

Article

Forecasting Taiwan Stock Return Using VIX and Volatility

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Abstract

This study investigates whether volatility-related variables and traditional financial predictors can explain and forecast Taiwan stock returns. Using the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and eight major Taiwan industry indices, we examine the predictive ability of long-term adjusted volatility (LVadj), short-term volatility (SV), the volatility index (VIX), idiosyncratic volatility (IVOL), the earnings-to-price ratio (EP), the book-to-market ratio (BM), and the turnover ratio (TURN). The sample period spans from January 2007 to December 2025. Univariate and bivariate predictive regression models are estimated using ordinary least squares (OLS) and exponentially weighted least squares (EWLS). The empirical results show that SV exhibits the strongest in-sample explanatory power for TAIEX returns, whereas TURN plays a more important role in explaining industry-level returns. Out-of-sample forecasting performance varies considerably across industries. For TAIEX returns, the combination of LVadj and TURN provides the strongest forecasting performance, while models incorporating SV and VIX perform relatively well in several industry sectors. Overall, the results suggest that volatility-related variables provide useful predictive information under certain model specifications and industry sectors, with EWLS generally outperforming conventional OLS estimation.

Keywords: Taiwan stock market; VIX; long-term adjusted volatility; idiosyncratic volatility; stock return predictability

1. Introduction

Forecasting stock returns has long been one of the central issues in empirical finance and asset pricing. Since stock prices reflect expectations regarding future cash flows, discount rates, and market uncertainty, identifying variables that contain predictive information for future returns is essential for portfolio management, asset allocation, and risk management. Among the numerous predictors examined in the literature, volatility-related variables have attracted considerable attention because volatility is closely associated with uncertainty, investor sentiment, and time-varying risk premia.

Volatility is commonly defined as the variability of asset prices and is typically measured by the standard deviation of stock returns (Hull, 2022). Under the mean–variance framework proposed by Markowitz (1952), investors require compensation for bearing greater risk. Sharpe (1964), Lintner (1965), and Mossin (1966) subsequently developed the Capital Asset Pricing Model (CAPM), suggesting that expected excess returns are determined by systematic risk. Fama and French (1992, 1993) further extend this framework by introducing the Fama–French three-factor model (FF3), incorporating market, size, and



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book-to-market factors to explain cross-sectional stock returns. Together, these theories provide the theoretical foundation for examining whether volatility-related variables contain predictive information about future stock returns.

However, the empirical relationship between volatility and stock returns remains inconclusive. Some studies suggest that higher volatility is associated with higher expected returns because investors require additional compensation for bearing uncertainty. For example, [Goyal and Santa-Clara \(2003\)](#) document a positive relation between aggregate stock variance and expected market returns, while [Fu \(2009\)](#) reports a positive relation between conditional idiosyncratic volatility and future returns. In contrast, [Ang et al. \(2006, 2009\)](#) show that stocks with high idiosyncratic volatility tend to earn significantly lower future returns, giving rise to the well-known idiosyncratic volatility (IVOL) puzzle. [Bali and Cakici \(2008\)](#) further argue that the IVOL effect is sensitive to empirical methodology and portfolio construction. Overall, the existing evidence suggests that the relationship between stock returns and volatility is time-varying and depends on market conditions and investor sentiment.

The volatility index (VIX) provides another important perspective for understanding market uncertainty and expected stock returns. Originally introduced by the Chicago Board Options Exchange (CBOE) based on [Whaley \(1993\)](#), the VIX measures market expectations of future volatility implied by option prices and is widely regarded as a “fear index.” [Fleming et al. \(1995\)](#) show that implied volatility contains valuable information for forecasting future market volatility, while [Bekaert et al. \(2013\)](#) argue that the VIX reflects both economic uncertainty and investor risk aversion, particularly during financial crises.

More recent studies continue to demonstrate that volatility-related measures contain substantial predictive information for future stock returns. [Detzel et al. \(2023\)](#) revisit the IVOL anomaly and show that volatility-related risks remain significantly priced in the cross-section of stock returns. [Chen et al. \(2022\)](#) further demonstrate that short-term and long-term volatility play different roles in predicting stock returns across investment horizons. More recent studies extend volatility forecasting toward more sophisticated frameworks. [Zhang et al. \(2024\)](#) propose an industry volatility concentration index that significantly predicts aggregate stock returns, while [Dai et al. \(2025\)](#) introduce a VIX-based indicator with strong in-sample and out-of-sample forecasting ability. Other studies emphasize asymmetry and nonlinear volatility dynamics. [Liu and Zhu \(2025\)](#) decompose idiosyncratic volatility into “good” and “bad” components and document that idiosyncratic asymmetry is negatively associated with future stock returns. [Zhao et al. \(2026\)](#) further identify nonlinear causality between volatility and returns across international markets.

Another important development concerns long-run volatility measures. [Qadan et al. \(2019\)](#) show that the relationship between idiosyncratic volatility and future stock returns depends on changes in the VIX. Specifically, when the VIX increases, the relationship becomes negative, whereas declining VIX levels are associated with a positive relationship between IVOL and future returns. [Qiu et al. \(2023\)](#) further introduce long-term adjusted volatility (LVadj), which isolates persistent long-run volatility information by removing short-term volatility noise. Their results indicate that LVadj possesses significant predictive power for future stock returns in both in-sample and out-of-sample analyses.

In addition to volatility-related variables, traditional valuation and liquidity indicators may also contain predictive information for future stock returns. Therefore, this study incorporates the earnings-to-price ratio (EP), book-to-market ratio (BM), and turnover ratio (TURN) as additional predictive variables. [Lamont \(1998\)](#) and [Lam \(2002\)](#) show that earnings-related variables are significantly associated with future stock returns. [Fama and French \(1992\)](#) demonstrate that the book-to-market ratio explains cross-sectional stock return variation, while [Pontiff and Schall \(1998\)](#) argue that BM contains predictive infor-

mation regarding future market returns. Meanwhile, the turnover ratio is widely used as a proxy for liquidity and investor trading activity. Rouwenhorst (1999) and Dey (2005) document a positive relationship between turnover and stock returns in emerging markets.

Although stock return predictability has been extensively examined in developed markets, evidence from Taiwan and other emerging markets remains relatively limited. For Taiwan, Chang et al. (2009) show that information embedded in the TAIEX options market contains predictive information about future stock returns. In the broader volatility literature, Ang et al. (2006, 2009), Qadan et al. (2019), Qiu et al. (2023), and Huang et al. (2023) document that volatility-related variables, such as idiosyncratic volatility, market uncertainty, and long-term volatility, contain useful information for forecasting future stock returns. Meanwhile, traditional return-predictability studies focus on valuation and trading-related variables, including the earnings-to-price ratio, book-to-market ratio, and turnover ratio (Lamont, 1998; Pontiff & Schall, 1998; Welch & Goyal, 2008). However, most existing studies focus on a single predictor or a single class of predictors and primarily focus on aggregate market returns. Moreover, relatively little evidence is available regarding whether the predictive ability of these variables differs across industries in emerging markets such as Taiwan.

To address these gaps, this study jointly examines four volatility-related variables (LVadj, SV, VIX, and IVOL) and three traditional financial predictors (EP, BM, and TURN) within a unified forecasting framework. In addition to the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX), this study also investigates eight major Taiwan industry indices, allowing us to explore sectoral heterogeneity in return predictability. Furthermore, both in-sample explanatory power and out-of-sample forecasting performance are evaluated. By jointly examining multiple volatility measures, traditional financial predictors, and industry-level heterogeneity, this study provides a comprehensive assessment of stock return predictability in the Taiwanese market and contributes new evidence from an important emerging-market economy.

This study makes several contributions to the return predictability literature. First, it extends the volatility forecasting literature to Taiwan's stock market, providing new evidence from an export-oriented emerging market with a globally important technology sector. Second, this study jointly examines multiple volatility-related predictors together with traditional valuation and liquidity variables within a unified empirical framework. Third, unlike most prior studies focusing solely on aggregate market returns, this study additionally investigates industry-level stock returns, allowing a more detailed examination of heterogeneous forecasting performance across industries. Fourth, this study evaluates both in-sample explanatory power and out-of-sample forecasting performance using rolling-window estimation, thereby providing more comprehensive evidence regarding the economic value of volatility-related predictors.

Methodologically, this study adopts the predictive regression framework widely used in the return forecasting literature. Idiosyncratic volatility is estimated using residual volatility derived from the Fama–French three-factor model following Ang et al. (2006) and Qadan et al. (2019). Long-term adjusted volatility is constructed following Qiu et al. (2023). Both univariate and bivariate predictive regressions are estimated to examine the individual and joint predictive ability of the explanatory variables. For in-sample analysis, adjusted R^2 is used to evaluate explanatory power. For out-of-sample forecasting, rolling-window estimation is implemented, and forecasting performance is evaluated using mean absolute error (MAE), root mean squared error (RMSE), and adjusted mean squared prediction error (MSPE_{adj}) suggested by Clark and West (2007). Both ordinary least squares (OLS) and exponentially weighted least squares (EWLS) methods are employed to compare forecasting performance under different weighting schemes.

The remainder of this paper is organized as follows. Section 2 introduces the research methodology, including volatility measurement, predictive regression models, and forecasting evaluation criteria. Section 3 describes the data and variable construction. Section 4 presents the in-sample empirical results. Section 5 reports the out-of-sample forecasting results. Section 6 concludes.

2. Methodology

This study investigates whether volatility-related variables and traditional financial predictors can explain and forecast Taiwan stock returns. Following the existing return predictability literature, we employ univariate and bivariate predictive regression models and apply the Sharpe ratio truncation to prevent unrealistic return forecasts. The primary explanatory variables include long-term adjusted volatility (LVadj), short-term volatility (SV), the volatility index (VIX), and idiosyncratic volatility (IVOL). In addition, the turnover ratio (TURN), earnings-to-price ratio (EP), and book-to-market ratio (BM) are included as traditional financial predictors. This section is organized as follows. Section 2.1 introduces the volatility measures, Section 2.2 presents the regression and forecasting models, and Section 2.3 describes the evaluation criteria for in-sample explanatory power and out-of-sample forecasting performance.

2.1. Volatility Measurement

Previous studies have proposed various measures of asset return volatility. In option pricing theory, the Black–Scholes–Merton model typically defines volatility as the standard deviation of asset returns. Because financial markets operate continuously, asset returns and their associated volatility measures can, in principle, be observed over arbitrarily short time intervals. Accordingly, many studies assume that logarithmic asset prices follow a continuous diffusion process (Andersen et al., 2001; Kambouroudi et al., 2021):

$$dp_t = \mu_t dt + \sigma_t dW_t \quad (1)$$

where μ_t represents the drift component, W_t denotes a standard Brownian motion, and σ_t represents the instantaneous volatility process. Following Kambouroudi et al. (2021), the integrated variance (IV) of the logarithmic price process is defined as

$$IV_t = \int_0^t \sigma_s^2 ds \quad (2)$$

where σ_s^2 denotes the instantaneous variance at time s . Because expected returns over very short intervals are typically close to zero, the integrated variance can be approximated by the integrated squared returns:

$$IV_t = \int_0^t \sigma_s^2 ds \approx \int_0^t r_s^2 ds \quad (3)$$

Accordingly, Andersen et al. (2001) show that realized volatility (RV) can be estimated by summing squared intraday returns:

$$RV_t = \sum_{i=1}^m r_{t,i}^2 \quad (4)$$

where $r_{t,i}$ denotes the i -th intraday return on day t , and m is the number of intraday observations within day t . As the sampling frequency increases, realized volatility converges to the integrated variance.

Following Qiu et al. (2023), long-term adjusted volatility (LVadj) is constructed to isolate persistent long-term volatility while removing short-term volatility noise. LVadj is defined as

$$LV_{adj_t} = LV_t - \beta_t \cdot SV_t \quad (5)$$

where LV_t denotes long-term volatility, SV_t represents short-term volatility, and β_t is the regression coefficient estimated from the relation between long-term and short-term volatility. Long-term volatility is measured as the standard deviation of monthly stock returns over the previous 24 months. Short-term volatility is defined as the annualized realized monthly volatility constructed from daily stock returns, following Welch and Goyal (2008):

$$SV_t = \sqrt{12 \times SVAR_t} \text{ and } SVAR_t = \sum_{d=1}^m r_{d,t}^2 \quad (6)$$

where $SVAR_t$ denotes the monthly realized variance, and m is the number of trading days in month t .

