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Speculative Volatility and Return Predictability: Evidence from the Japanese Equity Market

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Abstract

This study investigates the predictive power of speculative volatility for cross-sectional Japanese equity returns. We construct a latent Speculative Volatility Index (SVI) by applying principal component analysis to the returns of derivative-based and speculative trading indices. The empirical findings indicate that the first two principal components of the SVI significantly forecast stock returns across both market-wide and sector-specific equity indices, exhibiting consistent performance for both in-sample and out-of-sample testing. A long-short trading strategy based on SVI-implied signals from stock-level predictive regressions outperforms an inverse volatility benchmark, thereby validating the SVI's explanatory power as a novel asset pricing factor.

Keywords: Speculative Volatility Index; Principal component analysis; Return predictability; Asset pricing; Japanese Equity Market

Introduction

Stock return predictability remains central to asset pricing research. A growing body of evidence suggests that speculative trading and behavioral forces are key drivers of temporary mispricing, especially in markets with high segmentation, institutional frictions, or behavioral heterogeneity (Baker and Wurgler, 2007). While traditional models have often attributed return movements to macroeconomic shocks or firm-specific risk exposures, recent studies have emphasized the endogenous volatility induced by investor sentiment and speculative trading dynamics. Such behavioral dimensions introduce complexities into return predictability, market volatility, and cross-sectional variation that conventional models struggle to accommodate fully. These speculative forces, though often latent, exhibit a measurable footprint in trading activity, return reversals, and volatility spillovers across time and assets (Zhang et al., 2024).

The Japanese equity market presents a unique context characterized by distinct regulatory structures, demographic investor profiles, and exposure to unconventional monetary policies (Lau and Yip, 2023), which may magnify the influence of non-fundamental trading forces (Hamao, 2018). These conditions create an ideal setting for sentiment-driven distortions, necessitating precise measurement of speculative dynamics. This study responds to this distinctiveness by introducing a novel Speculative Volatility Index (SVI), derived from high-dimensional derivatives-based

indices returns, where principal component analysis (PCA) is employed to extract orthogonal dimensions of speculative activity, specifically isolating market-wide intensity and asymmetric positioning, within Japan's financial market.
This research is designed to move beyond noisy or single-variable proxies, integrating high-dimensional information into a parsimonious, economically interpretable factor structure that represents common speculative shocks. While PCA is commonly employed for dimensionality reduction (Stock and Watson, 2002), we align with Karolyi and Nieuwerburgh (2020) in emphasizing that extracted components must be validated through economic interpretation and predictive testing; a principle we rigorously uphold through extensive in-sample and out-of-sample forecasting. Our core research hypothesis states that the latent speculative volatility components extracted via principal component analysis, specifically the first and second principal components (SVI PC1 and PC2), possess statistically significant and economically meaningful predictive power for future stock returns across the Japanese market.
When speculative volatility is elevated, mispricing risk increases, and future returns decline as market corrections ensue. This aligns with behavioral models of overreaction and subsequent mean reversion, as formalized by Daniel et al. (2020) and Stambaugh and Yuan (2017), and reflects the empirical patterns observed by Soebhag (2023) in option-implied volatility asymmetries. Our empirical design includes multivariate predictive regressions, forecasting implications, and out-of-sample evaluation. We also construct a long-short portfolio strategy based on firm-level return forecasts conditioned on SVI signals. The results reveal statistically significant and economically meaningful predictive power, with SVI PC1 outperforming benchmark models in both aggregate market indices and sectoral TOPIX-17 ETFs. The findings are particularly pronounced in capital-intensive and sentiment-sensitive indices.

Literature Review

Theoretical Foundations of Speculation and Return Predictability

Empirical studies have increasingly demonstrated that speculative trading correlates with return predictability and systemic fragility. Wang (2023) shows that short-selling predicts near-term returns among investment-grade firms due to information opacity in distressed stocks. At the structural level, Galindo Gil and Lazo-Paz (2025) introduce an ETF-based fragility measure that outperforms traditional fund-flow metrics in predicting return volatility and comovements. This supports our methodological choice to include ETF- and derivative-linked variables in model construction. Likewise, Xu et al. (2021) isolated the speculative component in futures market maturity effects, demonstrating regulatory impacts on return structures. Similarly, Deschamps et al. (2025) distinguish between macroeconomic and financial uncertainty in China, finding that only the macroeconomic indicator commands a significant risk premium, further justifying our inclusion of macroeconomic controls when evaluating speculative return effects.
The behavioral speculative trading has also been empirically examined through the lens of belief heterogeneity. Zhang et al. (2024) construct a speculative trading proxy (SPT) that isolates the volume attributable to divergent investor opinions. Their study,

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conducted in the Chinese equity market, finds that high SPT is negatively associated with future returns, affirming that excessive speculation often precedes reversals; a finding echoed in our empirical results using PCA-extracted speculative factors. Zuo et al. (2023) provide a socio-cultural angle by showing that regions in China with higher gambling conviction rates exhibit greater stock crash risk, driven by overinvestment and excessive leverage. This relationship aligns with our hypothesis of sectoral heterogeneity, as industries with elevated speculative exposure are more likely to experience tail risk during market corrections. This behavioral mechanism arises from cognitive biases, such as loss aversion and diminishing sensitivity, which nonlinearly shape risk-taking behavior (Wang et al., 2022). When speculative intensity rises, investors often overextend exposure to high-growth assets, amplifying mispricing (Du et al., 2020). Chen et al. (2024) extend this behavioral characterization by contrasting the predictive value of margin trading and short-selling. While short-selling retains strong informational content, margin trading appears sentiment-driven and lacks forecasting power. The asymmetry aligns with earlier findings by Baker and Wurgler (2007), who argue that sentiment-driven mispricing disproportionately affects hard-to-value stocks; namely those that are small, illiquid, and volatile. Similarly, Gambarelli and Muzzioli (2025) states that sentiment-induced return effects are stronger and more persistent among small-cap firms in the Eurozone. Investor psychology drives persistent mispricing in segmented markets, as demonstrated by Chen et al. (2020), who attribute China's A-share premium to retail speculation amplified by arbitrage frictions. This behavioral divergence is further theorized by Shi (2019), whose ambiguity-augmented asset pricing model formalizes how uncertainty elevates risk premia and distorts valuations.

Critically, Ghazi et al. (2024) distinguish between speculative and non-speculative components of the equity risk premium, demonstrating that the speculative premium is tightly linked to market sentiment, while the non-speculative premium aligns with fundamental risk exposure. Cross-asset linkages are also shaped by speculation. Speculative-driven spillovers between equity and commodity markets intensify during macroeconomic shocks (Wang et al., 2023). These findings resonate with our observation that speculative volatility tends to exhibit stronger return predictability in economically sensitive sectors, such as Machinery and Raw Materials, which are more exposed to global demand and investor sentiment. Non-fundamental forces propagate through market microstructure channels. Fonseka et al. (2025) identify margin trading as a key catalyst for price synchronicity. Conversely, Xiang and Borjigin (2024) show hedge fund networks mitigate crash risk via information dissemination. Yang and Ferrer (2023) document pervasive explosivity across Chinese equity sectors, attributing bubble formation to structural inefficiencies and weak regulatory oversight. These explosive episodes exhibit cross-sector contagion. Such evidence implies that speculation's impact is *regime-contingent*; a nuance reflected in Chen's (2025) discovery of institutional rebalancing cascades, where regulatory thresholds mechanically induce large-cap reversals.

Predictive Techniques and Factor Modeling

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A central challenge in modeling speculative dynamics lies in effectively reducing dimensionality while preserving economic interpretability. Principal component analysis (PCA) remains a foundational tool in this regard (Stock and Watson, 2002). Recent innovations in predictive modeling offer complementary tools. Zuo and Jiang (2025) propose symbolic regression to identify nonlinear return drivers, while Umlandt (2023) introduces observation-driven updating framework for factor loadings and premia. Emerging techniques disentangle speculative signals. Li et al. (2024) propose stochastic conditional duration (SCD) models for futures markets and reveal intraday decoupling of volatility and trading intensity. Similarly, Altieri and Schnitzler (2023) refine investment-based predictors by isolating quarterly investment spikes as mispricing signals, distinct from traditional asset-growth anomalies. Yu et al. (2025) demonstrate that composite liquidity proxies outperform singular measures in explaining returns, advocating for multivariate approaches. Other studies provide further support for the use of latent volatility factors. Han et al. (2023) argue that liquidity shocks dominate idiosyncratic volatility in forecasting returns, while Liu and Zhu (2025) introduce good-minus-bad idiosyncratic volatility as a stronger predictor than skewness. These findings affirm our belief that volatility-based speculative metrics, when properly decomposed, offer richer information about return dynamics than first-moment variables alone. Stambaugh and Yuan (2017) and Daniel et al. (2020) develop mispricing-based factor models that outperform traditional frameworks by incorporating sentiment and behavioral anomalies which confirm the notion that psychological distortions can be systematically priced and predicted. Calice and Lin (2021) demonstrate that combining PCA-derived latent factors with macroeconomic variables improves forecasting performance which validates our model specification strategy and mitigates concerns regarding the pricing relevance of extracted components (Karolyi and Nieuwerburgh, 2020).

