supported if the Pearson correlation is positive, its Holm-adjusted p-value is below 0.05 and the bootstrap interval excludes zero.

In specification A, the Pearson correlation between GJR-GARCH γ and the orthogonalized TSMOM loading across the 22 assets is $r = 0.488$ (unadjusted $p = 0.021$, Holm-adjusted $p = 0.062$), with a bootstrap 95% interval of $[0.083, 0.745]$. The Spearman rank correlation is $\rho = 0.490$ (Holm-adjusted $p = 0.062$). The interval excludes zero but the Holm-adjusted p-value does not reach 0.05, so the rule is not met at the baseline. It is met in two of the six variants (daily weights, Holm-adjusted $p = 0.044$, and Student-t GARCH, $p = 0.037$) and not in the other four, where the Holm-adjusted p-value runs from 0.050 (126-day lookback) to 0.136 (mean of three signals, for which the interval also includes zero). We therefore regard the association in specification A as grid-dependent.

In specification B the correlation is $r = 0.767$ (Holm-adjusted $p < 0.001$) with a bootstrap 95% interval of $[0.409, 0.885]$, and the Spearman correlation is $\rho = 0.555$ (Holm-adjusted $p = 0.022$). The rule is met at the baseline and in all six variants; the largest Holm-adjusted p-value over the seven runs is 0.0006.

One conjecture fits the sign of the association where it is present: for assets with larger γ (stronger leverage effect), volatility rises more after negative returns, so a VIX-scaled position would shrink after losses, as a trend-following position does. The paper does not test this channel. Treasuries and gold have negative leverage-effect parameters ($\gamma = -0.016$ and -0.033) and negative loadings in specification B, the same sign pattern as the association; in A only the Treasury loading is negative.

Endogeneity. Both γ_i and $\hat{\beta}^{\perp}_{\mathrm{TSMOM},i}$ are estimated from the same return series. Assets with stronger return-volatility correlations may mechanically exhibit both a higher γ and a higher TSMOM loading in VT regressions, which creates a mechanical endogeneity concern in the cross-sectional regression ($N = 22$). We do not have a test that removes it: estimating the two quantities on non-overlapping windows is a natural check that we do not perform. A formal instrumental-variable approach would need a variable that moves the leverage effect without moving the loading through other channels, and suitable instruments are not available in a cross-section of only $N = 22$ mixed-class assets. We therefore interpret the γ–TSMOM link, where it exists, as an empirical regularity, not as a causally identified relationship or as evidence for a particular channel.

Table 3: Cross-Sectional Relation Between the Leverage-Effect Parameter and VT's TSMOM Loading ($N = 22$)

	Specification A	Specification B
Correlation of γ_i with $\hat{\beta}^{\perp}_{TSMOM,i}$ across 22 assets		
Pearson r	0.488	0.767
unadjusted p	0.021	<0.0001
Holm-adjusted p	0.062	0.0001
bootstrap 95% interval	[0.083, 0.745]	[0.409, 0.885]
Spearman ρ	0.490	0.555
Holm-adjusted p	0.062	0.022
Cross-sectional regressions of $\hat{\beta}^{\perp}_{TSMOM,i}$ (coefficient; HC3 p-value)		
M0, γ only: γ coefficient	0.370	0.642
HC3 p	0.041	0.001
M1, γ and non-equity dummy: γ coefficient	0.065	0.483
HC3 p (unadjusted)	0.686	0.013
HC3 p (Holm-adjusted)	0.686	0.026
dummy coefficient	−0.071	−0.037
dummy HC3 p	0.0009	0.115
M1a, dummy only: dummy coefficient	−0.077	−0.078
HC3 p	0.0006	0.013
Equity (N = 15) versus non-equity (N = 7)		
Mean loading, equity	0.098	0.113
Mean loading, non-equity	0.021	0.034
Welch t (equity minus non-equity)	3.69	2.69
Holm-adjusted p	0.027	0.035

Notes: Specification A pairs every asset with the SPY market and SPY TSMOM factors; specification B uses each asset's own factors. Both variables are full-sample estimates from the same return series. The bootstrap interval resamples the 22 asset pairs 10,000 times (percentile interval, seed 42). The Holm adjustment covers the four cross-sectional tests of each specification (Pearson, Spearman, the γ coefficient of M1 under HC3, and the Welch test). $D_{\text{non-eq}} = 1$ for the seven non-equity assets (GLD, TLT, USO, HYG, LQD, VNQ, SLV). HC3 p-values use the t distribution with $N - k$ degrees of freedom.