Unlike Qiu et al. (2023), this study estimates the coefficient β using ordinary least squares (OLS) within a rolling-window framework:

$$LV_t = \alpha + \beta_t \cdot SV_t + \varepsilon_t \quad (7)$$

Given an H -month rolling window, the OLS estimate of β_t is

$$\hat{\beta}_t = \frac{\sum_{i=t-H+1}^t (SV_i - \overline{SV}_t)(LV_i - \overline{LV}_t)}{\sum_{i=t-H+1}^t (SV_i - \overline{SV}_t)^2} \quad (8)$$

where $\overline{SV}_t = \frac{1}{H} \sum_{i=t-H+1}^t SV_i$ and $\overline{LV}_t = \frac{1}{H} \sum_{i=t-H+1}^t LV_i$ denote the average values of SV and LV, respectively, over the rolling window from month $t - H + 1$ to month t . This specification differs slightly from that of Qiu et al. (2023), who compute the rolling-window averages using observations from month $t - H$ to month $t - 1$. Because this study employs a relatively long rolling window ($H = 60$ months), the resulting estimates of β_t are expected to be very similar to those reported by Qiu et al. (2023). Nevertheless, we argue that both SV_t and LV_t are observable at time t and should therefore be included when estimating β_t . Accordingly, this study adopts the standard OLS estimator based on all observations available through month t . Because the relationship between long-term and short-term volatility may evolve over time, a rolling-window estimation procedure is employed to allow the coefficient β_t to vary dynamically.

To measure idiosyncratic volatility (IVOL), this study follows Ang et al. (2006) and Qadan et al. (2019) by estimating IVOL as the residual volatility from the Fama–French three-factor model:

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \text{ and } IVOL = \sqrt{\text{var}(\varepsilon_t^i)} \quad (9)$$

where r_t^i denotes the excess return of stock i , MKT_t is the market risk premium, SMB_t represents the size factor, and HML_t denotes the value factor. In this study, the market excess return is proxied by the excess return on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). The SMB factor is constructed as the return differential between small-cap and large-cap firms, whereas the HML factor is defined as the return differential between high and low book-to-market firms in Taiwan's stock market. Finally, idiosyncratic volatility is measured as the standard deviation of the residual term, ε_t^i .

Idiosyncratic volatility is estimated as the standard deviation of the residuals from the Fama–French three-factor model, following Ang et al. (2006) and Qadan et al. (2019). Although the Fama and French (2015) five-factor (FF5) model has gained increasing pop-

ularity, the FF3 specification is adopted in this study to maintain consistency with the dominant IVOL literature and facilitate comparisons with prior studies. Moreover, the profitability and investment factors in the FF5 model are less standardized in the Taiwanese market. Because the objective of this study is to obtain a measure of residual volatility rather than to compare alternative asset pricing models, the FF3 model provides a parsimonious and widely accepted framework for estimating IVOL.

2.2. Predictive Regression Models

The primary objective of this study is to examine whether volatility-related variables and traditional financial predictors can explain and forecast Taiwan stock returns. Following the existing return predictability literature, the primary explanatory variables include long-term adjusted volatility (LVadj), short-term volatility (SV), the volatility index (VIX), and idiosyncratic volatility (IVOL). In addition, the earnings-to-price ratio (EP), book-to-market ratio (BM), and turnover ratio (TURN) are included as traditional financial predictors. The turnover ratio is calculated as monthly trading volume divided by the number of shares outstanding. All predictor variables, including EP, BM, TURN, SV, LVadj, VIX, and IVOL, are measured at the end of month t and are used to forecast stock returns in month $t + 1$. Accordingly, the forecasting framework relies exclusively on information available at the end of month t , thereby avoiding look-ahead bias.

For convenience, the seven explanatory variables are denoted by $x_{1,t}$ to $x_{7,t}$, corresponding to LVadj, EP, BM, TURN, SV, VIX, and IVOL, respectively. Following the return predictability literature, this study focuses on univariate and bivariate predictive regressions to maintain model parsimony, economic interpretability, and forecasting robustness. Rather than identifying a statistically optimal forecasting model, the primary objective is to compare the predictive ability of volatility-related variables and traditional financial predictors within a parsimonious and economically meaningful framework. Many return predictability studies adopt univariate and bivariate predictive regressions to mitigate estimation error and overfitting associated with highly parameterized models, particularly when the sample size is limited (e.g., Welch & Goyal, 2008; Qiu et al., 2023). Because the out-of-sample period in this study comprises only 168 monthly observations, including a large number of predictors simultaneously would substantially increase parameter uncertainty and reduce forecasting stability. Accordingly, parsimonious model specifications are employed to facilitate transparent comparisons of the predictive ability of alternative forecasting variables while minimizing the risk of overfitting. Future research may explore alternative model-selection approaches, such as information criteria and cross-validation techniques, to identify optimal forecasting specifications.

For the TAIEX, the in-sample regression models are specified as follows:

$$\begin{cases} \text{M0:} & r_{m,t} = \alpha + \varepsilon_{m,t}, \varepsilon_{m,t} \sim N(0, \sigma^2) \\ \text{Mj:} & r_{m,t} = \alpha + \beta_1 \cdot x_{j,t} + \varepsilon_{m,t} \\ \text{Mjk:} & r_{m,t} = \alpha + \beta_1 \cdot x_{j,t} + \beta_2 \cdot x_{k,t} + \varepsilon_{m,t} \end{cases} \quad (10)$$

where M0 denotes the benchmark random walk model, Mj denotes a univariate predictive regression model with explanatory variable $x_{j,t}$, and Mjk denotes a bivariate predictive regression model with explanatory variables $x_{j,t}$ and $x_{k,t}$. The coefficients β_1 and β_2 measure the marginal predictive effects of the corresponding explanatory variables on future stock returns.

For out-of-sample forecasting, the predictor variables observed at the end of month t are used to forecast stock returns in month $t + 1$. The out-of-sample predictive regression model for the TAIEX is specified as follows:

$$\begin{cases} M0: & r_{m,t+1} = \alpha + \varepsilon_{m,t+1}, \varepsilon_{m,t+1} \sim N(0, \sigma^2) \\ Mj: & r_{m,t+1} = \alpha + \beta_1 \cdot x_{j,t} + \varepsilon_{m,t+1} \\ Mjk: & r_{m,t+1} = \alpha + \beta_1 \cdot x_{j,t} + \beta_2 \cdot x_{k,t} + \varepsilon_{m,t+1} \end{cases} \quad (11)$$

In addition to the aggregate market index, this study also examines the eight major Taiwan industry indices. Because stock returns may differ systematically across industries owing to unobserved, time-invariant industry characteristics, a panel data regression model with industry-specific fixed effects is employed for the in-sample analysis. Furthermore, as in the TAIEX specifications, each regression model includes either one or two explanatory variables to evaluate the explanatory power of alternative predictor combinations. To account for unobserved heterogeneity across industries, the intercept term is decomposed into a common intercept and an industry-specific fixed effect. Accordingly, the in-sample panel data regression model with industry-specific fixed effects is specified as follows:

$$\begin{cases} M0: & r_{i,t} = \alpha + \mu_i + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, \sigma^2) \\ Mj: & r_{i,t} = \alpha + \mu_i + \beta_1 \cdot x_{i,j,t} + \varepsilon_{i,t} \\ Mjk: & r_{i,t} = \alpha + \mu_i + \beta_1 \cdot x_{i,j,t} + \beta_2 \cdot x_{i,k,t} + \varepsilon_{i,t} \end{cases} \quad (12)$$

where α is the common intercept for all industries, μ_i denotes the industry-specific fixed effect that captures unobserved, time-invariant characteristics of industry i , $x_{i,j,t}$ represents the j -th explanatory variable for industry i at time t , and $\varepsilon_{i,t}$ is the error term.

The in-sample regression analysis in Equation (12) focuses primarily on evaluating the overall explanatory power of the predictors for stock returns while controlling for industry-specific fixed effects. Accordingly, the objective is not to identify differences in coefficient estimates across industries. However, because the predictive relationships may vary across industries, separate forecasting models are estimated for each industry to improve the accuracy of industry-level return forecasts. Accordingly, the out-of-sample forecasting models for the eight major Taiwan industry indices are specified as follows:

$$\begin{cases} M0: & r_{i,t+1} = \alpha_i + \varepsilon_{i,t+1}, \varepsilon_{i,t+1} \sim N(0, \sigma^2) \\ Mj: & r_{i,t+1} = \alpha_i + \beta_{i1} \cdot x_{i,j,t} + \varepsilon_{i,t+1} \\ Mjk: & r_{i,t+1} = \alpha_i + \beta_{i1} \cdot x_{i,j,t} + \beta_{i2} \cdot x_{i,k,t} + \varepsilon_{i,t+1} \end{cases} \quad (13)$$

where M0 denotes the benchmark random walk model without explanatory variables, Mj denotes a univariate predictive regression model, and Mjk denotes a bivariate predictive regression model estimated separately for each industry.

To avoid generating unrealistic return forecasts, this study adopts the Sharpe ratio truncation approach proposed by [Pettenuzzo et al. \(2014\)](#) and [Qiu et al. \(2023\)](#). The constrained forecast return is defined as follows:

$$\hat{r}_{constrained,i,t} = \begin{cases} 0 & \text{if } \frac{\sqrt{12}\hat{r}_{i,t+1}}{\hat{\sigma}_t} \leq 0 \\ \hat{r}_{i,t+1} & \text{if } 0 < \frac{\sqrt{12}\hat{r}_{i,t+1}}{\hat{\sigma}_t} < 1 \\ \frac{\hat{\sigma}_t}{\sqrt{12}} & \text{if } \frac{\sqrt{12}\hat{r}_{i,t+1}}{\hat{\sigma}_t} \geq 1 \end{cases} \quad (14)$$

where $\hat{r}_{i,t}$ denotes the unconstrained one-month-ahead forecast return, and $\hat{\sigma}_t$ is the un-weighted standard deviation of stock returns over the previous 60 months. The lower

bound is set to zero because investors generally avoid assets with negative expected returns, whereas the upper bound reflects the empirical observation that the Sharpe ratio of an unleveraged market portfolio rarely exceeds one. For both the OLS and EWLS forecasting models, the same truncation procedure is applied. Consequently, differences in forecasting performance between the two estimation methods arise solely from the estimation procedure rather than from differences in the truncation mechanism.

For out-of-sample forecasting, a rolling-window estimation procedure with a 60-month estimation window is employed to generate one-month-ahead return forecasts. Specifically, all predictor variables at time t are constructed exclusively from information available no later than the end of month t , while the forecasted return corresponds to month $t + 1$. Accordingly, the forecasting framework relies solely on information available at the forecast origin, thereby avoiding look-ahead bias. In addition to ordinary least squares (OLS), this study employs exponentially weighted least squares (EWLS) following [Hollstein et al. \(2020\)](#). Compared with OLS, EWLS assigns greater weights to more recent observations, allowing the forecasting model to adapt more quickly to changing market conditions. The EWLS weighting scheme is defined as follows:

$$W_{\tau} = 2^{-0.5(t-\tau)/H} \quad (15)$$

where H denotes the length of the rolling estimation window. Under this weighting scheme, the oldest observation within the rolling window receives approximately one-half the weight assigned to the most recent observation.

2.3. In-Sample and Out-of-Sample Performance Evaluation

To evaluate the explanatory power of the regression models, this study adopts the adjusted coefficient of determination ($\bar{R}_{adj}^2$) as the in-sample performance measure, following the return predictability literature. The adjusted R^2 is calculated as follows:

$$\bar{R}_{adj}^2 = 1 - \frac{SSE/(n-k-1)}{SST/(n-1)} \quad (16)$$

where SSE and SST denote the sum of squared errors and the total sum of squares, respectively, n is the number of observations, and k is the number of explanatory variables.

To evaluate out-of-sample forecasting performance, this study follows [Huang et al. \(2023\)](#) and employs the mean absolute error (MAE) and root mean squared error (RMSE) as measures of forecast accuracy. In addition, following [Clark and West \(2007\)](#), the adjusted mean squared prediction error ($MSPE_{adj}$) is adopted as a supplementary performance measure. [Clark and West \(2007\)](#) argue that conventional forecast comparison methods may be biased against larger nested models because parameter estimation introduces additional noise into the forecasts. The adjusted MSPE corrects for this bias and therefore provides a more appropriate comparison between a predictive regression model and the benchmark model. Accordingly, the evaluation measures are defined as follows:

$$MAE = \frac{1}{T-H} \sum_{t=H+1}^T |\hat{r}_t - r_t| \quad (17)$$

$$RMSE = \sqrt{\frac{1}{T-H} \sum_{t=H+1}^T (\hat{r}_t - r_t)^2} \quad (18)$$

$$MSPE_{adj} = \frac{1}{T-H} \sum_{t=H+1}^T \left[(r_t - \bar{r}_t)^2 - (r_t - \hat{r}_t)^2 + (\bar{r}_t - \hat{r}_t)^2 \right] \quad (19)$$

where $\hat{r}_t$ denotes the predicted return and $\bar{r}_t = \frac{\sum_{\tau=t-H+1}^t r_{\tau}}{H}$ represents the historical average return estimated over the rolling window. [Clark and West \(2007\)](#) show that the Clark-West

MSFE-adjusted test statistic, defined as $MSPE_{adj}$ divided by its standard error, is asymptotically standard normally distributed. A larger positive value of $MSPE_{adj}$ indicates a greater improvement in forecasting performance relative to the benchmark model. Accordingly, this study employs the Clark–West MSFE-adjusted test to examine whether a predictive regression model significantly outperforms the historical-average benchmark model (M0). A significantly positive Clark–West MSFE-adjusted test statistic indicates superior out-of-sample forecasting performance relative to the benchmark model.