Data and Methodology

Data Structure

This study utilizes a dataset consisting of 117 monthly observations, covering the period from September 2015 to May 2025. The dataset is structured around three primary domains, including Japanese indices returns, indicators of speculative activity, and macroeconomic control variables. The dependent variables comprise 24 return series that reflect the performance of key segments of the Japanese equity market. These include major aggregate indices such as the Nikkei 225 and the Tokyo Stock Price Index (TOPIX), as well as several sub-indices distinguished by market capitalization (e.g., TOPIX Core 30, TOPIX Mid 400, and TOPIX Small) and investment style (e.g., TOPIX Growth and TOPIX Value). In addition, we include the full set of 17 sector-specific indices from the TOPIX-17 classification, which disaggregate the Japanese market by economic activity of major industry groups in Japan. All stock return data were collected from the Stooq financial database[1]. To measure speculative dynamics in the Japanese financial market, we gathered 27 distinct indices capturing various

[1] The data were retrieved from the of official website of Stooq, available at https://stooq.com.

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dimensions of investor sentiment and speculative positioning in derivative-based indices. These series quantify speculative behavior involved in directional exposure measures such as bull and bear spreads, inverse positioning activity in futures and options markets, and complementary volatility metrics encompassing both implied and realized volatility indices specific to Japanese equities. Those various speculation- and volatility-sensitive indices serve as input variables for the construction of a novel Speculative Volatility Index (SVI) via principal component analysis. As explanatory controls in our predictive regressions, we incorporated a set of macroeconomic and financial indicators that are commonly associated with return predictability in asset pricing models. These include Core Consumer Price Index (CPI), 3-month interbank interest rates, industrial production, real broad effective exchange rate, and the Economic Policy Uncertainty (EPU) index for Japan[2]. The sample is divided into training and testing subsamples based on a 3:1 ratio to enable both in-sample estimation and out-of-sample forecasting analysis.

Construction of the Speculative Volatility Index (SVI)

To quantify latent speculative sentiment in the Japanese equity market, we construct a Speculative Volatility Index (SVI) using Principal Component Analysis (PCA) applied to a set of 27 standardized financial indices in the Japanese financial market. These input variables were selected to represent a broad cross-section of speculative dynamics and volatility-linked activity, encompassing derivatives-based exposures, leveraged and inverse flows, volatility instruments, and futures market positions across major Japanese indices. This approach follows the prior work that uses PCA to extract low-dimensional latent factors from high-dimensional speculative or sentiment-based data (e.g., Huang et al., 2014; Sun et al., 2016; Han & Kumar, 2013). Our PCA-based construction of speculative latent factors employs dimension reduction techniques to isolate systematic sentiment and risk exposures (e.g., Bianchi et al., 2020; Kelly et al., 2019).

Let $X_t = (x_{1t}, \dots, x_{27t})^{\top} \epsilon\, \mathbb{R}^{27}$ denote the vector of returns for *N=27* speculative-based indices at time t. We standardize each series across time to eliminate scale effects:

$$\tilde{x}_{it} = \frac{x_{it} - \bar{x}_i}{s_i}\,, for\ i = 1, \dots, N, \tag{1}$$

where $\tilde{x}_i$ and s_i are the sample mean and standard deviation of variable i, respectively. Let $\tilde{x}_i \epsilon\, \mathbb{R}$ denote the vector of standardized inputs. We form the standardized input matrix $X = [\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_T]^{\top} \epsilon\, \mathbb{R}^{T \times N}$. We apply principal component analysis to X by computing

$$\Sigma = \frac{1}{T-1} X^{\top} X, \tag{2}$$

And extracting its eigenvalue decomposition:

[2] The macroeconomic data were sourced primarily from the World Bank's Global Economic Monitor (GEM), available at https://datacatalog.worldbank.org ; interest rate data were obtained from the Federal Reserve Bank of St. Louis FRED database at https://fred.stlouisfed.org ; and the Japanese Economic Policy Uncertainty (EPU) index was retrieved from https://www.policyuncertainty.com .

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$$\Sigma = V \Lambda V^{\top}, \quad 3$$

Where $V = [V_1, V_2, \dots, V_N)]$ is the matrix of orthonormal eigenvectors (loadings), and $\Lambda = diag\ (\lambda_1, \lambda_2, \dots, \lambda_N)$ contains the ordered eigenvalues ($\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N$).

The first principal component (PC1) captures the dominant variation in speculative signals and serves as a composite proxy for speculative intensity in the market. The second principal component (PC2), which is orthogonal to PC1, is used to capture asymmetric or directional variations in speculative behavior, possibly reflecting shifts in investor positioning between long and short exposures. As illustrated in **Figure. 1**, PC1 explains 91.87% of the total variance in the speculative indicators, while PC2 accounts for an additional 3.66%. This concentration of explanatory power in the first two components justifies their joint inclusion in the return predictive regressions.

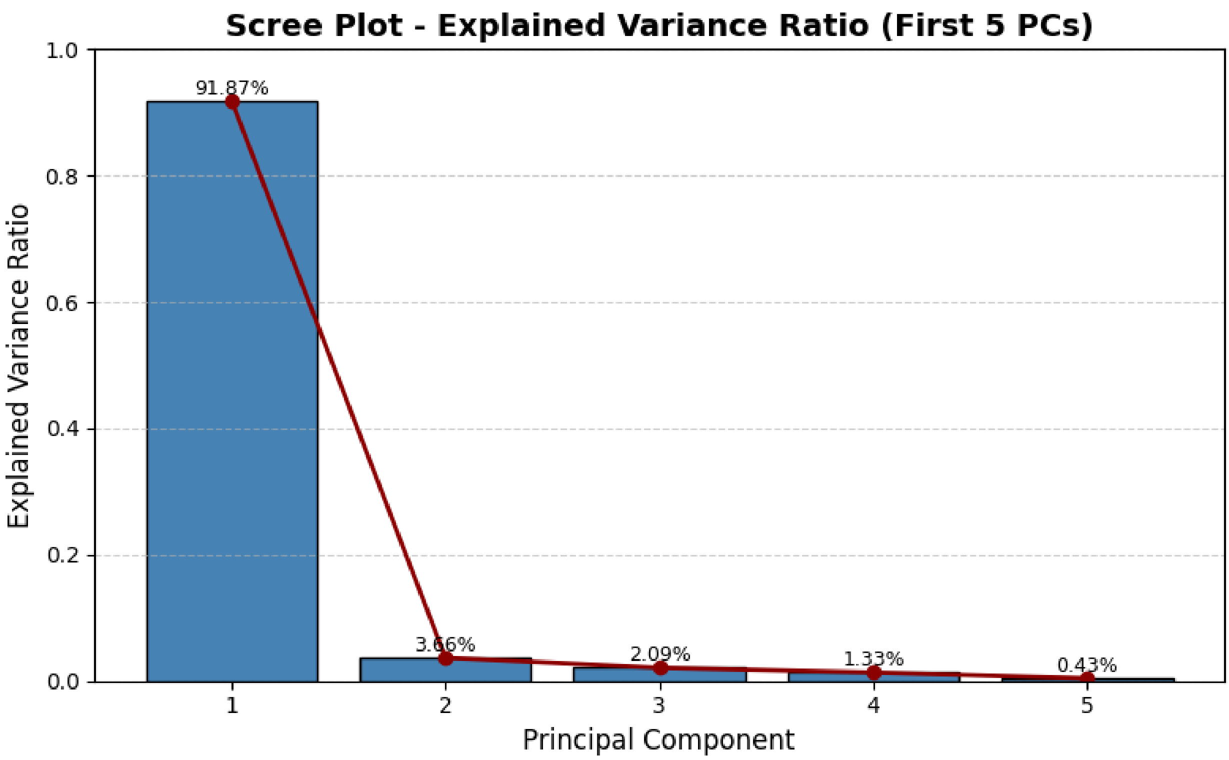

Figure. 1: Scree plot showing the explained variance ratio of the first five principal components derived from speculative return series.

Formally, the Speculative Volatility Index is then defined as:

$$SVI_t^{(PC1)} = W_1^{\top} X_t, \qquad SVI_t^{(PC2)} = W_2^{\top} X_t, \quad 4$$

where $SVI_t^{(PC1)}$ and $SVI_t^{(PC2)}$ represent the scores of the first and second principal components at time t, and $W_1, W_2 \in \mathbb{R}^{27}$ are the loading vectors corresponding to PC1 and PC2, respectively.

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To ensure the predictive validity of our regression models and prevent forward-looking bias, the construction of the Speculative Volatility Index (SVI) is based exclusively on lagged returns of the speculative indices. Specifically, the vector of speculative indicators used at time t, denoted $\tilde{x}_{t-1}$, reflects information that would have been available at the end of month $t-1$. This approach preserves the causal structure of the model by ensuring that no future information contaminates the regressors used for forecasting excess returns at time *t*. Therefore, the index is suitable for inclusion in out-of-sample predictive regressions and potential trading strategies, where the use of contemporaneous or future information would otherwise result in data snooping or look-ahead bias (Giglio and Xiu, 2021).

We examine the factor loadings of each speculative return series on the first two principal components, as illustrated in the accompanying heatmap **(Figure. 2)**. The loadings on PC1 exhibit consistent magnitudes around ±0.19 to ±0.20 across most speculative indices, demonstrating that PC1 represents a broad-based co-movement pattern and acts as a robust composite measure of overall speculative intensity in the Japanese financial market. In stark contrast, PC2 is characterized almost exclusively by a very high loading (0.992) on the Gold Double Bull ETN Index, while all other indices have loadings near zero or negligible values. This clearly indicates that PC2 isolates a distinct speculative dimension associated with gold-related instruments, capturing unique idiosyncratic variation orthogonal to the general market speculation reflected by PC1.