Continuous leverage-effect parameter vs. asset-class grouping. A second concern is that the γ–$\beta^{\perp}_{\text{TSMOM}}$ correlation may merely reflect a discrete equity-vs-non-equity grouping rather than a continuous gradient in the leverage-effect parameter: the seven non-equity assets (GLD, TLT, USO, HYG, LQD, VNQ, SLV) carry both a lower mean γ (0.046 vs. 0.132 for equities) and lower mean TSMOM loadings (0.021 vs. 0.098 in A, and 0.034 vs. 0.113 in B), which could mechanically drive the correlation. We add the non-equity dummy to the cross-sectional regression. In specification A the γ coefficient

is 0.065 (HC3 $p = 0.686$), against 0.370 without the dummy, and the dummy is -0.071 (HC3 $p < 0.001$). The rule that the coefficient be positive with an HC3 p-value below 0.10 is not met, and the smallest HC3 p-value over the baseline and the six variants is 0.490, so that verdict is robust. In specification B the coefficient is 0.483 (HC3 $p = 0.013$, Holm-adjusted $p = 0.026$) against 0.642 without the dummy, the dummy is -0.037 (HC3 $p = 0.115$), and the rule is met at the baseline and in all six variants (largest HC3 p-value over the seven runs 0.030). Whether any association with γ remains after the class control therefore depends on the specification.

The difference in mean loadings between equity and non-equity assets is present in both specifications at the baseline: Welch $t = 3.69$ in A (Holm-adjusted $p = 0.027$) and $t = 2.69$ in B ($p = 0.035$). In A the Holm-adjusted p-value is below 0.05 in all seven runs; in B it is above 0.05 in 2 of the six variants (largest value 0.061), so the class difference in B is not robust to every variant.

Taken together, the evidence does not support an unqualified statement that the leverage-effect parameter explains VT's TSMOM loading. The cross-sectional relation depends on whether the market and trend factors are common to all assets (A) or specific to each asset (B); the difference in loadings between equity and non-equity assets is present at the baseline in both. We report both outcomes and select neither.

3.3 Robustness: Fama–French Five-Factor Controls

Table 4 reports factor model regressions for the SPY 12/VIX strategy with progressively more controls. The TSMOM loading remains highly significant across all specifications: $\hat{\beta}^{\perp}_{\text{TSMOM}} = 0.114$ ($t = 7.13$) in M2 and 0.100 ($t = 6.06$) in M5, the full model with FF5, MOM and the BAB proxy. On the post-2011 sample the M5 loading is smaller but still significant (0.067, $t = 3.64$). The loading is therefore not explained away by these known risk factors. (The M2 t-statistic of 7.13 differs from the SPY value of 6.56 in Table 1 because the two regressions use different samples: $T = 5{,}084$ observations from January 2006 in the factor-control regressions and $T = 4{,}580$ from January 2008 in the 22-asset regressions.)

The incremental R^2 decomposition shows that TSMOM accounts for most of the explained variance beyond the market: $\Delta R^2_{\text{TSMOM}} = 0.0454$, compared with $\Delta R^2_{\text{FF5}} = 0.0022$, $\Delta R^2_{\text{MOM}} = 0.0004$ and $\Delta R^2_{\text{BAB}} = 0.0021$. The momentum factor (MOM) is positively related to the VT return in the full model ($t = 3.24$ in M5) even with TSMOM$^{\perp}$ in the model, so the two momentum measures are not interchangeable here.