3. Data Description

This study investigates whether VIX and other volatility-related variables can forecast Taiwan stock returns. The empirical analysis focuses on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and eight major Taiwan industry indices, including the cement, food, plastic and chemical, textile, machinery and electronics, paper, building and construction, and finance sectors. The sample period spans from January 2007 to December 2025, comprising 228 monthly observations.

The data used in this study were obtained primarily from the Taiwan Economic Journal (TEJ) database. Daily and monthly stock index returns, together with the monthly earnings-to-price ratio (EP), book-to-market ratio (BM), and turnover ratio (TURN), are collected from TEJ. In addition, the one-year time deposit interest rate published by the Central Bank of Taiwan for First Commercial Bank is adopted as the proxy for the risk-free rate. The VIX variable is measured using the Taiwan Volatility Index reported on the last trading day of each month. Consistent with the construction of the other predictor variables, VIX_t is used to forecast stock returns in month $t + 1$, ensuring that only information available at the end of the month is incorporated into the forecasting model. The raw data are first organized and formatted in Microsoft Excel and subsequently imported into R for variable construction, descriptive statistical analysis, rolling-window estimation, and forecasting analysis.

Table 1 reports the descriptive statistics and correlation matrix for TAIEX excess returns and the explanatory variables. During the sample period, the average monthly excess return on the TAIEX is 0.6026%, with a standard deviation of 5.2455%, indicating that Taiwan's stock market generated positive average returns while exhibiting considerable volatility. The maximum and minimum monthly excess returns are 14.9378% and −19.0565%, respectively, reflecting substantial market fluctuations during periods of market stress.

Table 1. Monthly descriptive statistics for TAIEX returns.

Variable	R_s (%)	LVadj (%)	EP	BM	TURN (%)	SV (%)	VIX
Mean (%)	0.6026	11.1513	0.0574	0.5511	12.2882	16.4245	19.6504
StDev (%)	5.2455	6.8860	0.0178	0.1008	4.5417	8.4616	7.4943
Min (%)	−19.0565	−8.3336	0.0107	0.3125	3.6424	5.9720	8.5700
Median (%)	0.8741	11.1007	0.0582	0.5571	11.8696	14.0918	18.1550
Max (%)	14.9378	29.4656	0.1261	0.9804	28.2207	58.3769	58.9100
<i>Correlation Matrix</i>							
R_s (%)	1.0000						
LVadj (%)	0.2807	1.0000					
EP	0.1347	0.3005	1.0000				
BM	0.1691	0.0365	0.5257	1.0000			
TURN (%)	0.0846	−0.2872	0.2186	0.3711	1.0000		
SV (%)	−0.3699	−0.0633	−0.2109	−0.3729	−0.2424	1.0000	
VIX	−0.2272	0.1234	−0.2439	−0.4358	−0.2618	0.8213	1.0000

There are a total of 228 monthly observations between January 2007 and December 2025. R_s represents the monthly excess return on TAIEX. EP, BM, and TURN stand for the earnings-to-price ratio, book-to-market ratio, and turnover ratio of TAIEX, respectively. LVadj and SV signify the long-term adjusted volatility and short-term volatility of TAIEX, respectively. VIX denotes the Taiwan Options Exchange Volatility index.

Regarding the volatility-related variables, the average values of long-term adjusted volatility (LVadj), short-term volatility (SV), and VIX are 11.1513%, 16.4245%, and 19.6504, respectively. The minimum value of LVadj is -8.3336% , indicating that short-term volatility occasionally exceeds long-term volatility during periods of heightened market uncertainty. Among the traditional financial predictors, the average earnings-to-price ratio (EP) and book-to-market ratio (BM) are 0.0574 and 0.5511, respectively, while the average turnover ratio (TURN) is 12.2882%, indicating relatively active trading in Taiwan's stock market.

The correlation matrix in Table 1 reveals several noteworthy relationships. TAIEX excess returns are positively correlated with LVadj, EP, BM, and TURN, with correlation coefficients of 0.2807, 0.1347, 0.1691, and 0.0846, respectively. In contrast, excess returns are negatively correlated with SV and VIX, with correlation coefficients of -0.3699 and -0.2272 , respectively. The negative association between stock returns and VIX is consistent with the interpretation of VIX as a market fear index. Moreover, LVadj exhibits only a weak negative correlation with SV (-0.0633), consistent with its construction as a long-term volatility measure adjusted for short-term volatility fluctuations. Meanwhile, VIX is positively correlated with LVadj (0.1234), suggesting that periods of elevated implied volatility are generally accompanied by higher long-term volatility.

Table 2 presents the descriptive statistics and correlation matrix for the TAIEX and the eight industry indices. Among all sectors, the machinery and electronics sector exhibits the highest average monthly excess return (0.8872%), followed by the food sector (0.7642%). In contrast, the plastic and chemical sector records the lowest average excess return (0.1999%). Regarding return volatility, the building and construction sector exhibits the largest standard deviation (8.2461%), indicating that this industry is particularly sensitive to economic conditions and policy changes. It also displays the widest return range, with a maximum monthly excess return of 60.5730% and a minimum return of -37.6466% , highlighting its substantial volatility.

The second part of Table 2 reports the correlation matrix among the TAIEX, the industry indices, and the explanatory variables. TAIEX excess returns are strongly positively correlated with all industry indices, with correlation coefficients ranging from 0.5768 for the food sector to 0.9456 for the machinery and electronics sector. Furthermore, all industry indices are positively correlated with one another, with correlation coefficients ranging from 0.4142 to 0.7276, suggesting that Taiwan's industries generally move together under common market conditions.

LVadj is positively correlated with the returns of all industries, with correlation coefficients ranging from 0.0600 for the paper sector to 0.3383 for the machinery and electronics sector. In contrast, SV is negatively correlated with most industry returns, except those of the paper sector, implying that higher short-term volatility is generally associated with lower stock returns. Similarly, VIX is negatively correlated with all industry returns, further supporting its role as a proxy for market fear and uncertainty.

The traditional financial predictors also exhibit meaningful relationships with industry returns. EP and BM generally display negative correlations with industry returns, whereas both variables are positively correlated with TAIEX returns. TURN is positively correlated with all industry returns, with correlation coefficients ranging from 0.1367 for the cement sector to 0.3230 for the paper sector, suggesting that greater trading activity is generally associated with stronger stock performance. Finally, IVOL exhibits both positive and negative correlations across industries, ranging from -0.2121 to 0.3690, indicating that the relationship between idiosyncratic volatility and stock returns varies substantially across sectors.

Table 2. Monthly descriptive statistics for eight sectoral index returns.

	TAIEX	Cement	Food	Plastic	Textiles	Machine	Paper	Building	Finance
Mean (%)	0.6026	0.2644	0.7642	0.1999	0.3091	0.8872	0.3797	0.4813	0.5018
StDev (%)	5.2455	7.0036	5.2633	5.3016	5.8057	5.7159	7.5795	8.2461	5.5399
Min (%)	−19.0565	−29.4154	−20.0425	−17.9600	−21.6654	−17.0232	−23.9761	−37.6466	−21.2759
Median (%)	0.8741	0.4655	0.6679	0.1863	0.2416	1.1111	−0.1429	0.3794	0.7927
Max (%)	14.9378	32.3651	25.6929	17.4395	21.3589	17.0043	34.1096	60.5730	27.1122
<i>Correlation Matrix</i>									
TAIEX	1.0000								
Cement	0.6109	1.0000							
Food	0.5768	0.7038	1.0000						
Plastic	0.7232	0.6011	0.5658	1.0000					
Textiles	0.6801	0.6853	0.6225	0.6926	1.0000				
Machine	0.9456	0.4359	0.4142	0.5359	0.4890	1.0000			
Paper	0.6467	0.6002	0.5301	0.6356	0.7131	0.4851	1.0000		
Building	0.6323	0.5487	0.5149	0.5669	0.6876	0.4609	0.6633	1.0000	
Finance	0.7605	0.5993	0.5414	0.5799	0.6858	0.5948	0.5663	0.7276	1.0000
LVadj	0.2807	0.0382	0.0900	0.2001	0.1668	0.3383	0.0600	0.1027	0.1299
EP	0.1347	−0.1105	−0.1432	−0.1219	−0.1675	−0.2188	−0.1033	−0.1878	−0.1077
BM	0.1691	−0.2626	−0.1108	−0.2745	−0.2450	−0.2168	−0.2115	−0.1640	−0.1937
TURN	0.0846	0.1367	0.2133	0.1649	0.2315	0.2658	0.3230	0.2817	0.2404
SV	−0.3699	−0.0837	−0.0947	−0.2356	−0.1878	−0.3449	0.0091	−0.0858	−0.1522
VIX	−0.2272	−0.1267	−0.0800	−0.1595	−0.1463	−0.2129	−0.1063	−0.0752	−0.2330
IVOL		0.1085	−0.0011	−0.0700	0.0000	−0.2121	0.3690	0.1687	0.0779

The sample consists of 228 monthly observations spanning from January 2007 to December 2025. TAIEX represents the monthly excess return on the TAIEX. EP, BM, and TURN denote the earnings-to-price ratio, book-to-market ratio, and turnover ratio of each index, respectively. LVadj and SV represent the long-term adjusted volatility and short-term volatility of each index, respectively. VIX denotes the Taiwan Options Exchange Volatility Index. IVOL represents the idiosyncratic volatility of each industry sector.

4. In-Sample Regression Results

This section presents the in-sample regression results for the TAIEX and the eight Taiwan industry indices. Section 4.1 reports the regression results for the TAIEX, whereas Section 4.2 presents the corresponding results for the eight industry indices. Because the TAIEX models do not include idiosyncratic volatility (IVOL), 22 regression models are estimated for the TAIEX, compared with 29 regression models for the industry indices.

4.1. In-Sample Regression Results for TAIEX

Table 3 reports the in-sample regression results for TAIEX excess returns. The intercept of the benchmark random walk model (M0) is 0.6026, indicating that the average monthly excess return on the TAIEX during the sample period is approximately 0.6026%.

We first examine the univariate regression models (M1–M6). The results indicate that TAIEX excess returns are significantly positively associated with long-term adjusted volatility (LVadj) and the earnings-to-price ratio (EP), whereas short-term volatility (SV) and VIX exhibit significantly negative coefficients. These findings are broadly consistent with the correlation matrix reported in Table 1. Specifically, the significantly negative coefficient on SV suggests that elevated short-term market volatility is associated with lower future stock returns, while the negative coefficient on VIX further supports its role as a proxy for market fear and uncertainty. Among the traditional financial predictors, EP exhibits a significantly positive relationship with TAIEX returns, indicating that stronger earnings-based valuation signals are associated with higher future returns. BM also has a positive coefficient, although its explanatory power is weaker than that of SV and LVadj. TURN is positively related to TAIEX returns; however, its coefficient is statistically insignificant in the univariate regression model.

Table 3. In-sample regression results for TAIEX return.