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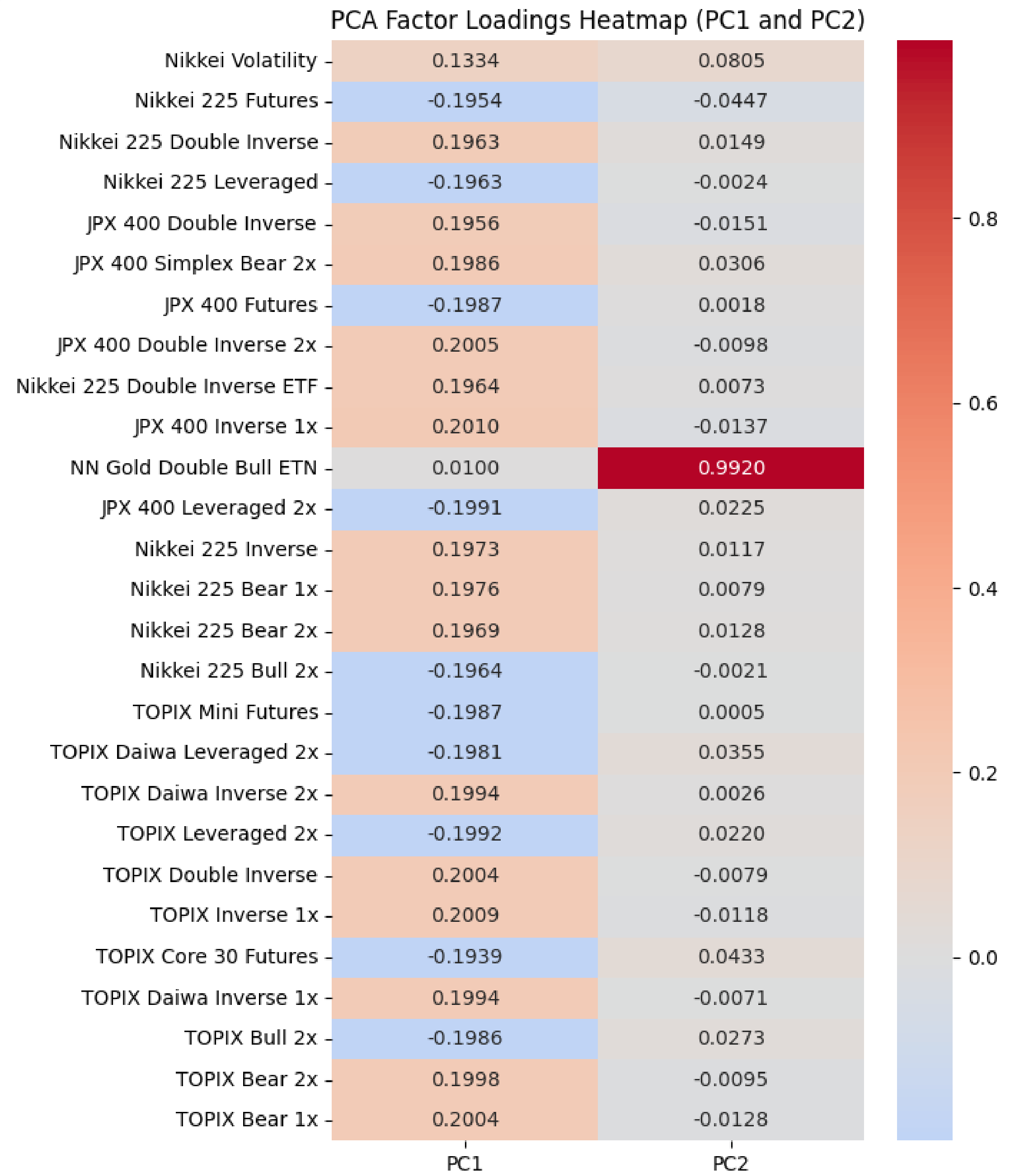

Fig. 2: Heatmap of factor loadings for the first two principal components (PC1 and PC2) across the 27 speculative indices returns.

Summary of Descriptive Statistics

To provide an overview of the distributional properties of the key variables employed in the empirical analysis, descriptive statistics is reported in **Table 1** for the full sample period. The summary includes equity market returns, principal components derived from speculative indicators, and macroeconomic control variables. For completeness,

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we report in the appendix the descriptive statistics for the 17 TOPIX sectoral indices ETFs and the 27 speculative indices used to construct the SVI in **Table A1**.

Table 1
Descriptive Statistics. Panel A summarizes the return characteristics of the main Japanese equity indices and sectoral aggregates. Panel B presents the properties of the first two principal components of speculative volatility (SVI PC1 and PC2). Panel C includes macroeconomic control variables.

Variable	Mean	Std Dev	Min	Max	Skew	Kurtosis
Panel A: Equity Market Indices						
Nikkei 225	0.0071	0.0475	-0.1053	0.1504	-0.2194	0.1831
TOPIX	0.006	0.0416	-0.104	0.1112	-0.4865	0.6327
TOPIX Core 30	0.0067	0.0451	-0.103	0.1172	-0.2873	0.2069
TOPIX Mid 400	0.005	0.0407	-0.1157	0.1094	-0.5861	0.9148
TOPIX Small Market	0.005	0.0407	-0.1157	0.1094	-0.5861	0.9148
TOPIX Growth	0.0059	0.0421	-0.1084	0.1282	-0.4287	0.8971
TOPIX Value	0.0062	0.0455	-0.1175	0.1024	-0.5097	0.5615
TOPIX-17 ETFs Avg.[3]	0.0058	0.0418	-0.1125	0.1034	-0.4361	3.5318
Panel B: SVI Components						
SVI PC1	0.0000	4.966	-12.897	13.9597	0.5133	0.5562
SVI PC2	0.0000	1.0083	-2.3045	3.6675	0.7317	1.7359
Panel C: Macroeconomic Controls						
CPI	0.0005	0.002	-0.015	0.005	-3.8943	28.798
EPU	115.608	29.9673	66.0836	213.6555	1.3262	2.1198
Interest Rate	0.0697	0.1739	-0.072	0.8209	3.1069	10.3777
Ind. Prod.	-0.0004	0.0235	-0.0923	0.0569	-0.8134	3.1612
Real FX	-0.0014	0.0193	-0.0602	0.0675	0.2388	1.5255

Model Specification
To investigate the predictive power of the constructed speculative volatility index (SVI), we employ a multivariate ordinary least squares (OLS) regression framework to examine its ability to predict future equity market returns. Our goal is to formally test whether latent speculative factors, extracted via principal component analysis (PCA) from a comprehensive set of speculative-based indices returns, carry predictive power. Accordingly, we test whether these components exhibit statistically and economically significant forecasting power for returns across the Japanese equity indices, thereby rejecting the null hypothesis of no predictive content in favor of the alternative that such speculative behavior dynamics hold explanatory value.

[3] This row represents the average return across the 17 TOPIX sector ETFs. For full descriptive statistics of each sectoral ETF index individually, refer to Table A1 in the appendix.

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Formally, let $r_{i,t+1}$ denotes the one-month-ahead excess return of equity index i at time $t+1$, then the predictive regression model is specified as follows:

$$r_{i,t+1} = \alpha_i + \beta_1 SVI_t^{(PC1)} + \beta_2 SVI_t^{(PC2)} + \gamma^\top Z_t + \varepsilon_{i,t+1}, \quad 5$$

where $r_{i,t+1}$ denotes the one-month-ahead excess return of equity index i at time $t+1$. $SVI_t^{(PC1)}$ and $SVI_t^{(PC2)}$ are the first and second principal components of the constructed speculative indices returns, respectively. We further augment the model with a vector of macroeconomic control variables denoted as Z_t. Each regression specification includes an index-specific idiosyncratic residual component denoted by $\varepsilon_{i,t+1}$. This regression framework provides a direct test of whether speculative signals, as synthesized through PCA, anticipate meaningful variations in market returns.

Evaluation of Forecasting Performance

Out-of-Sample Evaluation

We evaluate the out-of-sample performance of the predictive regression model to determine whether the SVI components hold meaningful predictive content beyond in-sample statistical significance. Forecast accuracy is evaluated using two key metrics. The first metric is the root mean squared error (RMSE), which captures the average magnitude of forecast errors and is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{T}\left(r_{i,t+1} - \hat{r}_{i,t+1}\right)^2} \quad 6$$

Where $r_{i,t+1}$ denotes the realized return of index i at $t+1$ $t+1$ and $\hat{r}_{i,t+1}$ is the predicted return from the model. A lower RMSE indicates a closer fit between predicted and realized returns. For comparative evaluation, we implement a naive forecasting model that persists the last observed return from the training sample as $\hat{r}_{i,t+1}^{naive} = r_{i,T_{train}}$ $\forall t \epsilon T_{test}$, where $\hat{r}_{i,t+1}^{naive}$. The second metric is the out-of-sample R^2, computed as:

$$R_{OS}^2 = 1 - \frac{\sum_{t=1}^{T}\left(r_{i,t+1} - \hat{r}_{i,t+1}^{Model}\right)^2}{\sum_{t=1}^{T}\left(r_{i,t+1} - \hat{r}_{i,t+1}^{Naive}\right)^2} \quad 7$$

where $\hat{r}_{i,t+1}^{Model}$ is SVI-based model's predicted returns. This metric quantifies the proportional reduction in forecast error variance achieved by the SVI-based model relative to the naive benchmark. A positive R_{OS}^2 indicates that the SVI-based model yields superior predictive accuracy compared to the baseline.