VT alpha moves from 1.22%/year (M1) to 1.11%/year (M5) and is not statistically significant at the 10% level in any specification (M5: $t = 1.39$, $p = 0.165$). The economic magnitude, about 111 basis points per year of unexplained alpha after controlling for eight factors (MKT, TSMOM$^{\perp}$, SMB, HML, RMW, CMA, MOM and BAB), is not trivial, but it is imprecisely estimated. The BAB proxy enters significantly ($t = -4.59$), and we do not interpret this further.

Table 4: Factor Model Controls: SPY 12/VIX Strategy

	M1 CAPM	M2 +TSMOM	M3 +FF5	M4 +MOM	M5 +BAB	M5 post-2011
α (%/yr)	1.22	1.22	1.25	1.22	1.11	0.57
t_{NW}	1.41	1.51	1.53	1.49	1.39	0.55
β_{MKT}	0.489^{***}	0.489^{***}	0.491^{***}	0.492^{***}	0.484^{***}	0.534^{***}
$\beta^{\perp}_{\text{TSMOM}}$	—	0.114^{***}	0.112^{***}	0.109^{***}	0.100^{***}	0.067^{***}
t_{NW} of $\beta^{\perp}_{\text{TSMOM}}$	—	7.13	6.77	6.59	6.06	3.64
β_{SMB}	—	—	−0.002	0.001	−0.014	−0.011
β_{HML}	—	—	-0.033^{**}	-0.025^{*}	−0.018	-0.031^{*}
β_{RMW}	—	—	−0.016	−0.016	−0.008	0.002
β_{CMA}	—	—	−0.012	−0.018	−0.011	0.011
β_{MOM}	—	—	—	0.014^{**}	0.022^{***}	0.028^{***}
β_{BAB}	—	—	—	—	-0.031^{***}	-0.033^{**}
R^2	0.838	0.883	0.886	0.886	0.888	0.888
ΔR^2	—	+0.045	+0.002	+0.000	+0.002	—
AIC	−46014	−47684	−47773	−47787	−47880	−35315
N	5,084	5,084	5,084	5,084	5,084	3,740

Notes: Nested factor-model regressions for the SPY 12/VIX strategy. Columns M1 to M5 use the common sample 2006-01-04 to 2026-03-20; the last column re-estimates M5 on the post-2011 sample (2011-05-06 to 2026-03-20), in which the BAB proxy is the SPLV−SPHB spread throughout. M2 adds TSMOM$^{\perp}$ (Eq. (3)) to MKT, so its α and MKT loading equal those of M1 by construction; M3 adds SMB, HML, RMW and CMA; M4 adds MOM; M5 adds BAB. FF5 factors and the momentum factor are from Kenneth French's library. The BAB proxy is the SPLV−SPHB return spread after May 2011 and the IWD−QQQ spread before; it is not the Frazzini–Pedersen factor. All t-statistics are Newey–West HAC with lag $\lfloor 4(T/100)^{2/9} \rfloor$ (9 at $T = 5{,}084$, 8 at $T = 3{,}740$). ***, **, * denote significance at the 1%, 5%, 10% levels.

4 Discussion

4.1 What the Evidence Says About VT and Trend Following

Our findings qualify, but do not reverse, the view that VT is repackaged trend following. Hood and Raughtigan (2025) report that a TSMOM factor accounts for a large share of VT alpha in a sample of 50 futures contracts. In our 22-asset cross-section, VIX-based VT loads significantly on TSMOM for 18 assets with SPY factors and 20 with each asset's own factors, and for SPY, where the alpha is the same in both, adding the raw TSMOM factor lowers that alpha by 30.3%. The sign and significance of the SPY loading are

robust to the VIX threshold and to Fama–French five-factor, momentum and betting-against-beta controls. At the same time, no asset has a CAPM alpha that is significantly positive after adjustment for 22 tests, so the fall in alpha is a statement about small, imprecisely estimated alphas, and the loading itself is heterogeneous: it is negative for long-term Treasuries and, with own factors, for gold, and it is not distinguishable from zero for a few non-equity assets whose identity depends on the specification.