Model	Independent Variables	α (%)	β_1	β_2	$\bar{R}_{adj}^2$ (%)
M0	constant	0.6026 *			0.0000
M1	LVadj	−1.7817 ***	0.2138 ***		7.4707
M2	EP	−1.6712	39.5964 **		1.3799
M3	BM	−4.2476 **	8.8008 **		2.4304
M4	TURN	−0.5987	9.776		0.2772
M5	SV	4.3686 ***	−0.2293 ***		13.2991
M6	VIX	3.7272 ***	−0.159 ***		4.7413
M12	LVadj & EP	−2.5746 **	0.2011 ***	16.2693	7.3406
M13	LVadj & BM	−6.2951 ***	0.2094 ***	8.2791 **	9.6098
M14	LVadj & TURN	−4.7775 ***	0.2532 ***	20.8032 ***	10.0627
M15	LVadj & SV	2.0079 **	0.1968 ***	−0.2192 ***	19.6181
M16	LVadj & VIX	1.5963	0.2388 ***	−0.1861 ***	14.0824
M23	EP & BM	−4.3618 **	18.6014	7.0697 *	2.2891
M24	EP & TURN	−2.2799 *	35.8709 *	6.6946	1.2644
M25	EP & SV	3.2395 **	17.4432	−0.2215 ***	13.2532
M26	EP & VIX	2.0213	24.7815	−0.1446 ***	4.9923
M34	BM & TURN	−4.3376 **	8.3107 **	2.9307 ***	2.0528
M35	BM & SV	3.1913	1.8865	−0.2209 ***	13.0280
M36	BM & VIX	0.7258	4.5046	−0.1326 ***	4.9304
M45	TURN & SV	4.4572	−0.6146	−0.2301 ***	12.9165
M46	TURN & VIX	3.2464 **	3.1204	−0.1541 ***	4.3865
M56	SV & VIX	3.0992 ***	−0.3492 ***	0.1648 **	14.7338

There are a total of 228 monthly observations spanning from January 2007 to December 2025. EP, BM, and TURN denote the earnings-to-price ratio, book-to-market ratio, and turnover ratio of the TAIEX, respectively. LVadj and SV represent the long-term adjusted volatility and short-term volatility of the TAIEX, respectively. VIX denotes the Taiwan Options Exchange Volatility Index. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Next, we examine the bivariate regression models to determine whether the explanatory power of individual predictors changes after controlling for additional variables. For the models including LVadj (M12–M16), the coefficient on LVadj remains significantly positive in nearly all specifications, indicating that the explanatory power of long-term adjusted volatility is robust to the inclusion of other predictors. Similarly, EP continues to exhibit positive coefficients in the bivariate models, although its statistical significance weakens after controlling for additional variables. BM also retains positive coefficients, but its statistical significance is generally limited. An interesting finding concerns the turnover ratio (TURN). Although TURN is insignificant in the univariate model, its coefficient becomes significantly positive in several bivariate specifications, particularly in models M14 and M34. This finding suggests that the predictive ability of turnover becomes more apparent after controlling for volatility-related variables.

Because each regression model contains at most two explanatory variables, the variance inflation factor (VIF) can be calculated directly from the correlation coefficient between the two predictors. Specifically, for model M56, the correlation coefficient between SV and VIX is 0.8213, as reported in Table 1. The corresponding VIF is $VIF = 1 \div (1 - 0.8213^2) = 3.0725$ which is the largest among all model specifications. Nevertheless, it remains well below the commonly used threshold values of 5 or 10, suggesting that multicollinearity is not severe. The second-highest correlation is observed between BM and EP (0.5257), corresponding to a VIF of only 1.3819 for model M23. For all remaining bivariate models, the absolute correlation coefficients are below 0.44, implying VIF values below 1.25. Therefore, although the relatively high correlation between SV and VIX may affect the individual coefficient estimates and contribute to the sign reversal

observed in model M56, the overall degree of multicollinearity is modest and does not appear sufficiently severe to invalidate the empirical results.

Among all explanatory variables, SV consistently exhibits the strongest explanatory power for TAIEX returns. Its coefficient remains significantly negative across most bivariate regression models, including M15, M25, M35, M45, and M56. Similarly, VIX retains significantly negative coefficients in most specifications. However, in model M56, the coefficient on VIX becomes significantly positive after controlling for SV. This result is likely attributable to the strong positive correlation between VIX and SV, implying that much of the predictive information contained in VIX is already captured by short-term volatility. Consequently, the remaining variation in VIX after controlling for SV may lead to an unstable coefficient estimate and the observed sign reversal.

Finally, the overall explanatory power of the regression models is evaluated using the adjusted coefficient of determination ($\bar{R}_{adj}^2$). Excluding the benchmark random walk model, the $\bar{R}_{adj}^2$ values range from 0.2772% (M4) to 19.6181% (M15: LVadj and SV). In general, models including SV exhibit substantially stronger explanatory power, with $\bar{R}_{adj}^2$ values ranging from 12.9165% to 19.6181%. Models containing LVadj also demonstrate relatively strong explanatory ability, particularly when combined with SV. Overall, the results indicate that SV is the strongest individual explanatory variable in the univariate regression models, whereas the combination of LVadj and SV provides the greatest explanatory power in the bivariate regression models for TAIEX returns.

4.2. In-Sample Regression Results for the Eight Industry Indices

Table 4 presents the results of 29 in-sample panel data regression models with industry-specific fixed effects for the eight Taiwan industry indices. The table consists of two panels. Panel A reports the common intercept (α) and the regression coefficients β_1 and β_2 , whereas Panel B reports the μ_i values, which represent the industry-specific fixed effects in the panel data regression model. The common intercept in the benchmark model (M0) is 0.4054, indicating that the average monthly excess return across the eight industries is approximately 0.4054% during the sample period.

We first examine the univariate regression models (M1–M7). The results show that LVadj, TURN, and IVOL exhibit significantly positive coefficients, whereas EP, BM, SV, and VIX exhibit significantly negative coefficients. The negative coefficients on SV and VIX are broadly consistent with the TAIEX results, suggesting that higher short-term volatility and greater market uncertainty are associated with lower industry stock returns. However, unlike the TAIEX results, EP and BM display significantly negative coefficients for the industry indices. This finding suggests that the valuation effect differs substantially between aggregate market returns and industry-level returns. Another noteworthy finding is that TURN exhibits significantly positive coefficients in both the univariate and bivariate regressions, in contrast to its statistically insignificant coefficient in the TAIEX regressions. This result implies that trading activity and liquidity play a more important role in explaining sector-level stock returns than aggregate market returns. In addition, IVOL consistently exhibits significantly positive coefficients, indicating that industries with higher idiosyncratic volatility tend to earn higher excess returns during the sample period.

We next examine the bivariate regression models. For models containing LVadj (M12–M17), the coefficient on LVadj remains significantly positive in most specifications, indicating that the explanatory power of long-term adjusted volatility is robust across different model specifications. Similarly, the coefficients on EP and BM remain significantly negative after controlling for additional variables, suggesting that the negative valuation effect at the industry level is relatively stable. The coefficient on TURN remains significantly positive in both the univariate and bivariate regressions, whereas the coefficient on SV

remains significantly negative across all specifications. These findings imply that greater trading activity is generally associated with higher industry returns, whereas elevated short-term volatility tends to reduce expected returns. The coefficients on VIX also remain significantly negative in all specifications, further supporting its role as a market fear index in Taiwan's stock market.

Panel B of Table 4 reports the industry-specific fixed effects (μ_i). Across the 29 regression models, the average values of μ_i for the cement, food, plastic and chemical, textile, machinery and electronics, paper, building and construction, and finance sectors are 0.1021%, −0.4805%, −0.4679%, −0.1039%, −0.2241%, 0.2493%, 0.2331%, and 0.6920%, respectively. These results indicate that the average fixed effects are positive for the cement, paper, building and construction, and finance sectors, but negative for the food, plastic and chemical, textile, and machinery and electronics sectors. Holding all other factors constant, the finance sector exhibits the highest average excess return, whereas the food sector exhibits the lowest average excess return. Furthermore, the fixed-effect intercepts for the machinery and electronics sector are predominantly significantly negative, whereas those for most other industries are not significantly different from zero. This finding suggests that the importance of incorporating industry-specific fixed effects into the panel regression framework may vary across industries.

Finally, we evaluate the explanatory power of the regression models using the adjusted coefficient of determination ($\bar{R}_{adj}^2$). Excluding the benchmark model, the $\bar{R}_{adj}^2$ values range from 1.1122% for M1 (LVadj) to 14.5270% for M45 (TURN and SV). In general, models containing TURN exhibit relatively strong explanatory power, with $\bar{R}_{adj}^2$ values ranging from 5.6266% to 14.5270%. Overall, the results indicate that TURN is the strongest individual explanatory variable in the univariate industry regressions, whereas the combination of TURN and SV provides the greatest explanatory power in the bivariate regression framework for the eight industry indices.

Table 4. In-sample regression results for eight sectoral returns.

Panel A. Common Intercept (α) and the Coefficients β_1 and β_2					
Model	Independent Variables	α (%)	β_1	β_2	$\bar{R}_{adj}^2$ (%)
M0	constant	0.4054 ***			−0.2845
M1	LVadj	−0.7811 ***	0.0785 ***		1.1122
M2	EP	2.7501 ***	−42.3979 ***		1.7801
M3	BM	6.7339 ***	−8.2822 ***		3.9093
M4	TURN	−1.7493 ***	0.2701 ***		5.6266
M5	SV	1.8331 ***	−0.0756 ***		1.2335
M6	VIX	2.7775 ***	−0.1207 ***		1.5286
M7	IVOL	−1.1637 ***	2.3570 ***		1.1621
M12	LVadj & EP	1.5468 ***	0.0752 ***	−41.1861 ***	3.0566
M13	LVadj & BM	5.4119 ***	0.0546 ***	−7.6305 ***	4.5308
M14	LVadj & TURN	−1.8492 ***	0.0109	0.2620 ***	5.5972
M15	LVadj & SV	0.6947 **	0.1035 ***	−0.0981 ***	3.5623
M16	LVadj & VIX	1.9047 ***	0.1110 ***	−0.1616 ***	4.1605
M17	LVadj & IVOL	−1.7937 **	0.0623 ***	1.8903 ***	1.9619
M23	EP & BM	7.4465 ***	−27.7292 ***	−7.2079 ***	4.6920
M24	EP & TURN	0.3593	−36.3585 ***	0.2578 ***	7.1221
M25	EP & SV	3.7201 ***	−37.9547 ***	−0.0644 ***	2.8441
M26	EP & VIX	4.1925 ***	−34.7420 ***	−0.0950 ***	2.8133
M27	EP & IVOL	1.1951 **	−45.6007 ***	2.6019 ***	3.5449
M34	BM & TURN	2.8807 ***	−5.5008 ***	0.2166 ***	7.2158

Table 4. Cont.

Panel A. Common Intercept (α) and the Coefficients β_1 and β_2								
Model	Independent Variables	α (%)			β_1	β_2	$\bar{R}_{adj}^2$ (%)	
M35	BM & SV	8.1847 ***			−8.3011 ***	−0.0761 ***	5.4498	
M36	BM & VIX	7.7603 ***			−7.4382 ***	−0.0851 ***	4.7402	
M37	BM & IVOL	5.1017 ***			−7.7206 ***	1.8072 ***	4.7202	
M45	TURN & SV	0.6204 ***			0.4752 ***	−0.2121 ***	14.5270	
M46	TURN & VIX	1.7052 ***			0.3525 ***	−0.2093 ***	10.6362	
M47	TURN & IVOL	−1.5237 ***			0.2890 ***	−0.5655	5.6319	
M56	SV & VIX	2.7072 ***			−0.0331	−0.0853 ***	1.6157	
M57	SV & IVOL	−0.2938			−0.3053 ***	9.7123 ***	12.1547	
M67	VIX & IVOL	1.6627 ***			−0.2202 ***	4.6084 ***	5.9514	
Panel B. Industry-Specific Fixed Effects of μ_i (%) Values								
Model	Cement	Food	Plastic	Textiles	Machine	Paper	Building	Finance
M0	−0.1410	0.2477	−0.2946	−0.1438	0.3873	−0.1111	0.0386	0.0169
M1	−0.3232	0.3657	0.0794	−0.1534	0.5935	−0.3960	−0.3450	0.1791
M2	−0.2135	−0.2511	−0.2627	−0.7465	0.3730	−0.6972	1.1285	0.6694
M3	1.0456	−2.4832 ***	−1.4396 **	0.5689	−2.0825 ***	2.7029 **	0.8320	0.8560
M4	0.3710	0.6035	−0.3630	0.1089	−1.2654 **	0.0008	−0.2885	0.8327 *
M5	−0.0396	0.1363	−0.4352	−0.1084	0.3765	0.0614	0.0679	−0.0590
M6	−0.1410	0.2477	−0.2946	−0.1438	0.3873	−0.1111	0.0386	0.0169
M7	−0.5610	−0.0766	−0.1097	−0.3408	1.4076 ***	−0.5971	−0.1220	0.3997
M12	−0.3859	−0.1239	0.0946	−0.7385	0.5710	−0.9533	0.7300	0.8060
M13	0.8257	−2.1864 ***	−1.0897	0.5061	−1.7449 ***	2.2835 *	0.5031	0.9026
M14	0.3304	0.6092	−0.3092	0.1000 **	−1.1873 **	−0.0421	−0.3319	0.8308 *
M15	−0.2494	0.2585	0.0158	−0.1105	0.6451	−0.2627	−0.4290	0.1321
M16	−0.3984	0.4144	0.2339	−0.1574	0.6787	−0.5137	−0.5035	0.2460
M17	−0.6223	0.0811	0.1502	−0.3095	1.3691 ***	−0.7268	−0.3944	0.4525
M23	0.8443	−2.4552 ***	−1.2702 *	0.0822	−1.7714 ***	1.9545 *	21.4420	1.1739
M24	0.2856	0.1595	−0.3325	−0.4194	−1.2024 *	−0.5069	0.6610	1.3552 **
M25	−0.1195	−0.2937	−0.3857	−0.6532	0.3654	−0.4889	1.0392	0.5364
M26	−0.2004	−0.1611	−0.2684	−0.6377	0.3756	−0.5914	0.9317	0.5516
M27	−0.6825	−0.6468	−0.0561	−1.0096 *	1.4983 ***	−1.2780 **	1.0335	1.1412 *
M34	1.0577	−1.2808 *	−1.1099	0.5322	−2.5784 ***	1.8475	0.3033	1.2284
M35	1.1503	−2.6015 ***	−1.5836 **	0.6062	−2.0990 ***	2.8828 **	0.8633	0.7815
M36	0.9246	−2.2049 ***	−1.3229 *	0.4962	−1.8308 ***	2.4161 **	0.7512	0.7705
M37	0.6431	−2.5467 ***	−1.2202	0.3695	−1.1327 ***	2.1394 *	0.6551	1.0926
M45	1.0446 **	0.5611	−0.8094 *	0.4004	−2.5510 ***	0.5699	−0.4550	1.2396 ***
M46	0.5272	0.7120	−0.3839	0.1860	−1.7695 ***	0.0349	−0.3883	1.0816 *
M47	0.5076	0.7062	−0.4122	0.1739	−1.6258 ***	0.1252	−0.2728	0.7980 *
M56	−0.0966	0.1989	−0.3562	−0.1283	0.3826	−0.0355	0.0514	−0.0163
M57	−1.4617 ***	−1.5387 ***	−0.1004	−0.8126	4.5481 ***	−1.4170 **	−0.5054	1.2877 ***
M67	−0.9621	−0.3864	0.0669	−0.5291	2.3822 ***	−1.0613 *	−0.2755	0.7653