Portfolio Construction and Trading Strategy

To examine the economic relevance and practical utility of the speculative volatility components, we implement a long-short trading strategy that exploits cross-sectional return predictability across a diversified portfolio of Japanese equities. Specifically, we construct monthly portfolios based on return forecasts generated from company-level

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predictive regressions that incorporate the first two principal components of the constructed SVI.
The stock universe comprises 25 large and mid-cap Japanese firms spanning diverse sectors from TOPIX-17 indices categorization. At each month t, we rank all stocks based on their predicted returns. We then form a market-neutral portfolio that takes equal-weighted long positions in stocks with positive signals and equal-weighted short positions in those with negative signals. The monthly return of the portfolio is computed as:

$$R_t^{signal} = \frac{1}{N_t^+}\sum_{i\epsilon L_t} R_{i,t} - \frac{1}{N_t^-}\sum_{j\epsilon S_t} R_{j,t} \qquad 8$$

Where L_t and S_t denote the sets of long and short positions at time t, with N_t^+ N_t^- as their respective counts. If no signal exceeds or falls below zero at a given time, the corresponding leg of the strategy is omitted, preserving the self-financing property while avoiding spurious exposure. To benchmark the trading strategy against a passive yet risk-aware alternative, we construct an inverse volatility-weighted portfolio, which allocates the investment inversely proportional to the historical volatility of each stock. Specifically, for each stock i, we compute its return standard deviation over the sample, then calculate the weights assigned to each asset as:

$$w_i^{Inv\ Vol} = \frac{\frac{1}{\sigma_i}}{\sum_{j=1}^{N}\frac{1}{\sigma_i}} \qquad 9$$

These weights are fixed throughout the investment horizon. The portfolio returns at time t are then computed as:

$$R_i^{Inv\ Vol} = \sum_{i=1}^{N} w_i^{Inv\ Vol} R_{i,t} \qquad 10$$

This portfolio is long-only and fully invested and serves as a robust comparator to evaluate whether the active strategy yields incremental performance over a volatility-balanced passive allocation. For both strategies, we compute standard performance measures including cumulative return, mean and standard deviation of monthly returns, and the annualized Sharpe ratio. These metrics provide a direct comparison between the active strategy, conditioned on speculative volatility signals, and passive allocation, thereby quantifying the economic relevance of latent speculative factors in both asset pricing and portfolio optimization.

Empirical Results

Market-Wide Return Predictability: Aggregate Equity Indices

Table 2 presents the empirical findings from the predictive regression model that examine the predictive power of the Speculative Volatility Index (SVI), constructed via principal components, to forecast returns across broad market and style-based Japanese equity indices. Across all major market indices, including Nikkei 225 and TOPIX, as well as the style-oriented Growth and Value indices in panel A of Table 2, the first

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principal component of the SVI (PC1) demonstrates consistent and statistically significant positive predictive power for one-month-ahead returns. This consistency suggests that PC1 captures a broad market sentiment or risk appetite component that translates into systematically higher expected returns. Its role is economically intuitive when speculative intensity increases, as reflected in elevated values of PC1, investors appear to demand or anticipate higher future returns, and these expectations are validated in realized performance.

The second principal component (PC2), which represents a more nuanced dimension of speculative activity orthogonal to the dominant market-wide component, displays weaker and more selective predictive power. While its coefficient estimates are positive across all specifications, significance emerges only in the Growth and broader TOPIX indices. This heterogeneity suggests that PC2's reflection of investor positioning nuances may differentially impact growth-oriented segments of the market. The weaker predictive power for Value indices is consistent with prior work of Nagel (2005) showing that speculative shock tends to have more limited effects on low-valuation stocks.

Turning to size-based indices, the results remain robust. PC1 continues to display positive and significant coefficients across large-cap (TOPIX Core 30), mid-cap (Mid 400), and small-cap market segments. Notably, PC2 retains marginal significance in these segments as well, hinting at a more pervasive speculative signal that may operate through size-related channels, possibly reflecting differing levels of investor attention or liquidity sensitivity. PC2 maintains marginal significance ($p < 0.10$) in these specifications, revealing a secondary speculative dimension that may propagate through size-dependent channels. This finding demonstrates how investor attention gradients across market caps can amplify speculative return predictability, particularly in less liquid small-cap equities where information diffusion occurs more gradually.

Interestingly, industrial production and the real broad effective exchange rate both emerge as significant negative predictors in all models, suggesting that contemporaneous contractions in industrial output and real effective appreciation may dampen expected returns. The real broad effective exchange rate shows significant negative coefficients a relationship that reflects the currency-valuation transmission channels identified in Japan's export-dependent equity markets. These results underscore the necessity of controlling for real economic activity and currency fluctuations when evaluating speculative factors.

Table 2

Predictive Regressions for Market and Capitalization-Based Indices. This table reports the results of predictive regressions examining the relationship between speculative volatility components (SVI PC1 and PC2) and returns on Japanese equity indices, with controls for macroeconomic fundamentals. Panel A presents estimates for broad market indices and style-based exposures, while Panel B reports results across market capitalization segments.

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Panel A: Broad Market & Style Indices				
	Aggregate Market Indices		Style Factor Exposure Indices	
	Nikkei 225	TOPIX	TOPIX Growth	TOPIX Value
SVI PC1	0.0005**	0.0005***	0.0004**	0.0005***
	(2.54)	(2.66)	(2.27)	(2.60)
SVI PC2	0.0130	0.0149*	0.0178**	0.0122
	(1.44)	(1.84)	(2.31)	(1.28)
CPI	1.9043	2.0859*	2.2643*	1.9058*
	(1.39)	(1.87)	(1.76)	(1.66)
EPU	-0.0003	-0.0004*	-0.0002	-0.0005**
	(-1.53)	(-1.92)	(-1.19)	(-2.43)
Interest Rate	0.0001	0.0364	0.0014	0.0711
	(0.00)	(0.58)	(0.03)	(0.89)
Ind. Prod.	-0.5894***	-0.4950***	-0.5029***	-0.4874***
	(-4.61)	(-3.98)	(-3.97)	(-3.55)
Real FX	-0.8590***	-0.7724***	-0.6354***	-0.9060***
	(-3.97)	(-4.39)	(-3.45)	(-4.76)
Adjusted R^2	0.189	0.201	0.151	0.222

Panel B: Market Capitalization Segments			
	TOPIX Core 30	TOPIX Mid 400	TOPIX Small Market
SVI PC1	0.0005***	0.0004**	0.0004**
	(2.73)	(2.34)	(2.34)
SVI PC2	0.0159*	0.0149*	0.0149*
	(1.75)	(1.82)	(1.82)
CPI	2.0573*	2.0690*	2.0690*
	(1.80)	(1.74)	(1.74)
EPU	-0.0004**	-0.0003	-0.0003
	(-2.11)	(-1.39)	(-1.39)
Interest Rate	0.0250	0.0406	0.0406
	(0.40)	(0.64)	(0.64)
Ind. Prod.	-0.5723***	-0.4375***	-0.4375***
	(-5.00)	(-3.05)	(-3.05)
Real FX	-0.8170***	-0.7201***	-0.7201***
	(-4.15)	(-4.09)	(-4.09)
Adjusted R^2	0.216	0.157	0.157

Note: Coefficients and robust t-statistics (in parentheses) are reported. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively

Sector-Level Predictability: TOPIX-17 Sectoral ETFs

This section extends our empirical analysis by examining the predictive power of speculative volatility for sectoral equity returns, utilizing the TOPIX-17 family of

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sectoral ETFs. The objective is to assess whether the informational content embedded in speculative sentiment exhibits heterogeneous predictive power across different sectors of the Japanese equity market.

The results in **Table 3** reveal a rich cross-sectional pattern in how speculative dynamics translate into return predictability at the sector level. Across Panel A, which includes financial and business service sectors, the results demonstrate modest but notable evidence of speculative return predictability. For instance, SVI PC1 exhibits statistically significant positive coefficients in the *Banks* and *IT Services* sectors, suggesting that periods of heightened speculative volatility tend to precede modest return increases in these segments. This result is consistent with narratives of procyclical risk-taking behavior within financial intermediation and the tech-related business services sector as innovation-driven sectors exhibit amplified sensitivity to sentiment shocks due to their growth optionality and valuation opacity. The banking sector's responsiveness aligns with the financial accelerator mechanism described by Bernanke et al. (1999), where speculative volatility propagates through credit channels and leverage cycles. In contrast, SVI PC2 emerges significantly only in *IT Services*, implying that momentum-based speculation plays a less consistent role in driving returns across financials. This distinction supports the behavioral segmentation where tech sectors attract trend-chasing speculation while banks remain more anchored to fundamental risk factors.