An important scope clarification is warranted. Our TSMOM factor is constructed on a per-asset basis in specification B (the sign of each asset's own past 252-day return) and on SPY in specification A, which differs fundamentally from the diversified trend-following strategies employed by managed-futures funds that trade across dozens of uncorrelated futures markets (Moskowitz et al., 2012). Our finding that VT loads on an asset-specific or SPY-based TSMOM factor should not be interpreted as evidence that VT replicates diversified CTA returns. The empirical implication is narrower: the VT strategies studied here load on trend exposure, and whether the size of that loading across assets is associated with the leverage-effect parameter depends on the specification.

The results are consistent with the critique of Cederburg et al. (2020) to the extent that the CAPM and factor-model alphas of the VT strategy are not significantly positive, but the paper does not estimate investor welfare and draws no conclusion about it.

4.2 What the Paper Does Not Show

Four limits on interpretation follow from the design. First, the leverage-effect link is an association between two quantities estimated on the same returns, and it is specification-dependent. Second, we do not test whether VT's maximum-drawdown reduction survives removal of the TSMOM exposure, and we do not decompose VT's benefit into a Sharpe-ratio channel and a drawdown channel. Third, the cross-sectional evidence rests on 22 assets, and the dummy-variable check in Section 3.2 cannot separate the leverage-effect and asset-class explanations sharply. Fourth, the VT returns carry no transaction costs and the factor decomposition is not a test of executable profitability.

4.3 Limitations

Several limitations should be noted. First, our sample of 22 assets, while spanning multiple asset classes, is smaller than the 50 futures contracts studied by Hood and Raughtigan (2025). Expanding to additional commodities, fixed-income instruments and currencies would strengthen the cross-sectional evidence. Second, the sample ends in March 2026 and the estimates use the Yahoo Finance price history downloaded on 3 October 2026; because that history is revised retroactively, a later download would give slightly different estimates (Section 2.7). Third, the GJR-GARCH γ estimation needs a long return history (the shortest sample in the panel, INDA, has 3,533 observations in specification A), which limits the method's applicability to newly listed securities. Fourth, the betting-against-beta factor is an ETF-based proxy spliced from two ETF spreads, not the Frazzini–Pedersen factor. Fifth, the VIX is a US volatility measure used as the VT input for every asset, including the single-country ETFs, and the 13-week Treasury bill yield is a contemporaneous daily proxy for the holding-period cash return. Sixth, the endogeneity of the cross-sectional regression discussed in Section 3.2 is not resolved: a formal instrumental-variable approach would provide stronger causal identification, and future work with a larger cross-section of futures contracts, as in Hood and Raughtigan (2025), could use within-asset-class variation to address it. Seventh, the outcome for specification A was not blind (Section 2.7).

5 Conclusion

This paper examines whether VIX-based volatility targeting is trend following by another name. In a cross-section of 22 assets, VT loads significantly on a time-series momentum factor for 18 assets when every asset is paired with SPY factors and for 20 when each asset uses its own factors, including all equity assets in both. For SPY, adding the raw factor lowers the CAPM alpha by 30.3%, although no CAPM alpha is significantly positive after adjustment. The sign and significance of the SPY loading are robust to the VIX threshold and to Fama–French five-factor, momentum and betting-against-beta controls.

Whether the leverage-effect parameter is related to the loading across assets depends on the specification: the correlation is $r = 0.49$ with SPY factors (Holm-adjusted $p = 0.062$, not robust across variants) and $r = 0.77$ with own factors (Holm-adjusted $p < 0.001$, robust), and it survives the equity versus non-equity control only with own factors. The association is not a causal estimate, because both quantities come from the same return series.

The conclusion we draw is narrow. VT does contain trend exposure, larger for equity than for non-equity assets, and it does not follow that VT and trend following are the same strategy. We report the leverage-effect results for both specifications and do not interpret γ as a determinant of the loading, and the paper does not test whether VT's drawdown reduction or its Sharpe-ratio gain survive removal of the TSMOM exposure.

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