A: Spanning from January 2007 to December 2025, the sample comprises 1824 observations (8 industry sectors $\times$ 228 months). EP, BM, and TURN denote the earnings-to-price ratio, book-to-market ratio, and turnover ratio, respectively. LVadj and SV represent long-term adjusted volatility and short-term volatility, respectively. VIX denotes the Taiwan Options Exchange Volatility Index, while IVOL represents industry-specific idiosyncratic volatility. The regressions are estimated using a panel data model with industry-specific fixed effects, where α denotes the common intercept. The superscripts **, and *** indicate statistical significance at the 5%, and 1% levels, respectively. B: Spanning from January 2007 to December 2025, the dataset consists of 1824 observations (8 sectors $\times$ 228 months). This table reports the industry-specific intercepts obtained from the regression models presented in the previous table. The reported values are calculated as the difference between the original intercept and the common intercept, α . The reported values represent μ_i in the panel data regression model with industry-specific fixed effects, where μ_i denotes the industry-specific fixed effect that captures the time-invariant characteristics of industry i . The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5. Out-of-Sample Forecast Performance

This study employs both ordinary least squares (OLS) and exponentially weighted least squares (EWLS) to evaluate the out-of-sample forecasting performance of volatility-related variables and traditional financial predictors for the TAIEX and the eight Taiwan industry indices. Forecast performance is evaluated using the mean absolute error (MAE), root mean squared error (RMSE), and adjusted mean squared prediction error ($MSPE_{adj}$). Following the return predictability literature, the forecasting performance of each predictive model is assessed relative to the benchmark random walk model (M0). Because the construction of certain predictor variables (e.g., LVadj) and the rolling-window forecasting procedure require an initial estimation period to estimate the time-varying coefficient (β_t), the out-of-sample evaluation begins in January 2012. Consequently, unlike the in-sample analysis, which covers the period from January 2007 to December 2025 (228 monthly observations), the out-of-sample forecasting performance is evaluated over the period from January 2012 to December 2025, comprising 168 monthly observations.

5.1. Out-of-Sample Forecast Results for TAIEX

Table 5 reports the out-of-sample forecasting performance of the 22 predictive models for TAIEX excess returns. We first examine the six univariate regression models. The results indicate that only LVadj and TURN exhibit meaningful forecasting ability relative to the benchmark random walk model. Specifically, the LVadj model (M1) produces lower RMSE values and positive $MSPE_{adj}$ values under both OLS and EWLS estimation. In particular, the EWLS specification of M1 achieves an $MSPE_{adj}$ value of 27.42%, suggesting that long-term adjusted volatility contains useful predictive information for future TAIEX returns.

Similarly, the TURN model (M4) demonstrates relatively strong forecasting performance. Under EWLS estimation, M4 produces lower MAE and RMSE values than the benchmark model and achieves a positive $MSPE_{adj}$ value of 27.37%. Under OLS estimation, the forecasting improvement is more limited, with MAE and $MSPE_{adj}$ only marginally outperforming the random walk benchmark. Overall, these results suggest that both long-term volatility information and trading activity provide incremental predictive information for TAIEX returns.

Next, we examine the forecasting performance of the 15 bivariate regression models. Considering all three evaluation criteria jointly, only three models (M14, M16, and M24) generally outperform the benchmark model. First, the M14 model, which combines LVadj and TURN, exhibits the strongest overall forecasting performance. Under EWLS estimation, M14 produces the lowest RMSE (4.1867%) and the largest $MSPE_{adj}$ value (58.25%) among all models reported in Table 5. This finding suggests that combining long-term volatility information with liquidity-related variables substantially improves forecasting performance.

Second, the M16 model, which combines LVadj and VIX, also performs well, particularly under EWLS estimation, where both RMSE and $MSPE_{adj}$ outperform the benchmark model. Third, the M24 model, which combines EP and TURN, exhibits favorable forecasting performance under EWLS estimation across all three evaluation criteria. Under OLS estimation, the MAE of M24 is also slightly lower than that of the benchmark model.

Several important findings emerge from Table 5. First, neither OLS nor EWLS consistently outperforms the other across all forecasting models, suggesting that the relative performance of the two estimation methods depends on the selected predictors. Second, bivariate regression models do not necessarily outperform their univariate counterparts. Third, most forecasting models fail to outperform the random walk benchmark, implying that forecasting aggregate stock returns remains highly challenging. Finally, based on the $MSPE_{adj}$ criterion, the M14 model (LVadj and TURN) exhibits the strongest forecasting per-

formance. Among the univariate models, LVadj appears to be the most effective individual predictor of TAIEX returns.

Table 5. The forecast performance for the TAIEX return.

Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	3.0964	3.0984	4.2279	4.2336	0.00	0.00
M1	LVadj	3.1112	3.1118	4.2137	4.2164	0.26	27.42
M2	EP	3.0984	3.1028	4.2441	4.2489	−0.09	−7.71
M3	BM	3.1174	3.1141	4.2490	4.2505	0.39	32.84
M4	TURN	3.0833	3.0872	4.2280	4.2245	0.24	27.37
M5	SV	3.1057	3.1115	4.2411	4.2508	0.03	−3.04
M6	VIX	3.1140	3.1196	4.2301	4.2351	0.15	13.33
M12	LVadj & EP	3.1280	3.1246	4.2497	4.2448	−0.01	6.84
M13	LVadj & BM	3.1156	3.1103	4.2485	4.2476	0.12	13.43
M14	LVadj & TURN	3.0976	3.0971	4.1922	4.1867	0.51 *	58.25 **
M15	LVadj & SV	3.1222	3.1238	4.2350	4.2426	0.19	13.35
M16	LVadj & VIX	3.1239	3.1253	4.2295	4.2277	0.23	25.87
M23	EP & BM	3.1042	3.1164	4.2552	4.2719	0.20	5.58
M24	EP & TURN	3.0956	3.0977	4.2336	4.2275	0.12	20.03
M25	EP & SV	3.1249	3.1278	4.2740	4.2765	−0.25	−25.06
M26	EP & VIX	3.1012	3.1101	4.2402	4.2440	0.10	8.17
M34	BM & TURN	3.1116	3.1042	4.2445	4.2362	0.44	47.95
M35	BM & SV	3.1149	3.1132	4.2629	4.2646	0.31	23.17
M36	BM & VIX	3.0930	3.0994	4.2313	4.2374	0.55	42.08
M45	TURN & SV	3.1042	3.0990	4.2570	4.2506	0.09	12.87
M46	TURN & VIX	3.1003	3.1031	4.2321	4.2369	0.31	25.12
M56	SV & VIX	3.1211	3.1329	4.2646	4.2734	−0.10	−15.12
Average		3.1084	3.1105	4.2402	4.2422	0.17	16.03

There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). The superscripts * and ** indicate the Clark–West MSPE-adjusted test statistic is significantly positive at the 10% and 5% levels, respectively, implying that the predictive model significantly outperforms the benchmark model (M0).

According to Clark and West (2007), a positive MSPE_{adj} indicates that a predictive model outperforms the benchmark random walk model (M0). As reported in Table 5, 17 of the 21 predictive models generate positive MSPE_{adj} values under both OLS and EWLS estimation. However, only the M14 model produces an MSPE_{adj} value that is significantly greater than zero, with statistical significance at the 10% level under OLS estimation and at the 5% level under EWLS estimation. These results suggest that although more than 80% of the predictive models exhibit some degree of forecasting improvement relative to the benchmark model, statistically significant forecasting gains are difficult to achieve. Therefore, while many predictors contain useful predictive information, only the combination of LVadj and TURN provides sufficiently strong and robust forecasting gains to significantly outperform the random walk benchmark.

5.2. Out-of-Sample Forecast Results for the Eight Industry Indices

Table 6 reports the out-of-sample forecasting results for the eight Taiwan industry indices. The results reveal substantial heterogeneity across industries, indicating that the predictive ability of volatility-related variables and traditional financial predictors differs considerably across sectors.

Table 6. A and B: The out-of-sample forecast performance for eight sectoral returns. C–H: The out-of-sample forecast performance for eight sectoral indexes.

Panel A: Cement Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	3.8116	3.8143	5.0098	5.0111	0.00	0.00
M1	LVadj	3.8214	3.8187	5.0218	5.0123	0.12	16.87
M2	EP	3.8388	3.8267	5.0554	5.0519	−0.22	−16.92
M3	BM	3.8597	3.8391	5.0740	5.0431	−0.14	16.88
M4	TURN	3.8606	3.8524	5.0603	5.0512	−0.13	−10.77
M5	SV	3.8245	3.8293	5.0202	5.0182	−0.01	2.15
M6	VIX	3.8448	3.8415	5.0217	5.0173	0.18	18.83
M7	IVOL	3.9196	3.9017	5.1298	5.1085	−0.59	−48.51
M12	LVadj & EP	3.8435	3.8395	5.0456	5.0399	0.12	9.77
M13	LVadj & BM	3.8510	3.8294	5.0562	5.0327	0.24	43.44
M14	LVadj & TURN	3.8749	3.8626	5.0666	5.0515	−0.05	1.65
M15	LVadj & SV	3.8475	3.8418	5.0255	5.0126	0.12	19.28
M16	LVadj & VIX	3.8211	3.8128	5.0026	4.9910	0.53	56.46
M17	LVadj & IVOL	3.8856	3.8754	5.0878	5.0747	−0.05	−7.21
M23	EP & BM	3.8326	3.8130	5.0618	5.0420	0.03	24.85
M24	EP & TURN	3.8623	3.8507	5.0766	5.0661	−0.37	−22.64
M25	EP & SV	3.8751	3.8595	5.0861	5.0725	−0.34	−23.36
M26	EP & VIX	3.8814	3.8509	5.0666	5.0514	−0.09	4.19
M27	EP & IVOL	3.9051	3.8901	5.1275	5.1161	−0.64	−51.28
M34	BM & TURN	3.8700	3.8470	5.0557	5.0249	0.09	37.19
M35	BM & SV	3.8468	3.8337	5.0535	5.0298	0.19	44.65
M36	BM & VIX	3.8659	3.8421	5.0512	5.0200	0.09	38.58
M37	BM & IVOL	3.9121	3.8926	5.1209	5.1016	−0.33	−16.59
M45	TURN & SV	3.8732	3.8698	5.0707	5.0609	−0.18	−13.88
M46	TURN & VIX	3.8430	3.8450	5.0389	5.0369	0.09	9.65
M47	TURN & IVOL	3.9368	3.9164	5.1401	5.1212	−0.84	−73.15
M56	SV & VIX	3.8593	3.8561	5.0625	5.0553	0.03	5.67
M57	SV & IVOL	3.8348	3.8198	5.0755	5.0565	−0.16	0.35
M67	VIX & IVOL	3.8876	3.8825	5.1356	5.1206	−0.76	−62.80
Average		3.8592	3.8481	5.0618	5.0483	−0.11	0.11

Panel B: Food Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	2.5660	2.5676	3.2866	3.2933	0.00	0.00
M1	LVadj	2.6017	2.6011	3.2838	3.2926	0.32	23.76
M2	EP	2.5933	2.5967	3.2831	3.2933	0.24	19.92
M3	BM	2.6398	2.6440	3.2929	3.3004	0.40	34.16
M4	TURN	2.5563	2.5590	3.3048	3.3162	−0.03	−5.12
M5	SV	2.5363	2.5360	3.2644	3.2680	0.26 *	26.66 **
M6	VIX	2.6422	2.6378	3.3067	3.3066	0.12	11.49
M7	IVOL	2.5542	2.5572	3.2910	3.2906	0.11	13.92
M12	LVadj & EP	2.5995	2.6059	3.2873	3.3000	0.34	24.80
M13	LVadj & BM	2.6642	2.6647	3.3202	3.3327	0.01	−3.81
M14	LVadj & TURN	2.5605	2.5633	3.2672	3.2764	0.45 *	38.90 *
M15	LVadj & SV	2.5841	2.5850	3.2484	3.2585	0.54 **	46.68 **
M16	LVadj & VIX	2.6161	2.6119	3.2902	3.2919	0.33	29.30
M17	LVadj & IVOL	2.6003	2.6047	3.2828	3.2852	0.36	31.87
M23	EP & BM	2.6525	2.6555	3.3014	3.3080	0.38	33.10

Table 6. Cont.