Notably, SVI PC1, which captures the dominant dimension of speculative volatility, demonstrates statistically significant and economically meaningful positive coefficients in a range of cyclical and capital-intensive sectors. These include machinery, steel and nonferrous metals, raw materials and chemicals, as well as automobiles and transportation equipment, as shown in Panel B of **Table 3**. This aligns with the notion that investor sentiment may amplify momentum in sectors that are more sensitive to business cycles or global industrial activity. In contrast, SVI PC1 appears largely uninformative in more defensively oriented sectors such as pharmaceuticals, retail trade, and electric utilities, as reported in Panel, where its coefficients are small and statistically insignificant. This asymmetry reinforces the hypothesis that speculative sentiment disproportionately influences return in economically sensitive industries, while playing a diminished role in sectors typically viewed as stable or insulated from macro-financial volatility. Nonetheless, SVI PC2 achieves significance in *Foods*, *Pharmaceuticals*, and *Electric Power & Gas*, indicating that momentum-chasing behavior can still influence returns in these sectors, albeit to a lesser and less systematic extent.

The persistent significance of industrial production and real exchange rate variables as negative predictors emphasizes the relevance of macroeconomic fundamentals in shaping expected returns. Their inclusion ensures that the incremental predictive power attributed to SVI components captures sentiment-induced variation orthogonal to traditional risk factors. This aligns with recent studies that emphasize the necessity of jointly modeling sentiment and fundamentals to obtain accurate forecasts (Rapach et al., 2016). Overall, the sectoral heterogeneity in the predictive strength of SVI components lends credence to the idea that speculative sentiment is not uniformly

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priced across the equity market but rather interacts with sector-specific characteristics such as cyclicality, capital intensity, and information asymmetry. The adjusted R^2 values, while moderate in absolute terms, tend to be higher in sectors where speculative variables are significant, particularly in heavy industry and materials, indicating improved explanatory power when incorporating speculative sentiment proxies.

Table 3

Predictive Regressions for TOPIX-17 Sectoral ETFs. This table presents regression results of TOPIX-17 sectoral ETFs on the first two principal components of speculative volatility (SVI PC1 and PC2) alongside macroeconomic controls. TOPIX-17 indices are categorized into three panels: Panel A includes financial and business services ETFs, Panel B comprises heavy industry and commodities, and Panel C includes consumer staples and utilities ETFs.

Panel 1: TOPIX-17 Financial & Business Services ETFs					
	Banks	Financials (Ex Banks)	Real Estate	IT Services	Commercial & Wholesale Trade
SVI PC1	0.0007**	0.0004	0.0002	0.0004**	0.0004
	(2.31)	(1.60)	(0.54)	(2.18)	(1.59)
SVI PC2	0.0087	0.0156	0.0170	0.0185**	0.0068
	(0.66)	(1.27)	(1.38)	(2.48)	(0.67)
CPI	2.8229*	0.8523	0.6137	1.1288	2.0854
	(1.74)	(0.60)	(0.28)	(1.01)	(1.31)
EPU	-0.0007***	-0.0004*	-0.0002	-0.0001	-0.0004*
	(-2.70)	(-1.94)	(-0.75)	(-0.82)	(-1.77)
Interest Rate	0.2852*	0.0589	0.1847*	0.0447	-0.1234**
	(1.94)	(0.47)	(1.68)	(1.20)	(-2.38)
Ind. Prod.	-0.7359***	-0.5278***	-0.5182**	-0.5020***	-0.4040**
	(-3.36)	(-3.11)	(-2.29)	(-4.17)	(-2.18)
Real FX	-1.2628***	-1.1803***	-0.9280***	-0.6291***	-0.6899***
	(-3.62)	(-4.96)	(-4.56)	(-3.79)	(-2.65)
Adjusted R^2	0.230	0.189	0.104	0.163	0.088

Panel B: TOPIX-17 Heavy Industry & Commodities ETFs							
	Industrial Inputs & Materials				Transport & Precision Manufacturing		
	Machinery	Steel & Nonferrous	Raw Materials & Chemicals	Construction & Materials	Automobiles Transportation Equipment	Transport & Logistics	Electric & Precision Instruments
SVI PC1	0.0009***	0.0009***	0.0005***	0.0002	0.0007**	-0.0002	0.0007***
	(3.67)	(3.01)	(2.98)	(1.10)	(2.56)	(-0.83)	(3.01)

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SVI PC2	0.0296***	0.0055	0.0107	0.0126	0.0228**	0.0246**	0.0171*
	(2.67)	(0.41)	(1.30)	(1.45)	(2.04)	(2.56)	(1.67)
CPI	2.4226	0.0927	2.1057*	2.2564*	1.6762	2.3299	2.9855
	(1.26)	(0.05)	(1.76)	(1.83)	(0.97)	(1.28)	(1.33)
EPU	-0.0006**	-0.0009***	-0.0004**	-0.0002	-0.0006**	0.0001	-0.0004**
	(-2.26)	(-2.87)	(-2.57)	(-0.87)	(-2.41)	(0.53)	(-2.19)
Interest Rate	0.0866	0.1016	-0.0487	0.0633	0.0191	0.0372	0.0068
	(1.21)	(1.19)	(-0.84)	(0.73)	(0.18)	(0.67)	(0.12)
Ind. Prod.	-0.7006***	-0.7623***	-0.3753**	-0.4125**	-0.5860***	-0.5598**	-0.6054***
	(-3.88)	(-3.70)	(-2.55)	(-2.46)	(-3.11)	(-2.46)	(-4.10)
Real FX	-1.0360***	-0.7323**	-0.6223***	-0.7802***	-1.2562***	-0.6830***	-0.7136**
	(-3.54)	(-2.23)	(-2.91)	(-3.92)	(-4.83)	(-3.66)	(-2.52)
Adjusted R^2	0.218	0.151	0.120	0.106	0.197	0.104	0.134

Panel C: TOPIX-17 Consumer Staples & Utilities ETFs

	Retail Trade	Foods	Pharmaceutical	Electric Power & Gas	Energy & Resources
SVI PC1	0.0001	-0.0001	-0.0002	-0.0002	0.0003
	(0.61)	(-0.54)	(-0.92)	(-0.83)	(1.26)
SVI PC2	0.0011	0.0118*	0.0166*	0.0214**	0.0062
	(0.13)	(1.68)	(1.85)	(2.25)	(0.46)
CPI	4.2184***	3.5900***	5.2035***	6.0677***	1.4481
	(2.98)	(3.08)	(3.73)	(4.57)	(0.62)
EPU	-0.0000	0.0001	0.0002	0.0001	-0.0007***
	(-0.15)	(0.57)	(0.81)	(0.27)	(-2.68)
Interest Rate	0.0530	-0.0448	-0.0709	-0.0335	0.0175
	(0.62)	(-0.78)	(-1.11)	(-0.33)	(0.15)
Ind. Prod.	-0.2959*	-0.2688*	-0.6299***	-0.0335	-0.6417***
	(-1.73)	(-1.77)	(-2.99)	(-0.18)	(-2.62)
Real FX	-0.3649*	-0.6079***	-0.8211***	-0.6977***	-1.1449***
	(-1.94)	(-3.96)	(-4.64)	(-3.27)	(-3.67)
Adjusted R^2	0.047	0.098	0.166	0.095	0.149

Note: Coefficients and robust t-statistics (in parentheses) are reported. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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Out-of-Sample Forecast Performance

We further conduct an out-of-sample forecast for the final 30 months of the sample period. We benchmark the forecasting performance of SVI-based model against a naive historical mean model, comparing both via the Root Mean Squared Error (RMSE) and the out-of-sample R^2 statistic, R^2_{OS}, following the procedure established by Campbell and Thompson (2007). The results, presented in **Table 4**, show the model's predictive value across a range of market indices. The SVI-based model consistently outperforms the historical mean benchmark, with substantial reductions in forecast errors, as it produces lower RMSE values. For instance, the model achieves substantial improvements for the Nikkei 225 and TOPIX, where RMSE is reduced by over 50% compared to the naive approach.

The findings from **Table 4** reveal a striking degree of predictive accuracy across a broad range of Japanese equity indices and sectoral ETFs. Most notably, the model achieves exceptional out-of-sample fit of R^2 values for broad-based indices such as the Nikkei 225 (0.7801), TOPIX (0.7520), and TOPIX Core 30 (0.7531), validating the systematic role of speculative dynamics in shaping aggregate return patterns. These exceptional results indicate that speculative volatility factors capture fundamental price formation processes that are especially prominent in Japanese large-cap equities.

Among style-based indices, TOPIX Growth stands out with an R^2_{OS} of 0.8665, the highest in the sample, suggesting that growth-oriented segments of the market are particularly sensitive to speculative sentiment as captured by our latent volatility factors. In contrast, TOPIX Value exhibits more moderate predictability (0.3643), indicating asymmetries in how different investment styles respond to speculative conditions. This remarkable result suggests growth-oriented stocks serve as particularly strong conduits for speculative sentiment, likely due to their characteristic reliance on long-duration cash flows and greater exposure to narrative-driven valuation shifts (Lettau & Wachter, 2007). This divergence in predictive accuracy between growth and value styles aligns with behavioral theories suggesting growth companies' valuations are more sensitive to changes in investor risk appetite and expectations about distant earnings (Campbell & Vuolteenaho, 2004).

Turning to sectoral performance, the model generates substantial forecasting gains in capital-intensive and sentiment-sensitive sectors. For example, TOPIX-17 Real Estate (0.7796), Machinery (0.7658), and Electric & Precision Instruments (0.8634) all display robust R^2_{OS} values, far exceeding what would be expected under naive assumptions. These results highlight the relevance of speculative volatility in capturing forward-looking investor behavior in sectors that are either innovation-driven or cyclically exposed. The Machinery sector's predictability reflects its dual dependence on global supply-chain sentiment and automation-driven investment cycles. The exceptional performance in Electric & Precision Instruments underscores the growing role of narrative-driven speculation in innovation-intensive industries. Meanwhile, traditionally defensive sectors such as Foods (–0.4785) and Electric Power & Gas (–0.4947) yield negative R^2_{OS} values, suggesting that the inclusion of speculative factors may provide little marginal benefit, or even introduce noise, when they are applied to

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return series governed more by fundamentals or regulated pricing structures. Similarly, the underperformance in Foods reflects the sector's well-documented resilience to sentiment shocks attributable to inelastic demand and stable cash flows. The results further suggest that the predictive utility of sentiment factors may be regime-dependent, warranting conditional application during periods of elevated market stress. Interestingly, a handful of sectors exhibit *inverse* performance relative to the benchmark, such as Financials (–0.8061) and Retail Trade (–0.8177). This implies that in certain segments, short-horizon fluctuations in speculative intensity may not align with pricing dynamics or could reflect transitory shocks not captured effectively by this model specification. Time-series plots comparing actual and predicted returns across all indices are presented in **Figure. A1** in the Appendix.

Table 4
This table reports out-of-sample performance for the SVI-based forecasting model relative to a naive benchmark across broad indices (Panel A) and sectoral TOPIX-17 ETFs (Panel B). Metrics include the root mean squared error (RMSE) of each model and the out-of-sample R^2_{OS}.

Index	SVI model's RMSE	Naive RMSE	R^2_{OS}
Panel A: Broad Market & Style Indices			
Nikkei 225	0.0424	0.0904	0.7801
TOPIX	0.0339	0.0681	0.7520
TOPIX Core 30	0.0376	0.0758	0.7531
TOPIX Mid 400	0.0348	0.0615	0.6790
TOPIX Small Market	0.0348	0.0615	0.6790
TOPIX Growth	0.0309	0.0844	0.8665
TOPIX Value	0.0438	0.0550	0.3643
Panel B: TOPIX-17 ETFs			
Banks	0.0879	0.1109	0.3716
Financials	0.0670	0.0498	-0.8061
Automobiles & Transportation	0.0821	0.1345	0.6277
IT Services	0.0435	0.0598	0.4708
Real Estate	0.0561	0.1196	0.7796
Machinery	0.0467	0.0965	0.7658
Steel & Nonferrous Metals	0.0438	0.0516	0.2802
Retail Trade	0.0387	0.0287	-0.8177
Raw Materials & Chemicals	0.0327	0.0530	0.6187
Pharmaceuticals	0.0416	0.0574	0.4742
Foods	0.0547	0.0450	-0.4785
Energy Resources	0.0522	0.0874	0.6432
Electric Power & Gas	0.0584	0.0478	-0.4947
Electric & Precision Instruments	0.0449	0.1215	0.8634
Construction & Materials	0.0506	0.0591	0.2676

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Commercial & Wholesale Trade	0.0476	0.0711	0.5521
Transportation & Logistics	0.0397	0.0467	0.2764

Trading Strategy Performance

To assess the economic relevance of speculative volatility in an applied portfolio context, we implement a long-short trading strategy based on stock-level predictive regressions using the principal components of the SVI. This strategy is benchmarked against a passive, volatility-aware alternative based on an inverse volatility-weighted portfolio. Both approaches are evaluated over the out-of-sample period.

The SVI-based long-short strategy demonstrates a notably higher cumulative return over the sample period, achieving approximately 117.8%, in stark contrast to the relatively modest 5.8% cumulative return generated by the inverse volatility strategy. On a monthly basis, the average return further emphasizes this disparity. The SVI strategy delivers an average monthly return of 0.95%, which is nearly twenty times larger than the 0.05% average monthly return recorded by the inverse volatility strategy. This substantial differential proves the greater return potential associated with the SVI-based approach. While the SVI-based strategy generates substantially higher cumulative returns than the inverse volatility benchmark, it exhibits a lower annualized Sharpe ratio of 0.37 compared to 1.58, reflecting greater return volatility inherent in the more aggressive positioning. This outcome is consistent with the theoretical expectation that strategies grounded in speculative volatility, rather than conventional risk premia, are inherently designed to exploit temporary mispricing rather than systematic compensation for risk-bearing. Speculative volatility, by construction, captures transitory deviations from fundamental values driven by investor disagreement, sentiment-driven overreaction, and divergent beliefs (Yu and Yuan, 2011; Baker and Wurgler, 2007). Therefore, it reflects the presence of noise trading and behavioral inefficiencies rather than stable, persistent risk exposures. Although these mispricing episodes can generate alpha in the form of abnormal returns, their timing and magnitude are inherently volatile, leading to elevated return dispersion. This high volatility inflates the denominator of the Sharpe ratio and may obscure the economic value of the signal when evaluated solely through standard risk-adjusted metrics. This aligns with recent findings by Han and Kumar (2013), who demonstrate that sentiment-driven strategies often yield economically meaningful returns but suffer from lower Sharpe ratios due to increased volatility and noise. Therefore, these enhanced returns come with increased volatility. The SVI strategy's standard deviation of monthly returns stands at 8.95%, significantly exceeding the mere 0.11% observed for the inverse volatility strategy. This elevated variability may imply heightened risk exposure. The hit rate metric reveals a complementary dimension of performance. The inverse volatility strategy outperforms with a superior hit rate of 70.1%, compared to 59.8% for the SVI strategy. This illustrates that while the volatility-weighted strategy sacrifices return potential, it offers more consistent performance and a significantly better risk-adjusted profile. These

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performance dynamics are consistent with the modest out-of-sample forecast accuracy observed at the aggregate level, with an RMSE of 0.0344 and an out-of-sample R^2 of 0.1451. In sum, the results suggest that speculative volatility signals, though noisy, do convey predictive information exploitable in long-short strategies.

Conclusion

This study contributes to the expanding body of empirical asset pricing literature by presenting new evidence on the predictive power of PCA-based speculative volatility index (SVI) derived from a broad array of derivatives-based sentiment and speculative-based indices returns. Our findings indicate that speculative factors, when distilled through low-dimensional latent factors, exhibit substantial predictive power for in-sample and out-of-sample contexts.

The first principal component of the SVI emerges as a consistent and statistically significant predictor of future returns across nearly all specifications. Its positive coefficients align with theoretical models that associate rising investor risk appetite with greater demand for risk assets, subsequently earning higher returns. This is consistent with behavioral asset pricing theories that emphasize the role of sentiment and belief dispersion in generating mispricing (Daniel et al., 2020; Baker and Wurgler, 2007; Gambarelli and Muzzioli, 2025). The second principal component demonstrates more selective predictive power. Its influence is strongest in innovation-intensive and growth-oriented segments of the market. The high loading of PC2 on gold-related ETNs further implies that this component may reflect episodic shifts in investor hedging demand or inflation expectations, which are more likely to influence equity pricing in macro-sensitive or defensive sectors.

The out-of-sample forecasting performance of the SVI-based model is particularly noteworthy. Across a broad range of market and sector indices, our model consistently outperforms naive historical mean benchmarks in terms of both root mean squared error (RMSE) and out-of-sample R^2. The model delivers exceptionally high R^2 values with the highest reaching 0.8665 for the TOPIX Growth index. The SVI framework offers a replicable and scalable tool for integrating sentiment risk into allocation and risk management decisions. Its interpretability, rooted in observable market activity, allows for transparent signal construction.

Future research could expand the framework in several directions involving the integration of nonlinear dimensionality reduction and time-varying factor estimation techniques to better capture the dynamic structure of speculative volatility. Advanced dynamic factor machine learning models could allow latent speculative factors to evolve flexibly over time, capturing both smooth transitions and abrupt sentiment reversals.

Appendix

Table A1

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Descriptive Statistics of Monthly Returns: Sectoral ETFs and Speculative Indices. This table reports summary statistics monthly return characteristics of two sets of indices: (i) Panel A includes 17 sectoral equity indices from the TOPIX family; (ii) Panel B shows indices representing speculative trading activity used to construct the SVI. The full sample spans September 2015 to May 2025.