Panel B: Food Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M24	EP & TURN	2.5744	2.5770	3.2958	3.3033	0.14	11.72
M25	EP & SV	2.5566	2.5642	3.2598	3.2657	0.41 **	38.80 **
M26	EP & VIX	2.6305	2.6255	3.3014	3.3003	0.25	24.29
M27	EP & IVOL	2.5949	2.6045	3.2965	3.2993	0.19	19.76
M34	BM & TURN	2.6098	2.6235	3.2849	3.2977	0.34	24.70
M35	BM & SV	2.6048	2.6092	3.2512	3.2649	0.62 **	52.04 **
M36	BM & VIX	2.6534	2.6641	3.3042	3.3185	0.30	19.29
M37	BM & IVOL	2.6446	2.6489	3.2897	3.2948	0.39	36.92
M45	TURN & SV	2.5555	2.5562	3.3137	3.3187	−0.03	−2.12
M46	TURN & VIX	2.6106	2.6128	3.3043	3.3067	0.10	10.34
M47	TURN & IVOL	2.5639	2.5640	3.3266	3.3321	−0.07	−6.93
M56	SV & VIX	2.5813	2.5738	3.2464	3.2445	0.54 **	56.69 **
M57	SV & IVOL	2.5648	2.5611	3.2812	3.2847	0.21	21.00
M67	VIX & IVOL	2.6426	2.6374	3.3133	3.3046	0.09	17.36
Average		2.6015	2.6032	3.2895	3.2954	0.25	22.40
Panel C: Plastic Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	3.4282	3.4211	4.6032	4.6010	0.00	0.00
M1	LVadj	3.4172	3.4206	4.6251	4.6347	−0.06	−18.28
M2	EP	3.4511	3.4424	4.6405	4.6309	−0.20	−16.62
M3	BM	3.4703	3.4528	4.6662	4.6438	−0.27	−14.02
M4	TURN	3.4088	3.4047	4.5944	4.5974	0.28	21.72
M5	SV	3.4406	3.4418	4.6255	4.6317	0.01	−10.47
M6	VIX	3.4102	3.4099	4.6040	4.6057	0.35	23.72
M7	IVOL	3.4102	3.4099	4.6040	4.6057	0.02	6.63
M12	LVadj & EP	3.4226	3.4273	4.6387	4.6471	−0.09	−23.61
M13	LVadj & BM	3.4649	3.4631	4.6714	4.6752	−0.27	−36.38
M14	LVadj & TURN	3.4113	3.4135	4.6268	4.6390	0.10	−5.55
M15	LVadj & SV	3.4413	3.4521	4.6328	4.6476	0.03	−18.35
M16	LVadj & VIX	3.4207	3.4267	4.6518	4.6480	−0.10	−16.18
M17	LVadj & IVOL	3.4074	3.4165	4.5966	4.6110	0.32	12.56
M23	EP & BM	3.5312	3.4963	4.7403	4.7022	−0.70	−49.03
M24	EP & TURN	3.4477	3.4467	4.6538	4.6453	−0.17	−17.21
M25	EP & SV	3.4490	3.4547	4.6421	4.6464	−0.04	−17.50
M26	EP & VIX	3.4687	3.4699	4.6436	4.6495	0.05	−13.23
M27	EP & IVOL	3.4760	3.4675	4.6465	4.6417	−0.16	−17.95
M34	BM & TURN	3.4637	3.4476	4.6827	4.6648	−0.34	−25.74
M35	BM & SV	3.5075	3.4925	4.7161	4.7105	−0.65	−69.44
M36	BM & VIX	3.4996	3.4791	4.7215	4.6987	−0.56	−48.45
M37	BM & IVOL	3.5195	3.5002	4.6924	4.6680	−0.46	−30.66
M45	TURN & SV	3.4675	3.4760	4.6644	4.6757	−0.24	−40.13
M46	TURN & VIX	3.4141	3.4172	4.6154	4.6204	0.33	19.03
M47	TURN & IVOL	3.4447	3.4440	4.6168	4.6224	0.15	6.09
M56	SV & VIX	3.4422	3.4502	4.6270	4.6351	0.11	−5.15
M57	SV & IVOL	3.4551	3.4720	4.6632	4.6774	−0.27	−45.80
M67	VIX & IVOL	3.4347	3.4434	4.6434	4.6477	0.06	−8.62
Average		3.4492	3.4469	4.6466	4.6457	−0.10	−15.81

Table 6. Cont.

Panel D: Textiles Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	3.5389	3.5416	4.7398	4.7383	0.00	0.00
M1	LVadj	3.5660	3.5700	4.7647	4.7623	0.05	−0.74
M2	EP	3.5525	3.5400	4.7700	4.7533	−0.01	11.60
M3	BM	3.5421	3.5412	4.7283	4.7276	0.55	51.91
M4	TURN	3.5784	3.5682	4.7883	4.7678	−0.22	−3.72
M5	SV	3.5176	3.5229	4.7380	4.7402	0.27	18.92
M6	VIX	3.5230	3.5242	4.7180	4.7135	0.60	57.58
M7	IVOL	3.5495	3.5515	4.7795	4.7792	−0.13	−14.95
M12	LVadj & EP	3.5824	3.5698	4.7943	4.7812	−0.16	−15.04
M13	LVadj & BM	3.5870	3.5835	4.7616	4.7583	0.25	19.38
M14	LVadj & TURN	3.5975	3.5869	4.7958	4.7731	−0.10	3.99
M15	LVadj & SV	3.5437	3.5441	4.7351	4.7342	0.45	39.05
M16	LVadj & VIX	3.5708	3.5792	4.7570	4.7612	0.27	16.85
M17	LVadj & IVOL	3.5563	3.5585	4.7766	4.7733	0.06	2.25
M23	EP & BM	3.5926	3.5808	4.7859	4.7712	0.17	26.16
M24	EP & TURN	3.5854	3.5704	4.7882	4.7663	0.02	22.13
M25	EP & SV	3.5305	3.5298	4.7712	4.7572	0.08	13.46
M26	EP & VIX	3.5733	3.5551	4.7733	4.7542	0.20	27.70
M27	EP & IVOL	3.5481	3.5418	4.7735	4.7673	0.09	8.64
M34	BM & TURN	3.5544	3.5492	4.7531	4.7449	0.39	42.16
M35	BM & SV	3.5460	3.5430	4.7447	4.7506	0.49	35.99
M36	BM & VIX	3.5824	3.5756	4.7636	4.7579	0.25	24.96
M37	BM & IVOL	3.5488	3.5451	4.7445	4.7561	0.47	29.77
M45	TURN & SV	3.5595	3.5664	4.7639	4.7651	0.18	12.46
M46	TURN & VIX	3.5790	3.5722	4.7719	4.7575	0.25	31.00
M47	TURN & IVOL	3.6127	3.6083	4.8214	4.8154	−0.34	−29.30
M56	SV & VIX	3.5383	3.5416	4.7258	4.7264	0.50	43.03
M57	SV & IVOL	3.4913	3.5040	4.7463	4.7558	0.26	11.39
M67	VIX & IVOL	3.5048	3.5067	4.7361	4.7305	0.53	48.50
Average		3.5561	3.5533	4.7603	4.7543	0.19	18.45
Panel E: Machinery Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	3.9081	3.9132	5.1663	5.1743	0.00	0.00
M1	LVadj	3.9094	3.9107	5.1346	5.1445	0.55	51.08
M2	EP	3.9052	3.9145	5.1935	5.2039	−0.23	−24.30
M3	BM	3.9482	3.9559	5.2159	5.2172	−0.12	−7.05
M4	TURN	3.9190	3.9249	5.1862	5.1867	−0.13	−5.42
M5	SV	3.9241	3.9244	5.1918	5.1941	−0.14	−11.67
M6	VIX	3.9570	3.9650	5.1857	5.1945	−0.02	−5.64
M7	IVOL	3.9246	3.9310	5.2124	5.2165	−0.29	−26.51
M12	LVadj & EP	3.9235	3.9203	5.1792	5.1850	0.17	17.03
M13	LVadj & BM	3.9426	3.9427	5.1459	5.1423	0.70	78.58
M14	LVadj & TURN	3.9200	3.9223	5.1665	5.1777	0.27	22.08
M15	LVadj & SV	3.9205	3.9249	5.1600	5.1743	0.40	29.04
M16	LVadj & VIX	3.9616	3.9605	5.1822	5.1835	0.12	14.87
M17	LVadj & IVOL	3.9254	3.9244	5.2004	5.2010	0.02	5.93
M23	EP & BM	3.9675	3.9644	5.2240	5.2261	0.19	20.11
M24	EP & TURN	3.9393	3.9563	5.2150	5.2249	−0.35	−37.51

Table 6. Cont.

Panel E: Machinery Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M25	EP & SV	3.9375	3.9319	5.2261	5.2180	−0.48	−34.96
M26	EP & VIX	3.9527	3.9666	5.2163	5.2323	−0.31	−43.48
M27	EP & IVOL	3.9185	3.9292	5.2240	5.2300	−0.33	−33.12
M34	BM & TURN	4.0269	4.0253	5.2727	5.2578	−0.54	−34.67
M35	BM & SV	3.9317	3.9206	5.2196	5.2103	0.26	36.05
M36	BM & VIX	3.9871	3.9717	5.2348	5.2219	0.14	18.70
M37	BM & IVOL	3.9254	3.9363	5.2289	5.2378	−0.14	−16.16
M45	TURN & SV	3.9592	3.9540	5.2350	5.2286	−0.55	−43.03
M46	TURN & VIX	3.9648	3.9750	5.2050	5.2205	−0.15	−26.04
M47	TURN & IVOL	3.9441	3.9483	5.2345	5.2313	−0.45	−34.91
M56	SV & VIX	3.9856	3.9849	5.2139	5.2115	−0.23	−16.17
M57	SV & IVOL	3.9470	3.9405	5.2501	5.2513	−0.54	−50.12
M67	VIX & IVOL	3.9489	3.9599	5.2098	5.2237	−0.13	−22.05
Average		3.9434	3.9460	5.2036	5.2069	−0.08	−6.18
Panel F: Paper Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	5.2610	5.2573	7.0893	7.0903	0.00	0.00
M1	LVadj	5.3175	5.3009	7.1514	7.1278	−0.73	−40.48
M2	EP	5.2935	5.2692	7.1120	7.0921	0.29	50.66
M3	BM	5.3800	5.3695	7.2079	7.1964	−1.26	−114.04
M4	TURN	5.3495	5.3366	7.2119	7.2043	−1.44	−135.18
M5	SV	5.2892	5.2858	7.1327	7.1184	−0.48	−27.98
M6	VIX	5.2619	5.2643	7.0957	7.0937	0.46	41.68
M7	IVOL	5.3617	5.3456	7.2208	7.2148	−1.24	−118.14
M12	LVadj & EP	5.3013	5.2771	7.1113	7.0871	0.23	49.02
M13	LVadj & BM	5.4142	5.4030	7.2606	7.2432	−1.86	−174.46
M14	LVadj & TURN	5.3840	5.3705	7.2379	7.2334	−1.77	−174.30
M15	LVadj & SV	5.3271	5.3030	7.1752	7.1304	−0.98	−37.17
M16	LVadj & VIX	5.2892	5.2943	7.1252	7.1278	0.03	−7.71
M17	LVadj & IVOL	5.3827	5.3713	7.2405	7.2357	−1.54	−153.25
M23	EP & BM	5.3692	5.3624	7.2234	7.2075	−0.94	−66.89
M24	EP & TURN	5.4070	5.3599	7.2567	7.2258	−1.43	−110.92
M25	EP & SV	5.3193	5.2935	7.1629	7.1314	−0.34	2.48
M26	EP & VIX	5.2637	5.2637	7.0851	7.0814	0.68	68.26
M27	EP & IVOL	5.3816	5.3529	7.2559	7.2366	−1.37	−122.78
M34	BM & TURN	5.4071	5.3877	7.2578	7.2495	−1.88	−181.03
M35	BM & SV	5.3782	5.3730	7.2164	7.2017	−1.14	−103.11
M36	BM & VIX	5.3228	5.3190	7.1513	7.1484	−0.17	−18.85
M37	BM & IVOL	5.3965	5.3928	7.2662	7.2568	−1.59	−153.92
M45	TURN & SV	5.3477	5.3462	7.2234	7.2279	−1.42	−147.61
M46	TURN & VIX	5.3304	5.3200	7.1928	7.1928	−0.69	−76.87
M47	TURN & IVOL	5.3604	5.3518	7.1772	7.1690	−0.51	−41.66
M56	SV & VIX	5.3047	5.3048	7.1574	7.1589	−0.32	−38.43
M57	SV & IVOL	5.3369	5.3299	7.2272	7.2259	−1.21	−121.68
M67	VIX & IVOL	5.3237	5.3066	7.1847	7.1771	−0.46	−43.68
Average		5.3366	5.3252	7.1823	7.1712	−0.80	−68.90

Table 6. Cont.

Panel G: Building Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	3.8773	3.8669	5.1696	5.1592	0.00	0.00
M1	LVadj	3.8548	3.8563	5.1296	5.1275	0.63 **	54.42 *
M2	EP	3.9739	3.9701	5.2432	5.2399	−0.53	−59.13
M3	BM	3.8750	3.8676	5.2121	5.1911	0.33	32.70
M4	TURN	3.8909	3.8872	5.1788	5.1719	0.19	5.91
M5	SV	3.8637	3.8608	5.1388	5.1282	0.63 **	56.77 **
M6	VIX	3.8872	3.8825	5.1716	5.1668	0.42	28.13
M7	IVOL	3.8466	3.8481	5.1476	5.1443	0.42	30.91
M12	LVadj & EP	3.9029	3.9059	5.1775	5.1766	0.20	8.60
M13	LVadj & BM	3.8715	3.8879	5.1422	5.1554	1.16 *	78.38
M14	LVadj & TURN	3.8585	3.8648	5.1335	5.1379	0.89 **	68.23 *
M15	LVadj & SV	3.8458	3.8444	5.1132	5.1057	0.99 **	88.13 **
M16	LVadj & VIX	3.8729	3.8665	5.1657	5.1602	0.51	37.52
M17	LVadj & IVOL	3.8393	3.8458	5.1306	5.1327	0.72 *	54.97
M23	EP & BM	3.8499	3.8494	5.1973	5.1777	0.63	57.85
M24	EP & TURN	3.9641	3.9529	5.2268	5.2150	−0.20	−24.94
M25	EP & SV	3.9465	3.9385	5.2086	5.1808	−0.01	8.93
M26	EP & VIX	3.9413	3.9323	5.2128	5.1954	−0.07	−3.17
M27	EP & IVOL	3.9383	3.9323	5.2252	5.2094	−0.26	−21.87
M34	BM & TURN	3.8978	3.8875	5.2036	5.1896	0.40	28.41
M35	BM & SV	3.8826	3.8778	5.2232	5.2083	0.62	39.39
M36	BM & VIX	3.8709	3.8597	5.2083	5.1936	0.38	28.07
M37	BM & IVOL	3.8922	3.8934	5.2253	5.2235	0.31	5.33
M45	TURN & SV	3.8666	3.8630	5.1640	5.1481	0.53	48.16
M46	TURN & VIX	3.8938	3.8879	5.1713	5.1707	0.58	36.79
M47	TURN & IVOL	3.8496	3.8472	5.1721	5.1626	0.42	30.47
M56	SV & VIX	3.9139	3.9042	5.2046	5.1999	0.13	−1.88
M57	SV & IVOL	3.9009	3.9074	5.1669	5.1711	0.42	19.48
M67	VIX & IVOL	3.9181	3.9189	5.1800	5.1896	0.43	13.38
Average		3.8906	3.8876	5.1817	5.1743	0.37	25.86

Panel H: Finance Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M0	constant	2.9322	2.9334	3.8740	3.8807	0.00	0.00
M1	LVadj	2.9765	2.9677	3.9114	3.9111	−0.18	−12.77
M2	EP	2.9797	2.9807	3.9168	3.9167	−0.25	−21.12
M3	BM	2.9048	2.8993	3.8608	3.8644	0.69 *	70.06 *
M4	TURN	2.9261	2.9270	3.8897	3.8934	0.13	12.21
M5	SV	2.9259	2.9334	3.8634	3.8708	0.29	25.00
M6	VIX	2.9297	2.9380	3.8604	3.8670	0.26	25.34
M7	IVOL	2.9293	2.9310	3.9067	3.9100	−0.04	−3.23
M12	LVadj & EP	3.0257	3.0118	3.9690	3.9597	−0.54	−44.91
M13	LVadj & BM	2.9203	2.9227	3.8733	3.8858	0.57	48.66
M14	LVadj & TURN	2.9295	2.9265	3.8889	3.8891	0.06	10.18
M15	LVadj & SV	2.9189	2.9228	3.8679	3.8712	0.28	28.57
M16	LVadj & VIX	2.9419	2.9416	3.8705	3.8704	0.24	26.59
M17	LVadj & IVOL	2.9510	2.9557	3.9274	3.9341	−0.19	−20.94
M23	EP & BM	2.9107	2.9138	3.8513	3.8669	0.59 *	47.85 *
M24	EP & TURN	2.9165	2.9208	3.8617	3.8762	0.31	22.29

Table 6. Cont.

Panel H: Finance Sector							
Model	Predictive Variables	MAE (%)		RMSE (%)		MSPE _{adj} (% ²)	
		OLS	EWLS	OLS	EWLS	OLS	EWLS
M25	EP & SV	2.9353	2.9413	3.8833	3.8864	0.18	14.57
M26	EP & VIX	2.9579	2.9614	3.8927	3.8977	0.05	3.98
M27	EP & IVOL	2.9440	2.9460	3.9220	3.9209	−0.14	−12.71
M34	BM & TURN	2.9096	2.8966	3.8764	3.8736	0.47	50.61
M35	BM & SV	2.9227	2.9236	3.8875	3.8954	0.74 *	66.38
M36	BM & VIX	2.9232	2.9203	3.8980	3.8966	0.87 *	81.65 *
M37	BM & IVOL	2.9505	2.9548	3.8904	3.8934	0.32	32.55
M45	TURN & SV	2.9400	2.9360	3.9044	3.9046	0.11	11.00
M46	TURN & VIX	2.9421	2.9325	3.8858	3.8784	0.21	27.92
M47	TURN & IVOL	2.9423	2.9370	3.9289	3.9283	−0.09	−5.87
M56	SV & VIX	2.9768	2.9675	3.9207	3.9118	−0.09	0.15
M57	SV & IVOL	2.9772	2.9818	3.9665	3.9704	−0.36	−36.23
M67	VIX & IVOL	2.9597	2.9623	3.9192	3.9207	−0.04	−2.92
Average		2.9414	2.9412	3.8939	3.8966	0.15	15.34

A: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). However, none of the MSPE_{adj} values are significantly greater than zero according to the Clark–West MSPE-adjusted test at the 10% significance level, indicating that none of the predictive models significantly outperform the benchmark model (M0). B: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). The superscripts *, and ** indicate the Clark–West MSPE-adjusted test statistic is significantly positive at the 10%, and 5%, levels, respectively, implying that the predictive model significantly outperforms the benchmark model (M0). C: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). However, none of the MSPE_{adj} values are significantly greater than zero according to the Clark–West MSPE-adjusted test at the 10% significance level, indicating that none of the predictive models significantly outperform the benchmark model (M0). D: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). However, none of the MSPE_{adj} values are significantly greater than zero according to the Clark–West MSPE-adjusted test at the 10% significance level, indicating that none of the predictive models significantly outperform the benchmark model (M0). E: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). However, none of the MSPE_{adj} values are significantly greater than zero according to the Clark–West MSPE-adjusted test at the 10% significance level, indicating that none of the predictive models significantly outperform the benchmark model (M0). F: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). However, none of the MSPE_{adj} values are significantly greater than zero according to the Clark–West MSPE-adjusted test at the 10% significance level, indicating that none of the predictive models significantly outperform the benchmark model (M0). G: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). The superscripts *, and ** indicate the Clark–West MSPE-adjusted test statistic is significantly positive at the 10%, and 5% levels, respectively, implying that the predictive model significantly outperforms the benchmark model (M0). H: There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. MAE, RMSE, and MSPE_{adj} denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of MSPE_{adj} indicates a greater improvement in forecasting performance relative to the benchmark model (M0). The superscripts * indicate the Clark–West MSPE-adjusted test statistic is significantly positive at the 10% levels, respectively, implying that the predictive model significantly outperforms the benchmark model (M0).

For the cement sector (Panel A), only the M16 model (LVadj and VIX) exhibits consistent forecasting ability. Except for a slightly higher MAE under OLS estimation, all remaining performance measures outperform the benchmark random walk model. Under EWLS estimation, M16 achieves the lowest RMSE (4.9910%) and the largest MSPE_{adj} value (56.46%²), indicating that combining long-term adjusted volatility with implied market volatility substantially improves forecasting performance for cement stocks.

For the food sector (Panel B), forecasting performance is relatively strong compared with that of several other industries. The SV model (M5) under EWLS estimation produces the lowest MAE (2.5360%), whereas the combined SV and VIX model (M56) achieves the lowest RMSE (3.2445%) and the highest MSPE_{adj} value (56.69%²). These findings suggest that short-term volatility and implied market uncertainty play important roles in predicting food-sector returns. Moreover, a relatively large number of forecasting models outperform the benchmark model in this sector, particularly under the RMSE and MSPE_{adj} criteria.

For the plastic and chemical sector (Panel C), models M4, M6, M17, and M46 exhibit relatively strong forecasting performance. Among them, the TURN model (M4) produces the lowest MAE (3.4047%), the lowest RMSE (4.5974%), and the second-highest MSPE_{adj} value (21.72%²). The VIX model (M6) achieves the largest MSPE_{adj} value (23.72%²). The M17 model (LVadj and IVOL) produces the lowest MAE (3.4074%) under OLS estimation, whereas M46 (TURN and VIX) outperforms the benchmark model on all remaining evaluation measures except RMSE and generates the third-largest MSPE_{adj} value (19.03%²) under EWLS estimation. Nevertheless, forecasting performance in this sector is generally weak, as fewer than half of the forecasting models generate positive MSPE_{adj} values.

For the textile sector (Panel D), the VIX model (M6) performs best overall. Under both OLS and EWLS estimation, all three forecasting performance measures outperform the benchmark model. In particular, M6-EWLS achieves the lowest RMSE and the largest MSPE_{adj} value (57.58%²). The combined VIX and IVOL model (M67) also performs well, producing the second-largest MSPE_{adj} value (48.50%²). These results further support the view that VIX serves as an effective market fear index and contains useful predictive information for sectoral stock returns.

For the machinery and electronics sector (Panel E), the forecasting performance of most models is relatively weak. Nevertheless, the LVadj model (M1) and the combined LVadj and BM model (M13) outperform the benchmark model under the RMSE and MSPE_{adj} criteria. In particular, M13-EWLS produces the highest MSPE_{adj} value (78.58%²), whereas M1-OLS generates the lowest RMSE (5.1346%). These findings suggest that long-term volatility and valuation-related variables are particularly informative for Taiwan's technology-intensive machinery and electronics sector.

For the paper sector (Panel F), forecasting performance is generally weak. First, none of the forecasting models produces a lower MAE than the benchmark model (M0). Second, under the RMSE criterion, only M12-EWLS (LVadj and EP) and M26 (EP and VIX) outperform the benchmark model. Finally, although several models generate positive MSPE_{adj} values, none are statistically significant. Overall, M26-EWLS achieves the lowest RMSE (7.0814%) and the largest MSPE_{adj} value (68.26%²), suggesting that combining valuation information with implied volatility improves forecasting performance in the paper sector.

For the building and construction sector (Panel G), the combined LVadj and SV model (M15) exhibits the strongest forecasting performance across all evaluation criteria. Under EWLS estimation, M15 produces the lowest RMSE (5.1057%) and the highest MSPE_{adj} value (88.13%²). In addition, a relatively large number of forecasting models outperform the benchmark model in this sector, suggesting that volatility-related variables contain particularly strong predictive information for building and construction stock returns.