Panel A: TOPIX-17 Sectoral Indices ETFs						
Index	Mean	Std Dev	Min	Max	Skew	Kurtosis
TOPIX-17 Banks ETF	0.0068	0.0676	-0.203	0.1552	-0.4843	0.4038
TOPIX-17 Financials ETF	0.0084	0.0555	-0.1623	0.1351	-0.2814	0.4535
TOPIX-17 Automobiles & Transportation ETF	0.0047	0.0616	-0.1555	0.1663	0.0774	0.1351
TOPIX-17 IT Services ETF	0.0077	0.0409	-0.1238	0.1039	-0.6448	1.3758
TOPIX-17 Real Estate ETF	0.0036	0.056	-0.1591	0.1745	0.0381	1.3994
TOPIX-17 Machinery ETF	0.009	0.06	-0.1591	0.1392	-0.4483	0.1428
TOPIX-17 Steel & Nonferrous ETF	0.005	0.0667	-0.1648	0.1638	-0.288	-0.1816
TOPIX-17 Retail Trade ETF	0.0054	0.0392	-0.1507	0.0985	-0.8054	1.8391
TOPIX-17 Raw Materials & Chemicals ETF	0.0047	0.0435	-0.1452	0.1353	-0.2733	1.2616
TOPIX-17 Pharmaceutical ETF	0.0033	0.0513	-0.155	0.1436	-0.3408	0.93
TOPIX-17 Foods ETF	0.003	0.0376	-0.1141	0.0837	-0.3865	0.1176
TOPIX-17 Energy Resources ETF	0.0073	0.07	-0.1603	0.155	-0.1927	-0.4782
TOPIX-17 Electric Power & Gas ETF	0.0002	0.0476	-0.1153	0.1295	0.131	-0.0021
TOPIX-17 Electric Precision Instruments ETF	0.0098	0.0552	-0.1592	0.1558	-0.5012	0.9889
TOPIX-17 Construction Materials ETF	0.0051	0.0451	-0.1346	0.11	-0.375	0.5857
TOPIX-17 Commercial & Wholesale Trade ETF	0.0117	0.0519	-0.0996	0.1501	0.2517	0.0275

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TOPIX-17 Transportation & Logistics ETF	0.0024	0.0506	-0.2146	0.176	-0.5217	3.6682
Panel B: Speculative Activity-Based Indices Used in SVI Construction						
Nikkei Volatility	0.0186	0.2258	-0.3714	1.3029	1.8916	7.9058
Nikkei 225 Futures	0.0072	0.0486	-0.1057	0.16	-0.1345	0.1257
Nikkei 225 Double Inverse	-0.0239	0.0902	-0.2545	0.2123	0.4357	-0.0609
Nikkei 225 Leveraged	0.0151	0.097	-0.2104	0.319	-0.1244	0.1328
JPX 400 Double Inverse	-0.0225	0.0801	-0.2094	0.2984	0.8637	1.8534
JPX 400 Simplex Bear 2x	-0.0228	0.0796	-0.2062	0.2567	0.729	1.1265
JPX 400 Futures	0.0061	0.0429	-0.105	0.1282	-0.3492	0.6053
JPX 400 Double Inverse 2x	-0.0162	0.0809	-0.2136	0.2204	0.6451	0.747
Nikkei 225 Double Inverse ETF	-0.0237	0.0897	-0.2542	0.2104	0.457	-0.0028
JPX 400 Inverse 1x	-0.0074	0.041	-0.1119	0.1068	0.5571	0.6629
NN Gold Double Bull ETN	0.0218	0.0694	-0.1371	0.2751	0.7559	1.6339
JPX 400 Leveraged 2x	0.011	0.0855	-0.1991	0.257	-0.2749	0.5388
Nikkei 225 Inverse	-0.0113	0.0464	-0.1353	0.1045	0.3832	-0.0917
Nikkei 225 Bear 1x	-0.0112	0.0462	-0.1351	0.1079	0.38	-0.0224
Nikkei 225 Bear 2x	-0.0233	0.0905	-0.2534	0.2129	0.4557	-0.0398
Nikkei 225 Bull 2x	0.0152	0.0971	-0.2085	0.3205	-0.1207	0.1391
TOPIX Mini Futures	0.006	0.0423	-0.1069	0.116	-0.4692	0.6007
TOPIX Daiwa Leveraged 2x	0.0135	0.0845	-0.2045	0.2287	-0.4058	0.4021
TOPIX Daiwa Inverse 2x	-0.022	0.0794	-0.1945	0.228	0.7731	0.934

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TOPIX Leveraged 2x	0.0108	0.0841	-0.2041	0.2315	-0.391	0.4803
TOPIX Double Inverse	-0.016	0.0801	-0.1965	0.2284	0.7518	0.8867
TOPIX Inverse 1x	-0.0073	0.0406	-0.1024	0.1105	0.6651	0.7573
TOPIX Core 30 Futures	0.0065	0.0447	-0.1032	0.117	-0.2727	0.1951
TOPIX Daiwa Inverse 1x	-0.0104	0.0408	-0.1057	0.1079	0.6515	0.7836
TOPIX Bull 2x	0.0136	0.0846	-0.202	0.225	-0.4115	0.4268
TOPIX Bear 2x	-0.0219	0.0799	-0.1962	0.2229	0.7343	0.8017
TOPIX Bear 1x	-0.0105	0.0401	-0.1028	0.1086	0.6526	0.7173

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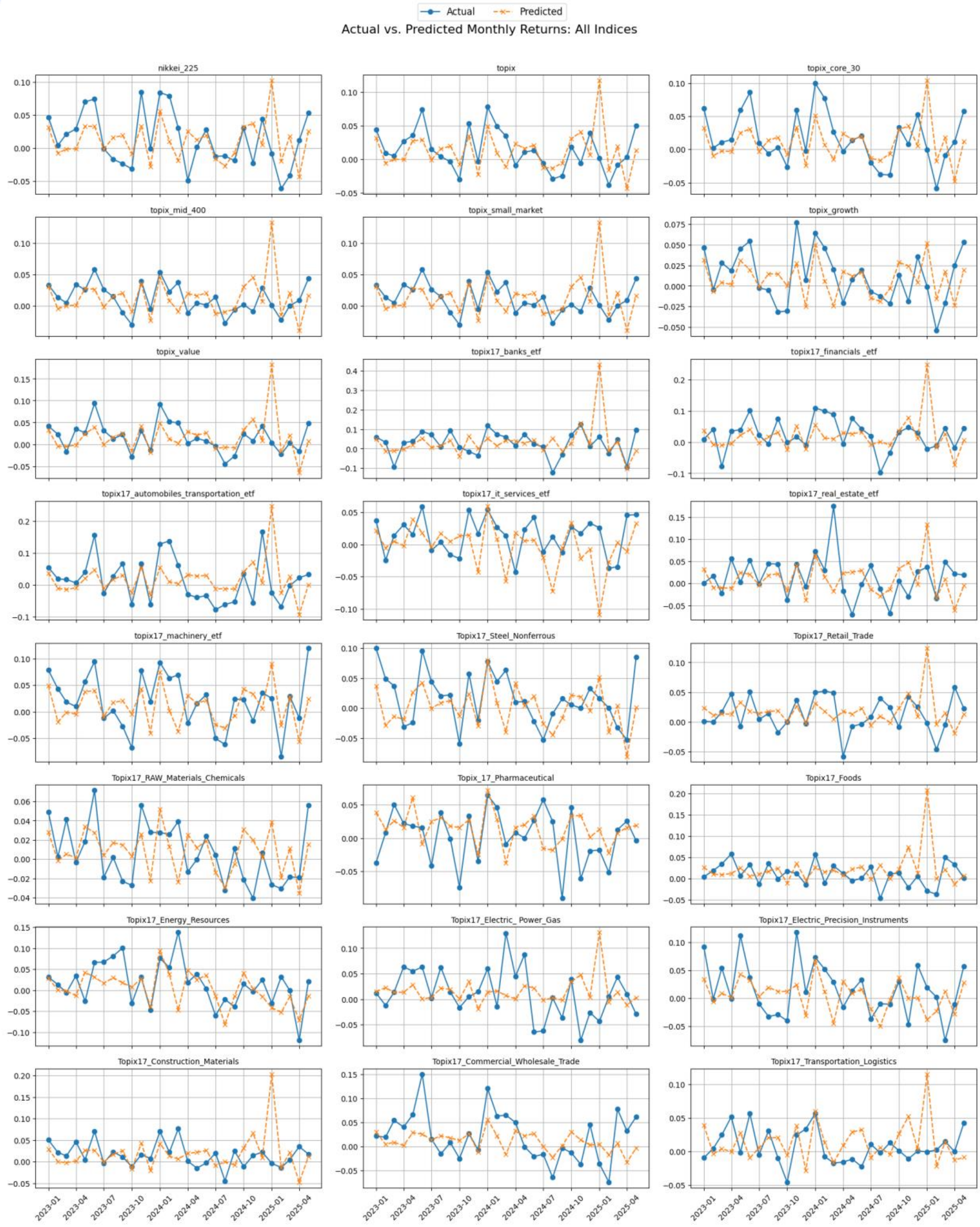

Figure.A1

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Plots of actual vs. predicted monthly returns for 24 equity indices. This figure presents time-series plots comparing the actual monthly returns with the out-of-sample predicted values generated by the SVI-based regression models across all 24 Japanese equity indices. Each subplot corresponds to one index.