Finally, for the finance sector (Panel H), the BM model (M3), the combined EP and BM model (M23), the combined BM and TURN model (M34), and the combined BM and VIX model (M36) perform relatively well. Under OLS estimation, M3 produces the lowest MAE (2.9048%), whereas M23 achieves the lowest RMSE (3.8513%). Under EWLS estimation, M34 generates the lowest MAE (2.8966%), while M36 achieves the highest $MSPE_{adj}$ value (81.65%²). Although most $MSPE_{adj}$ values in the finance sector are positive, only a small number are statistically significant at the 10% level.

According to Clark and West (2007), a positive $MSPE_{adj}$ indicates that a predictive model outperforms the benchmark model (M0). Excluding the benchmark model, this study evaluates 28 forecasting models for each industry index. Across the eight industries, this yields a total of 448 $MSPE_{adj}$ values (28 models $\times$ 2 estimation methods $\times$ 8 industries). Under OLS estimation, 12, 15, 12, 21, 10, 4, 23, and 18 models generate positive $MSPE_{adj}$ values for the cement, food, plastic and chemical, textile, machinery and electronics, paper, building and construction, and finance sectors, respectively. Under EWLS estimation, the corresponding numbers are 17, 24, 6, 23, 10, 5, 23, and 19. Overall, approximately 54% (242/448) of the forecasting models outperform the benchmark model. However, only 15 and 14 $MSPE_{adj}$ values are statistically significant at the 5% and 10% significance levels, respectively. In other words, only 6.47% (29/448) of the $MSPE_{adj}$ values are significantly positive at the 10% level. Similar to the TAIEX results, although more than half of the forecasting models outperform the benchmark model, only a small proportion achieve statistical significance.

Finally, Table 7 summarizes the best forecasting models according to the different evaluation criteria. Several important conclusions emerge. First, the highest $MSPE_{adj}$ values across industries are generally obtained under EWLS estimation, implying that assigning greater weights to recent observations improves forecasting performance. Second, M15-EWLS (LVadj and SV) and M16-EWLS (LVadj and VIX) exhibit the strongest forecasting performance for the building and construction and cement sectors, respectively. These findings are broadly consistent with Qiu et al. (2023), who argue that long-term adjusted volatility is an effective predictor of stock returns. Third, because stock returns are generally negatively related to volatility, both SV and VIX possess meaningful predictive ability. This result is also consistent with Whaley (2009), who argues that VIX is negatively associated with stock returns and serves as an effective indicator of future market performance.

Table 7. The best forecasting model under different performance criteria.

Sectors	MAE (%)	RMSE (%)	$MSPE_{adj}$ (% ²)
TAIEX	M4-OLS	M14-EWLS	M14-EWLS
Cement	M16-EWLS	M16-EWLS	M16-EWLS
Food	M5-EWLS	M56-EWLS	M56-EWLS
Plastic	M4-EWLS	M4-OLS	M4-EWLS
Textiles	M57-OLS	M6-EWLS	M6-EWLS
Machinery	M2-OLS	M1-OLS	M13-EWLS
Paper	M6-OLS	M26-EWLS	M26-EWLS
Building	M15-EWLS	M15-EWLS	M15-EWLS
Finance	M34-EWLS	M23-OLS	M3-EWLS

There are a total of 168 monthly observations spanning the period from January 2012 to December 2025. Table 7 summarizes the return forecasting results for the TAIEX and the eight industry indices, highlighting the models that exhibit the best performance for each evaluation criterion. MAE, RMSE, and $MSPE_{adj}$ denote the mean absolute error, root mean squared error, and adjusted mean squared prediction error, respectively. A larger positive value of $MSPE_{adj}$ indicates a greater improvement in forecasting performance relative to the benchmark model (M0).

In addition, Figure 1 presents the actual and predicted stock indices for the TAIEX and the eight industry indices based on the best forecasting model selected according

to the $MSPE_{adj}$ criterion. As shown in Figure 1, the predicted indices closely track the movements of the corresponding actual indices throughout the out-of-sample period. Although forecasting performance varies across industries, the figure provides visual evidence that the selected models generally capture the overall dynamics of stock index movements, thereby complementing the statistical results reported in Tables 5–7.

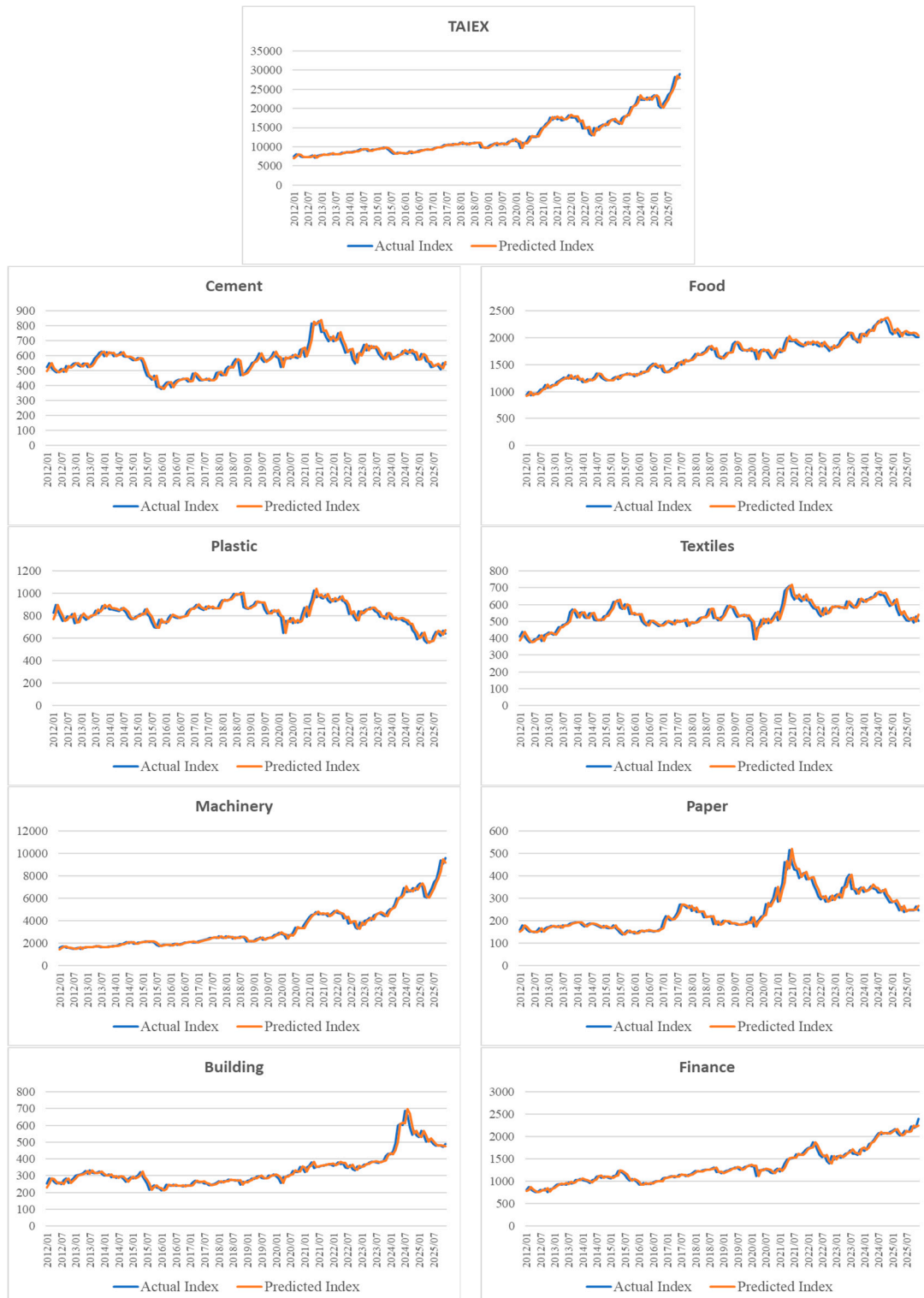


Figure 1. Predicted and actual stock indices using the best forecasting model.

6. Conclusions

This study investigates whether volatility-related variables and traditional financial predictors can explain and forecast Taiwan stock returns. Using the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and eight major Taiwan industry indices, we examine the predictive ability of long-term adjusted volatility (LVadj), short-term volatility (SV), the volatility index (VIX), idiosyncratic volatility (IVOL), the earnings-to-price ratio (EP), the book-to-market ratio (BM), and the turnover ratio (TURN). The sample period spans from January 2007 to December 2025. To evaluate both explanatory power and forecasting performance, this study employs univariate and bivariate predictive regression models estimated using ordinary least squares (OLS) and exponentially weighted least squares (EWLS). Both in-sample and out-of-sample analyses are conducted to provide a comprehensive assessment of the predictive ability of these variables.

Several important findings emerge from the empirical analysis. First, for the in-sample regression analysis of TAIEX returns, short-term volatility (SV) exhibits the strongest explanatory power among all individual predictors, whereas the combination of LVadj and SV yields the highest adjusted R^2 . The coefficients on SV and VIX are generally significantly negative, indicating that elevated market volatility and investor fear are associated with lower future stock returns. In contrast, LVadj consistently exhibits positive coefficients, suggesting that long-term volatility contains useful predictive information for future market performance. Among the traditional financial predictors, EP exhibits a significantly positive relationship with TAIEX returns, whereas TURN becomes more important after controlling for volatility-related variables in the bivariate regression models.

Second, the industry-level regression results reveal substantial heterogeneity across sectors. TURN and IVOL generally exhibit significantly positive coefficients, whereas SV and VIX remain significantly negative across most specifications. Compared with aggregate market returns, the turnover ratio plays a more important role in explaining industry-level stock returns, suggesting that liquidity and trading activity are closely associated with sectoral performance in Taiwan's stock market. Moreover, the explanatory power of volatility-related variables differs considerably across industries, indicating that industry characteristics influence how volatility information is transmitted into future stock returns.

Third, the out-of-sample forecasting results indicate that predicting Taiwan stock returns remains challenging. Although several predictive models generate forecasting improvements relative to the benchmark random walk model, only a limited number achieve statistically significant outperformance according to the Clark–West test. For TAIEX returns, the combination of LVadj and TURN exhibits the strongest forecasting performance, whereas the best-performing models vary substantially across industries. Models incorporating SV and VIX perform relatively well in the food and textile sectors, whereas valuation-related variables, such as EP and BM, appear more informative for the finance sector. These findings suggest that the predictive ability of volatility-related variables is limited and highly industry-specific rather than universally applicable across all sectors.

Fourth, the empirical results provide some evidence that EWLS may improve out-of-sample forecasting performance by assigning greater weights to recent observations. However, the superiority of EWLS over OLS is not universal and depends on the selected predictors and industry characteristics. This finding suggests that the relationship between volatility-related variables and stock returns may evolve over time, although the magnitude of the forecasting gains remains modest.

Overall, this study contributes to the return predictability literature by providing comprehensive evidence from Taiwan's stock market, an important emerging and technology-

oriented economy. By jointly examining multiple volatility-related variables and traditional financial predictors for both aggregate market returns and industry-level returns, this study shows that volatility-related variables may contain useful predictive information under certain model specifications and for specific industries. At the same time, the evidence indicates that stock return predictability remains limited and that forecasting performance varies substantially across sectors. Therefore, volatility-related variables should be viewed as complementary forecasting indicators rather than universally reliable predictors of future stock returns.

Despite these contributions, several limitations provide directions for future research. First, although the out-of-sample evaluation period contains 168 monthly observations, it spans several episodes of extreme market stress, including the 2008 global financial crisis and the COVID-19 pandemic. Because the relationships between volatility-related variables and stock returns may vary across market regimes, future research may investigate the stability of forecasting performance using longer sample periods, crisis versus non-crisis subsample analyses, or regime-switching models to capture potential structural changes in return predictability.

Second, this study focuses on monthly data and employs parsimonious linear forecasting models to mitigate overfitting concerns. Future research may extend the analysis by using higher-frequency data, incorporating additional international financial, macroeconomic, and geopolitical risk variables, or adopting more sophisticated forecasting techniques, such as nonlinear models, machine learning algorithms, and alternative model-selection procedures (e.g., AIC, BIC, and cross-validation), to identify optimal forecasting specifications.

Finally, this study evaluates stock return predictability primarily from a statistical forecasting perspective. Future research may further investigate the economic value of the proposed forecasting models by incorporating them into portfolio management and asset allocation frameworks. Such analyses could examine whether the forecasting gains documented in this study translate into economically meaningful investment benefits, including higher average returns, improved Sharpe ratios, greater Jensen's alpha, higher certainty-equivalent returns, enhanced utility gains, and superior transaction-cost-adjusted portfolio performance. These extensions would provide a more comprehensive assessment of the practical usefulness of volatility-related variables for investment decision-making and risk management.

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