References

Altieri, M., & Schnitzler, J. (2023). Quarterly investment spikes, stock returns, and the investment factor. *Journal of Financial Markets*, *66*, 100835. https://doi.org/10.1016/j.finmar.2023.100835

Baker, M. P., & Wurgler, J. A. (2007). Investor Sentiment in the Stock Market. Journal of Economic Perspectives, 21(2), 129–151. https://doi.org/10.2139/ssrn.962706

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). Chapter 21 the financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, 1341–1393. https://doi.org/10.1016/s1574-0048(99)10034-x

Bianchi, D., Büchner, M., Hoogteijling, T., & Tamoni, A. (2020). Corrigendum: Bond Risk Premiums with machine learning. *The Review of Financial Studies*, *34*(2), 1090–1103. https://doi.org/10.1093/rfs/hhaa098

Calice, G., & Lin, M.-T. (2021). Exploring risk premium factors for country equity returns. Journal of Empirical Finance, 63, 294–322. https://doi.org/10.1016/j.jempfin.2021.07.003

Campbell, J. Y., & Thompson, S. B. (2007). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*(4), 1509–1531. https://doi.org/10.1093/rfs/hhm055

Campbell, J. Y., & Vuolteenaho, T. (2004). Bad beta, good beta. *American Economic Review*, *94*(5), 1249–1275. https://doi.org/10.1257/0002828043052240

Chen, H. (2025). Diversification driven demand for large stock. Journal of Financial Economics, 172, 104109. https://doi.org/10.1016/j.jfineco.2025.104109

Chen, J., Tian, G., & Yang, F. (2020). Individual investors' propensity to speculate and A-share premiums in China's A-shares and H-shares. Emerging Markets Review, 100689. https://doi.org/10.1016/j.ememar.2020.100689

Chen, Z., Li, P., Wang, Z., & Zhang, B. (2024). Leveraged trading and stock returns: Evidence from international stock markets. *Journal of Financial Markets*, *69*, 100907. https://doi.org/10.1016/j.finmar.2024.100907

Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short- and Long-Horizon Behavioral Factors. The Review of Financial Studies, 33(4), 1673–1736. https://doi.org/10.1093/rfs/hhz069

Deschamps, B., Fei, T., Jiang, Y., & Liu, X. (2025). Uncertainty and cross-sectional stock returns: Evidence from China. *Journal of Banking & Finance*, *171*, 107374. https://doi.org/10.1016/j.jbankfin.2024.107374

Dichev, I. D., & Zheng, X. (2024a). The volatility of stock investor returns. *Journal of Financial Markets*, *70*, 100927. https://doi.org/10.1016/j.finmar.2024.100927

Du, K., Fu, Y., Qin, Z., & Zhang, S. (2020). Regime shift, speculation, and stock price. *Research in International Business and Finance*, *52*, 101181. https://doi.org/10.1016/j.ribaf.2020.101181

Fonseka, M., Ma, Y., Bei, C., & Samarakoon, L. P. (2025). The effect of margin trading, stock index futures, and firm characteristics on stock price synchronicity: Evidence from China. Journal of International Financial Markets, Institutions and Money, 102, 102165. https://doi.org/10.1016/j.intfin.2025.102165

Galindo Gil, H., & Lazo-Paz, R. (2025). An ETF-based measure of stock price fragility. *Journal of Financial Markets*, *72*, 100946. https://doi.org/10.1016/j.finmar.2024.100946

Gambarelli, L., & Muzzioli, S. (2025). News sentiment indicators and the cross-section of stock returns in the European Stock Market. *International Review of Economics & Finance*, *101*, 104207. https://doi.org/10.1016/j.iref.2025.104207

Ghazi, S., Schneider, M., & Dorobiala, Z. (2024). Speculative and non-speculative equity premia. Economics Letters, 236, 111619–111619. https://doi.org/10.1016/j.econlet.2024.111619

Giglio, S., & Xiu, D. (2021). Asset pricing with omitted factors. *Journal of Political Economy*, *129*(7), 1947–1990. https://doi.org/10.1086/714090

Hamao, Y. (2018). Japanese Financial Market Research: A Survey. Asia-Pacific Journal of Financial Studies, 47(3), 361–380. https://doi.org/10.1111/ajfs.12214

Han, B., & Kumar, A. (2013). Speculative retail trading and asset prices. *Journal of Financial and Quantitative Analysis*, *48*(2), 377–404. https://doi.org/10.1017/s0022109013000100

Han, Y., Hu, O., & Huang, Z. (2023). A tale of idiosyncratic volatility and illiquidity shocks: Their correlation and effects on stock returns. *International Review of Financial Analysis*, *86*, 102517. https://doi.org/10.1016/j.irfa.2023.102517

Huang, D., Jiang, F., Tu, J., & Zhou, G. (2014a). Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, *28*(3), 791–837. https://doi.org/10.1093/rfs/hhu080

Karolyi, G. A., & Nieuwerburgh, S. (2020). New methods for the cross-section of returns. The Review of Financial Studies, 33(5), 1879–1890. https://doi.org/10.1093/rfs/hhaa019

Kelly, B. T., Pruitt, S., & Su, Y. (2019a). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics*, *134*(3), 501–524. https://doi.org/10.1016/j.jfineco.2019.05.001

Lau, W., & Yip, T.-M. (2023). The effect of different periods of unconventional monetary policies on Japanese financial markets. Journal of Financial Economic Policy, 15(3), 263–279. https://doi.org/10.1108/jfep-11-2022-0275

LETTAU, M., & WACHTER, J. A. (2007). Why is long-horizon equity less risky? A duration-based explanation of the value premium. *The Journal of Finance*, *62*(1), 55–92. https://doi.org/10.1111/j.1540-6261.2007.01201.x

Volume. 4 Issue No. 3 (2025)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

Li, L., Cheng, T. Y., Li, Z., & Huang, Y. (2024). Price duration, returns, and volatility estimation: Evidence from China's stock index futures market. *Borsa Istanbul Review*, *24*, 60–70. https://doi.org/10.1016/j.bir.2024.06.008

Liu, Y., & Zhu, Y. (2025b). Good idiosyncratic volatility, bad idiosyncratic volatility, and the cross-section of Stock returns. *Journal of Banking & Finance*, *170*, 107343. https://doi.org/10.1016/j.jbankfin.2024.107343

Nagel, S. (2005). Short sales, institutional investors and the cross-section of Stock returns. *Journal of Financial Economics*, *78*(2), 277–309. https://doi.org/10.1016/j.jfineco.2004.08.008

Rapach, D. E., Ringgenberg, M. C., & Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, *121*(1), 46–65. https://doi.org/10.1016/j.jfineco.2016.03.004

Shi, Z. (2019). Time-varying ambiguity, credit spreads, and the levered equity premium. Journal of Financial Economics, 134(3), 617–646. https://doi.org/10.1016/j.jfineco.2019.04.013

Soebhag, A. (2023). Option gamma and stock returns. *Journal of Empirical Finance*, *74*, 101442. https://doi.org/10.1016/j.jempfin.2023.101442

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing Factors. The Review of Financial Studies, 30(4), 1270–1315. https://doi.org/10.1093/rfs/hhw107

Stock, J. H., & Watson, M. W. (2002). Forecasting using principal components from a large number of predictors. Journal of the American Statistical Association, 97(460), 1167–1179. https://doi.org/10.1198/016214502388618960

Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance*, *73*, 147–164. https://doi.org/10.1016/j.jbankfin.2016.09.010

Umlandt, D. (2023). Score-driven asset pricing: Predicting time-varying risk premia based on cross-sectional model performance. Journal of Econometrics, 237(2), 105470. https://doi.org/10.1016/j.jeconom.2023.05.007

Wang, C., Li, T., Sensoy, A., Cheng, F., & Fang, Z. (2024). Economic policy uncertainty and options market participation: Hedge or speculation? *Borsa Istanbul Review*, *24*, 50–59. https://doi.org/10.1016/j.bir.2024.04.006

Wang, H., Nguyen, D. K., Xiong, X., & Dai, P.-F. (2022). Portfolio choice under loss aversion and diminishing sensitivity: A theoretical extension. *Annals of Operations Research*, *347*(1), 69–85. https://doi.org/10.1007/s10479-022-05081-9

Wang, S.-F. (2023a). Return predictability of short-selling and financial distress firms: Evidence from Korean Stock Market. *Pacific-Basin Finance Journal*, *82*, 102198. https://doi.org/10.1016/j.pacfin.2023.102198

Wang, Shu, Zhou, B., & Gao, T. (2023). Speculation or actual demand? the return spillover effect between stock and commodity markets. *Journal of Commodity Markets*, *29*, 100308. https://doi.org/10.1016/j.jcomm.2022.100308

Xiang, Y., & Borjigin, S. (2024). Hedge funds network and stock price crash risk. The North American Journal of Economics and Finance, 75, 102288. https://doi.org/10.1016/j.najef.2024.102288

Volume. 4 Issue No. 3 (2025)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Xu, K., Xiong, X., & Li, X. (2021). The maturity effect of stock index futures: Speculation or carry arbitrage? *Research in International Business and Finance*, *58*, 101473. https://doi.org/10.1016/j.ribaf.2021.101473

Yang, H., & Ferrer, R. (2023). Explosive behavior in the Chinese stock market: A sectoral analysis. Pacific-Basin Finance Journal, 81, 102104–102104. https://doi.org/10.1016/j.pacfin.2023.102104

Yu, B., Dong, L., Qin, Z., & Lam, K. S. K. (2025). What is the best composite liquidity proxy for explaining stock returns? evidence from the Chinese Stock Market. Pacific Basin Finance Journal, 91, 102686. https://doi.org/10.1016/j.pacfin.2025.102686

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean–variance relation. Journal of Financial Economics, 100(2), 367–381. https://doi.org/10.1016/j.jfineco.2010.10.01

Zhang, T., Li, J., & Xu, Z. (2024). Speculative trading, stock returns and asset pricing anomalies. *Emerging Markets Review*, *61*, 101165. https://doi.org/10.1016/j.ememar.2024.101165

Zuo, J., Qiu, B., Zhu, G., & Lei, G. (2023). Local speculative culture and stock price crash risk. *Research in International Business and Finance*, *64*, 101851. https://doi.org/10.1016/j.ribaf.2022.101851

Zuo, X., & Jiang, A. (Andrew). (2025a). Symbolic modeling for Financial Asset Pricing. The Journal of Finance and Data Science, 11, 100150. https://doi.org/10.1016/j.jfds.2025.100150